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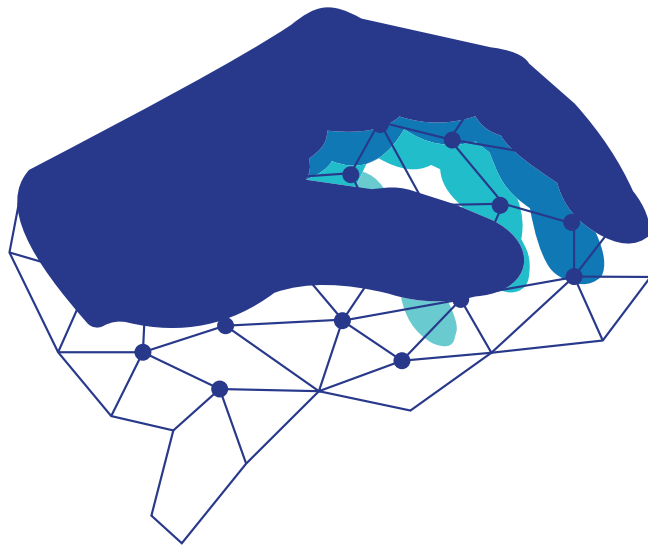
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Integrative Neuroscience and Cognition Center - UMR 8002

**Sensorimotor control of the upper limb and
its functional substitutes using a non-invasive
brain-machine interface on amputees**



Corentin PIOZIN

Thèse de doctorat en Neurosciences et troubles neuronaux
Dirigée par **Florian WASZAK**

Soutenue le 28 Novembre 2022
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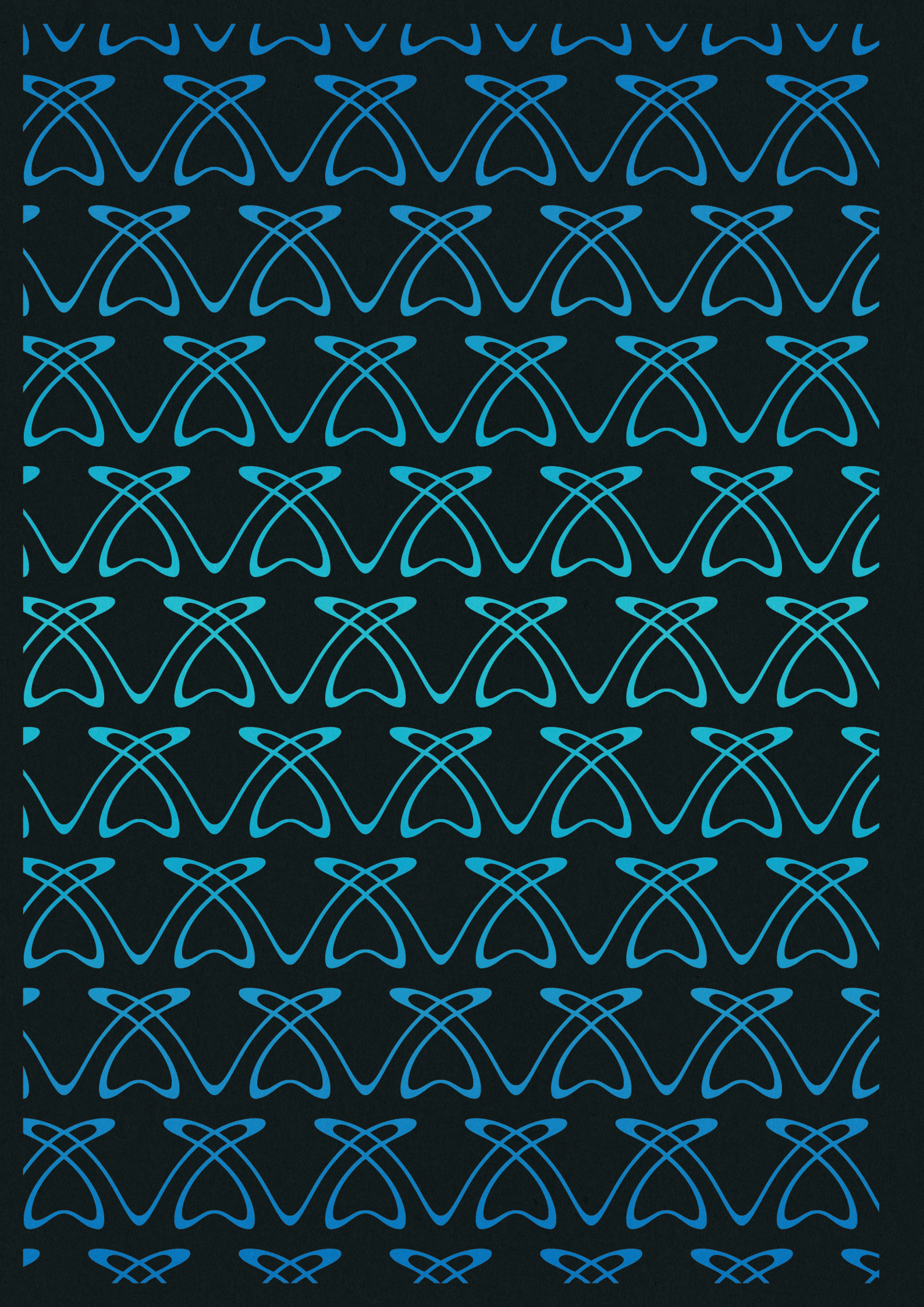
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PhD Thesis in Neuroscience

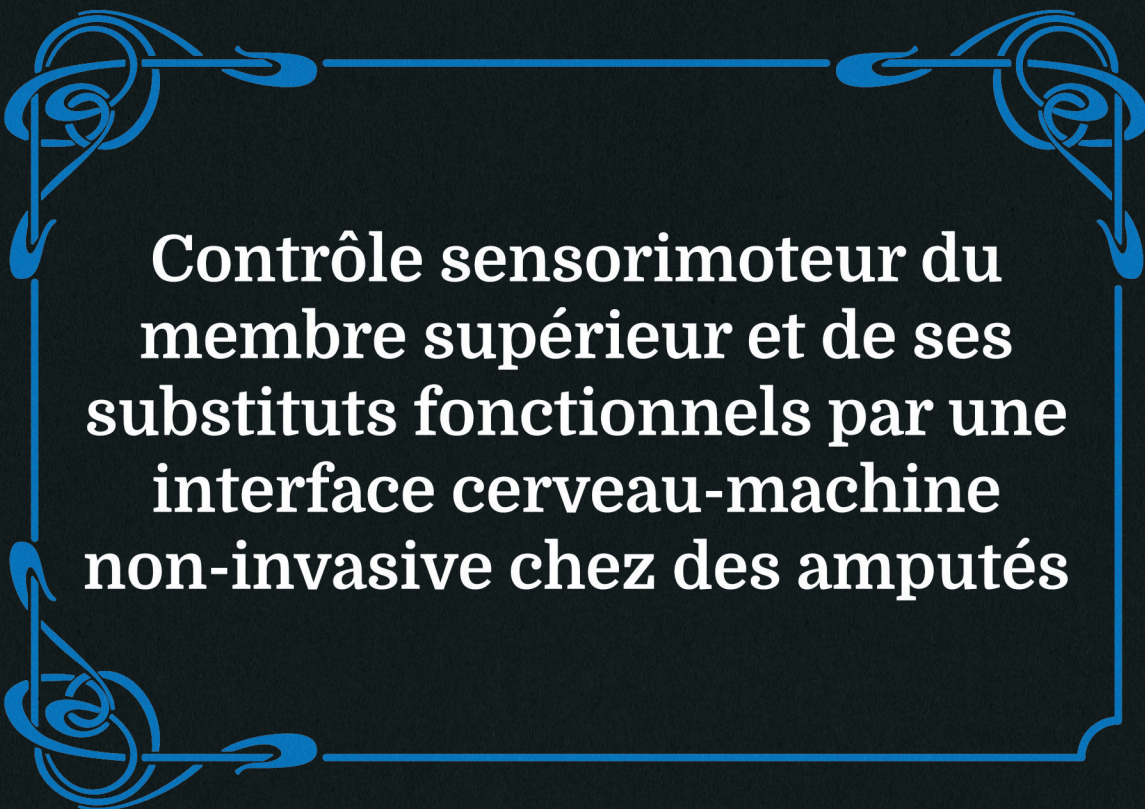
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Frontières de l'Innovation en Recherche et Education



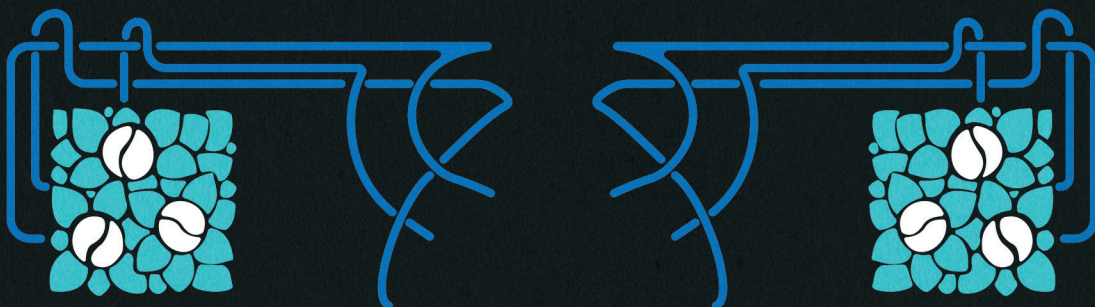
**Contrôle sensorimoteur du
membre supérieur et de ses
substituts fonctionnels par une
interface cerveau-machine
non-invasive chez des amputés**

Supervised

by

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Résumé

Contrôle sensorimoteur du membre supérieur et de ses substituts fonctionnels par une interface cerveau-machine non invasive chez les amputés

Les amputations du membre supérieur ne concernent qu'une relativement faible partie des amputations à travers le monde (entre 20 et 30%) et une partie encore plus restreinte dispose d'accès à des prothèses et aux soins qui doivent leur être accordés. Étonnamment l'accès à ces dispositifs ne garantissent pas l'utilisation des prothèses chez les personnes amputées pour un usage quotidien ; ils soulignent en effet un certain nombre d'inconvénients dont une fatigue à l'utilisation ou le manque de retour sensoriel qui font qu'une partie de ces personnes vont arrêter d'utiliser leurs prothèses. Ces inconvénients que l'on retrouve même dans les prothèses myoélectriques, c'est-à-dire celles qui utilisent l'activité des muscles résiduels au niveau du moignon de l'utilisateur, peuvent s'expliquer par des limitations provenant à la fois du type et de la qualité du signal qui est enregistré au niveau des muscles mais provenant aussi du traitement et du décodage de ce dernier et laissent donc de la place pour une amélioration du contrôle des prothèses.

Ce projet de thèse s'inscrit donc dans cette démarche en s'intéressant au développement d'un système de contrôle basé sur les interfaces cerveau-machine afin d'améliorer à la fois la dextérité et la robustesse des prothèses lors d'activités de la vie quotidienne. Suivant une première partie faisant une revue de littérature particulièrement sur l'amputation, les prothèses et les interfaces cerveau machine, les travaux expérimentaux et de développement entrepris dans le cadre de cette thèse sont présentés dans le manuscrit dans la deuxième partie, où les chapitres représentent les axes de développement de cette interface cerveau-machine ainsi que les expérimentations et les résultats obtenus.

Nous y présentons en parallèle le travail expérimental, effectué à la fois chez des sujets amputés (des utilisateurs de prothèses myoélectriques) et chez des sujets sains via plusieurs sessions d'enregistrements non invasifs de l'activité cérébrale (EEG) de mouvements de prises d'objets, ainsi que les travaux de développement du système; nous nous intéressons plus particulièrement à la problématique de modifications des prothèses myoélectriques pour qu'elles soient utilisables par une interface cerveau-machine. Nous mettons par conséquent l'accent sur les techniques de traitement du signal mais aussi les algorithmes de classification/décodage à utiliser afin de garantir la meilleure performance de contrôle pour la prothèse. Dans un second temps, le travail expérimental s'intéresse aussi au côté « cerveau » de l'interface cerveau-machine où nous avons cherché à savoir quelles régions du cerveau permettent d'obtenir les meilleures performances mais aussi quels systèmes d'enregistrement peuvent être

utilisés pour une telle application. De plus nous présentons dans cette partie comment limiter au maximum le nombre d'électrodes sur le système EEG sans perdre en capacité de contrôle du système.

La seconde partie du manuscrit présente également l'analyse et l'interprétation des résultats obtenus lors de tests de contrôle du système en temps réel et nous y présentons notamment des pistes d'améliorations permettant d'obtenir de meilleures performances. Finalement le dernier chapitre de la deuxième partie se penche sur la question du retour sensoriel utilisé dans le cadre du contrôle de prothèse et présente la partie sensorielle du système qui a été développé au cours de ce travail de thèse. Là encore les résultats liés à l'utilisation du retour sensoriel ont été discutés par la comparaison des résultats provenant des algorithmes de classifications. Dans l'ensemble, ce travail permet d'envisager le développement d'un système commercial permettant le contrôle de prothèse myoélectrique par une interface cerveau-machine non invasive et bénéficiant d'un retour sensoriel.

Mots clés : amputation, contrôle moteur, EEG, exécution motrice, interface cerveau-machine, membre supérieur, prothèse myoélectrique, retour sensoriel

Abstract

Sensorimotor control of the upper limb and its functional substitutes by a non-invasive brain-machine interface on amputees

Upper limb amputations account for a relatively small proportion of amputations worldwide (between 20 and 30%) and an even smaller proportion have access to prostheses and the care they require. Surprisingly, access to these devices does not guarantee that amputees will use their prostheses daily; indeed, they point to several disadvantages, including fatigue and lack of sensory feedback, which cause some amputees to stop using their prostheses. These disadvantages, which are found even in myoelectric prostheses, i.e. those that use the activity of the residual muscles from the user's stump, can be explained by limitations arising both from the type and quality of the signal that is recorded at the muscles' level but also from the processing and decoding of the latter, and therefore leave room for improvement in the control of prostheses.

This thesis project is in line with this approach by focusing on developing a control system based on brain-machine interfaces to improve both the dexterity and the robustness of prostheses during activities of daily living. Following a first part reviewing the literature, particularly on amputation, prostheses, and brain-machine interfaces, the experimental and developmental work undertaken in the framework of this thesis is presented in the manuscript in the second part, where the chapters represent the developmental axes of this brain-machine interface as well as the experiments and results obtained.

In parallel, we present the experimental work, carried out both with amputees (users of myoelectric prostheses) and with healthy subjects via several sessions of non-invasive recordings of brain activity (EEG) of object grasping movements, as well as the development work of the system; we are particularly interested in the problem of modifying myoelectric prostheses so that they can be used by a brain-machine interface. We, therefore, focus on the signal processing techniques and classification/decoding algorithms to be used to ensure the best control performance for the prosthesis. In a second step, the experimental work also focuses on the «brain» side of the brain-machine interface where we have investigated which brain regions provide the best performance and which recording systems can be used for such an application. Furthermore, we present in this part how to limit the number of electrodes on the EEG system to a maximum without losing the ability to control the system.

The second part of the manuscript also presents the analysis and the interpretation of the results obtained during tests of real-time control of the system and we present in particular tracks of improvements allowing to obtain better performances. Finally, the last chapter of the second part deals with the issue of sensory feedback used in the framework of prosthesis control and presents the sensory part of the system that was developed during this thesis. Again the results related to the use of sensory feedback have been discussed by comparing the results from the classification algorithms. Overall, this work allows us to consider the development of a commercial system allowing the control of myoelectric prosthesis by a non-invasive brain-machine interface and benefiting from sensory feedback.

Keywords : amputation, motor control, EEG, motor execution, brain-machine interface, upper limb, myoelectric prosthesis, sensory feedback

Résumé substantiel

Les amputations, qu'elles soient du membre inférieur ou du membre supérieur, ont des implications à la fois au niveau économique et social mais représentent aussi un important problème de santé publique. Bien qu'elles ne constituent qu'environ un quart du nombre total d'amputations, les amputations du membre supérieur peuvent encore bénéficier de plus de recherches scientifiques et technologiques. Néanmoins, certains obstacles freinent ces possibles avancées. D'une part des rapports indiquent que seulement environ 10% des amputés du membre supérieur ont accès aux dispositifs et aux soins associés à leur handicap, et l'on peut ajouter que ces 10% se trouvent majoritairement dans les pays à revenus élevés ce qui limite l'accès aux prothèses pour la plus grande partie des amputés du membre supérieur. D'autre part, une étude s'intéressant à l'abandon de l'utilisation des prothèses a montré que suivant la catégorie d'âge, entre 10 et 50% des personnes amputées interrogées avaient arrêté d'utiliser leurs dispositifs (Biddiss and Chau, 2007). Selon eux ils n'étaient pas adaptés pour une utilisation de la vie quotidienne, que ce soit à cause de la fatigue engendrée par leur utilisation, le poids et le manque de confort associés aux prothèses ou bien parce que ces personnes sont à même de faire autant, voire plus de tâches sans leurs prothèses. De plus, l'absence de sensation pendant le contrôle de la prothèse fait aussi partie des facteurs pesant sur l'abandon des prothèses.

Cette problématique d'abandon est d'autant plus critique en raison des implications psychologiques, fonctionnelles et sociales causées par une amputation. En effet, après un tel traumatisme et la difficile acceptation de la perte du membre par les personnes affectées, vient le processus de reconstruction de ces personnes. Le rôle de la prothèse est ici primordial car elle permet à la fois de retrouver une partie de la fonctionnalité perdue avec le membre original mais elle permet aussi de faire accepter ce corps reconstruit par ses proches et son environnement (Crawford, 2015). L'utilisation de la prothèse va aussi avoir un impact concernant les questions liées aux sensations de membre fantôme qui sont ressenties chez une majorité des personnes amputées. En effet, de nombreuses études ont souligné que l'utilisation de prothèse peut permettre la conservation du schéma corporel (body schema) chez les amputés (Mayer et al., 2008 ; Giummara et al. 2011), voire même de s'approprier totalement le dispositif (la notion d'embodiment) lorsqu'ils l'utilisent (Eskiizmirli and Goffette, 2015). Cela permet possiblement d'empêcher l'observation de « télescopage » du membre fantôme comme c'est le cas pour environ 20% de cette population (Giummara and Moseley, 2011). L'appropriation de la prothèse par les amputés est un phénomène complexe pour lequel ils doivent faire avec moins d'informations sensorielles qu'avec leur membre original. De leurs prothèses, les amputés n'ont majoritairement accès qu'à des informations extéroceptives comme la vision et l'audition (ils se servent notamment des sons provenant de la prothèse afin d'évaluer les mouvements qu'ils sont en train de faire). De plus, ils intègrent aussi les informations provenant de leurs

moignons afin d'avoir à la fois des informations extéroceptives (via la zone de contact entre la prothèse et le moignon) mais aussi proprioceptives (la position du bras dans l'espace). Néanmoins comme nous l'avons vu précédemment, cela n'est pas suffisant pour empêcher l'abandon des prothèses par les utilisateurs. Cela signifie que les avantages apportés par les prothèses actuelles ne s'imposent pas par rapport aux inconvénients.

Si nous nous intéressons aux modèles de prothèses qui sont communément utilisées par les amputés du membre supérieur, les prothèses myoélectriques, nous pouvons en effet noter certaines raisons susceptibles d'engendrer l'arrêt de leur utilisation. Ces prothèses se basent sur l'enregistrement de l'activité musculaire par des électrodes de surfaces (aussi appelées électrodes EMG) sur les muscles du moignon. Pour une majorité des amputés, deux électrodes EMG sont utilisées et placées sur des muscles antagonistes, que ce soit sur le bras ou l'avant-bras, mais cela dépend fortement du niveau d'amputation ainsi que de la qualité des muscles au niveau du moignon. Cette stratégie de contrôle, bien qu'étant la plus répandue actuellement, n'est pas la plus intuitive car elle va faire appel à des muscles qui ne sont pas ou peu impliqués dans les mouvements qui sont effectués sur le membre originel. De plus, l'efficacité des électrodes EMG peut être réduite à la fois par les contraintes qui sont appliquées sur la prothèse pendant l'utilisation mais aussi par la transpiration pouvant apparaître à l'interface entre la prothèse et le moignon de l'utilisateur. Le fait d'utiliser seulement deux électrodes de surfaces afin de contrôler l'ensemble des mouvements de la prothèse amène les amputés à devoir passer dans certains cas d'un mode de contrôle à l'autre via un switch, qui peut être physique avec l'utilisation d'un bouton ou bien via la co-contraction des deux muscles utilisés. Là encore, ce type de contrôle est souvent considéré comme peu intuitif par les utilisateurs et il est notamment rappelé dans la littérature que ces derniers ne sont pas amenés à exploiter toutes les possibilités de leurs prothèses, se contentant de quelques mouvements afin d'effectuer la majorité des tâches quotidiennes (Resnik et al., 2018 ; Simon et al., 2019).

La recherche s'est donc intéressée à ce problème d'intuitivité du contrôle en développant des solutions alternatives pour le contrôle des prothèses. La méthode TMR (Targeted Muscle Reinnervation) cherche à utiliser les nerfs auparavant reliés aux muscles du bras afin d'innover des muscles du torse et utiliser l'activité musculaire résultante afin de contrôler une plus grande variété de mouvements sur les prothèses (Kuiken et al., 2004 ; Miller et al., 2008 ; de Keating and Pierrart, 2019). Néanmoins cette méthode est principalement destinée aux amputations au-dessus du coude car elle peut engendrer une perte de fonctionnalité pour les autres niveaux d'amputations. Pour les amputations en-dessous du coude, un certain nombre d'études dans la littérature s'est intéressé à la technique de « Pattern Recognition » qui consiste en l'utilisation d'un grand nombre d'électrodes de surfaces autour de l'avant-bras. Cette méthode repose sur le constat que l'activité musculaire pour plusieurs répétitions d'un même mouvement est reproductible chez les amputés et que différents mouvements vont entraîner un motif (un "Pattern" en anglais) différent au niveau de l'activité musculaire

(Hudgins et al., 1993). Néanmoins il est difficile de voir les améliorations apportées par cette technique pour le contrôle de prothèse chez les personnes amputées car, soit la performance n'est pas suffisamment satisfaisante, soit le nombre de sujets testés ne permet pas de statuer sur les bénéfices de cette méthode (Jarrassé et al., 2018; Resnik et al., 2018; Kuiken et al., 2016).

Les avancées ont de fait du mal à sortir de l'environnement du laboratoire et peu d'études cherchent à évaluer l'impact de ces méthodes dans un environnement écologique pour les utilisateurs. De plus, ces avancées nécessitent un lien plus important entre les mondes académiques et industriels car ils peuvent s'aider mutuellement tout en incluant les personnes amputées dans les discussions (Farina et al., 2021). Il reste donc une place importante pour le développement d'un système qui pourrait aller plus loin dans le contrôle des prothèses, en offrant à la fois une dextérité plus importante ainsi que plus de robustesse pour une utilisation dans la vie quotidienne.

C'est ici qu'entrent en jeu les interfaces cerveau-machine dont la conceptualisation remonte aux années 70 avec les travaux de Jacques J. Vidal (Vidal, 1973) qui a émis l'hypothèse de pouvoir contrôler un ordinateur en utilisant l'activité cérébrale d'une personne. Il divisait alors une interface cerveau-machine (ICM) en plusieurs parties. La première concerne l'enregistrement de l'activité cérébrale qui peut être fait de façons plus ou moins invasives, respectivement en implantant une matrice d'électrodes au niveau d'une région d'intérêt du cortex (via l'enregistrement des potentiels d'actions au niveau des neurones), en déposant sur le cortex une nappe flexible d'électrodes (par ElectroCorticoGraphie ou ECoG) ou bien en utilisant un ensemble d'électrodes à la surface du scalp afin d'enregistrer l'activité électrique générée par le cerveau (par ElectroEncephaloGraphie ou EEG). De la même manière que pour la technique de Pattern Recognition, ici il est supposé que l'activité cérébrale va être répétable lorsque l'on va demander à un sujet d'effectuer ou d'imaginer une tâche plusieurs fois. On va donc trouver différents types d'interfaces cerveau-machine suivant leurs utilisations : les ICM passives vont reconnaître des changements dans l'activité cérébrale d'un sujet (Pei and Li, 2021), les ICM réactives vont utiliser un stimulus entraînant une réponse spécifique dans l'activité cérébrale (Guger et al., 2012) alors que les ICM actives vont nécessiter que le sujet effectue une tâche (principalement mentale, comme imaginer le mouvement d'un membre) afin de déclencher une action. L'activité cérébrale doit donc se répéter pour la même tâche mais aussi différer suffisamment d'une tâche à l'autre, ce afin d'être efficacement reconnue par l'interface. On peut ensuite trouver différents types de contrôle pour ces ICM, elles peuvent être synchrone ou asynchrone. Une ICM synchrone signifie qu'un stimulus va apparaître chez le sujet pour déclencher la réponse spécifique ou bien pour lui indiquer de réaliser une tâche mentale. Une ICM asynchrone ne se base sur aucun stimulus ou aucune indication pour le contrôle par l'utilisateur, l'activité cérébrale est suivie continuellement et l'action est déclenchée dès que la tâche effectuée par le sujet est détectée par l'interface (généralement un ordinateur). De fait les ICM asynchrones permettent d'avoir un contrôle plus naturel pour les utilisateurs mais elles sont aussi plus à même d'être source d'erreur via une

mauvaise reconnaissance de la tâche par l'interface.

Dans ce projet nous nous sommes intéressés à l'utilisation de méthodes d'enregistrement non-invasif afin de procéder à nos expérimentations, nous parlerons donc des prochaines étapes sous le prisme des signaux EEG. Une fois l'activité cérébrale enregistrée il est nécessaire dans un deuxième temps de procéder à son traitement dans le but de mettre en lumière les motifs obtenus lorsque le sujet a réalisé les différentes tâches. La première étape est de nettoyer le signal obtenu en le filtrant par exemple afin de réduire le bruit ou bien pour minimiser les artefacts pouvant être présents. La deuxième est d'extraire les caractéristiques du signal, c'est-à-dire trouver ce qui va distinguer les tâches les unes des autres. Pour cela il est possible de regarder le signal de différentes façons ce qui va amener à l'utilisation de différentes techniques, que ce soit par la transformation de Fourier, par la décomposition en ondelette, par l'utilisation de la technique de Common Spatial Patterns (CSP) ou en passant par l'utilisation de la géométrie Riemannienne en considérant que la différence entre deux tâches mentales pouvait se ramener à un problème de distance (Barachant et al., 2010). Une fois que la différence entre les motifs d'activité cérébrale est optimisée, le signal traité est envoyé à des algorithmes de classification dont le but est de reconnaître les tâches mentales en leur associant une classe, une étiquette. Il existe une variété importante d'algorithmes qui peuvent être utilisés dans le cas des interfaces cerveau-machine ; ils peuvent essayer de reproduire ce qui se passe à l'échelle du cerveau comme c'est le cas avec les réseaux de neurones artificiels ou bien utiliser des fonctions linéaires ou non-linéaires afin de créer des frontières de décisions entre les classes à séparer. L'obtention d'un modèle qui va servir à classifier l'activité cérébrale se fait en plusieurs étapes. La première consiste à évaluer la capacité de généralisation du modèle notamment en utilisant la procédure de « Cross Validation » ; la base de données est alors divisée en deux parties différentes, un jeu d'entraînement et un jeu de test. Le modèle est créé en utilisant le jeu d'entraînement puis est testé avec le jeu de test. En répétant ce processus avec différents jeux d'entraînement et de test, il est possible d'obtenir une performance du modèle. Si cette performance est suffisamment satisfaisante, le modèle est entraîné sur l'ensemble du jeu de données puis il sera testé lorsque de nouvelles données seront acquises. Pour évaluer la performance du modèle, un certain nombre de métriques peuvent être utilisées, que ce soit par le calcul de « l'Accuracy », de la « Precision » ou du « Recall », ou bien en s'intéressant à la distinction entre les différentes classes en utilisant la géométrie Riemannienne (Lotte and Jeunet, 2018).

La dernière étape est d'utiliser la sortie des algorithmes de décisions afin de contrôler la "machine" dans l'ICM. Il est possible de trouver à la fois des applications médicales et non-médicales. En effet on trouve dans la littérature différents exemples où un utilisateur peut contrôler un jeu vidéo ou bien des instruments de musique via son activité cérébrale (Congedo et al., 2011 ; le travail de l'artiste Molécule avec le projet "Brain Performance Mix"). Les ICM constituent aussi un outil prometteur pour le domaine du neurofeedback avec notamment le développement de compagnon pouvant aider à l'apprentissage (Pillette et al., 2020). Les applications médicales

représentent néanmoins la majeure partie des travaux dans la littérature. Les ICM peuvent en effet être destinées à surveiller les cycles du sommeil (Radhakrishnan et al., 2022) ou bien à offrir un nouveau moyen de communication à des patients atteint de sclérose latérale amyotrophique (Guy et al., 2018). On trouve une variété d'études dans le domaine de la neuroréhabilitation et du neurofeedback dont le but peut être par exemple de restaurer au mieux les fonctions motrices de patients ayant eu des accidents vasculaires cérébraux (Ramos-Murguialday et al., 2013, Herrera Altamira et al., 2022). De plus les ICM peuvent aussi être utilisées afin de contrôler des dispositifs d'assistances pour les personnes en situation de handicap ou à mobilité réduite ; on trouve dans la littérature des études s'intéressant au contrôle de fauteuil roulant (Liu et al., 2019) ou bien d'exosquelette (Benabid et al., 2019) pour des patients para ou tétraplégiques. La partie des dispositifs d'assistance qui nous intéresse ici dans cette thèse concerne les bras robotiques ainsi que les prothèses ; dans ce domaine on peut noter des études montrant le contrôle de bras à plusieurs degrés de libertés via des enregistrements invasifs (Collinger et al., 2013 ; Flesher et al., 2021) ou semi-invasifs (Wang et al., 2013) mais peu d'études s'intéressent à ce type de contrôle en utilisant des signaux enregistrés de façon non-invasives (Abdullah et al., 2019 ; Edelman et al., 2019) et encore moins pour un contrôle de prothèse chez des personnes amputées (Yanagisawa et al., 2020 ; Sattar et al., 2022).

C'est donc ici que l'objet de cette thèse s'insère, à travers la collaboration entre le laboratoire et l'entreprise Ottobock afin de développer un système ICM destiné aux personnes amputées pour le contrôle de leurs prothèses, en offrant des performances de contrôle équivalentes voire supérieures au contrôle myoélectrique mais aussi en ajoutant une dimension supplémentaire via l'utilisation d'un dispositif de retour sensoriel afin de voir en quoi l'ajout de ces informations peut influencer sur l'utilisateur.

La première étape du projet a été de définir les exigences liées au système que nous avons à développer. Pour cela nous avons établi un cahier des charges fonctionnel dont le but est de regrouper les différentes fonctions que doit respecter le système. Plus particulièrement, les fonctions principales du système sont en premier lieu de pouvoir permettre à des amputés de contrôler leurs prothèses en utilisant leur cerveau et en second lieu d'amener un retour sensoriel à ces utilisateurs. Les fonctions de contraintes, qui restreignent le développement du système, vont veiller à ce que la taille du système ne soit pas trop importante afin par exemple de pouvoir s'insérer à la fois dans le matériel de base (par exemple dans l'emboiture de la prothèse) mais aussi via l'utilisation d'un système EEG intégré dans une casquette ou similaire. Le système doit de plus être capable de résister à différents environnements tout en étant utilisable sans fil et possiblement avec un smartphone. Enfin certains aspects comme disposer d'un côté ludique, être esthétique et n'être pas trop cher constituent là encore des critères à respecter pour le système. Le but de ce projet de thèse est donc de commencer le développement de ce système en veillant à respecter au mieux le cahier des charges. Notre approche s'est basée sur trois axes de développement, à savoir :

- L'enregistrement des signaux EEG afin de trouver un système adéquat pour l'enregistrement tout en limitant au plus le nombre d'électrodes utilisées et garantissant une bonne performance de l'ICM.
- L'extraction des caractéristiques et la classification à partir des signaux, ici nous avons testé différentes techniques et algorithmes et les avons comparés afin de sélectionner les méthodes optimales.
- Le retour sensoriel et voir la contribution de ce dernier sur la performance de contrôle de l'ICM.

Afin d'étudier ces différents axes de recherches, nous avons mis au point une expérience réalisée à la fois avec des sujets amputés (grâce à notre partenaire l'Institut Robert Merle d'Aubigné à Valenton) et des sujets sains. Le protocole expérimental consiste en trois sessions d'enregistrement EEG dans lesquelles nous demandons aux sujets de faire une tâche de saisie d'objet dans deux conditions : en Exécution Motrice, où ils vont exécuter le mouvement avec leur prothèse ou leur main dominante, et en Imagerie Motrice, où ils vont devoir imaginer la même séquence de mouvement. Nous avons utilisé trois objets différents, représentant à la fois des objets de la vie quotidienne ou bien des objets que les amputés ont eu l'occasion de manipuler lorsqu'ils ont appris à utiliser leur prothèse myoélectrique. Dans la deuxième session les sujets n'utilisent plus leur prothèse ou leur main mais doivent utiliser une prothèse modifiée dont l'ouverture et la fermeture sont contrôlées par l'ordinateur lors de la séquence en Execution Motrice. Pour la troisième session, les sujets utilisent là encore la prothèse modifiée mais nous ajoutons un bracelet de retour sensoriel qui va vibrer lorsque les sujets vont tenir un objet avec la prothèse. Le but des enregistrements EEG était aussi d'avoir accès à des répétitions de mouvements pour quatre mouvement différents : une fermeture complète de la main, une demi-fermeture, une ouverture complète de la main ainsi qu'un état de repos.

Le but de ce premier travail a été de tester différentes combinaisons de techniques d'extraction des caractéristiques et de comparer la performance obtenue avec différents algorithmes de classification. En particulier nous avons choisi de nous intéresser à trois techniques d'extraction des caractéristiques : la méthode de « Common Spatial Patterns (CSP) », la technique de décomposition en ondelettes (Wavelet Decomposition, WD), et l'orthonormalisation de Gram-Schmidt (GSO). Concernant les algorithmes de classifications, nous avons utilisé un réseau de neurones artificiels ainsi que deux machines à vecteur de support, l'une avec un noyau linéaire et l'autre avec un noyau RBF (Radial Basis Function). De cette étude préliminaire nous avons montré que la combinaison des techniques CSP+WD offrait les meilleures performances devant les combinaisons CSP+WD+GSO, CSP+GSO et WD+GSO. Nous n'avons pas observé de différences significatives entre les trois algorithmes de classification utilisés. De plus, en comparant les résultats des sujets sains avec ceux des sujets amputés, nous avons observé que les deux groupes avaient des performances similaires et ce malgré la différence de système EEG qui a été utilisé entre les deux groupes (système à 64

électrodes avec les sujets sains et système à 16 électrodes avec les sujets amputés). Ces résultats ont permis de conforter notre choix d'utiliser un système portable contenant moins d'électrodes pour le développement de notre système ICM.

Le deuxième travail s'est proposé d'aller plus loin en nous intéressant plus particulièrement à la problématique du nombre d'électrodes. Pour la partie d'extraction des caractéristiques, et basé sur les résultats précédents, nous avons utilisé la combinaison CSP+WD. Concernant la partie classification nous avons réutilisé les trois algorithmes différents et avons ajouté un algorithme d'analyse discriminant linéaire (LDA). Nous nous sommes aussi intéressés à l'application de la géométrie Riemannienne sur nos données comme méthode alternative d'extraction des caractéristiques et de ce fait, nous avons ajouté deux algorithmes utilisés dans ce cadre, l'algorithme de « Minimal Distance to Mean (MDM) » et celui de « Tangent Space SVM (TS-SVM) ». Premièrement nous avons comparé les différents algorithmes de classification entre eux et nous avons montré que les quatre algorithmes utilisés avec notre première méthode ne différaient pas entre eux. Les performances du TS-SVM sont quant à elles supérieures à une partie des algorithmes, et l'inverse pour le MDM. La comparaison entre les deux groupes, sujets sains et sujets amputés, a montré une différence significative pour certains des modèles de classification avec une performance supérieure pour les sujets sains par rapport aux amputés, avec des résultats allant d'environ 60% jusqu'à près de 100%. Majoritairement, nous n'avons pas trouvé de différences significatives entre les conditions d'exécution motrice et d'imagerie motrice pour les deux groupes de sujets ce qui indique que l'exécution ou l'imagination d'un même mouvement n'entraîne pas de différences au niveau des performances des algorithmes. Concernant l'évolution de la performance de classification au cours des trois sessions, nous n'avons pas obtenu de différences entre ces dernières avec une performance relativement stable pour les deux groupes de sujets. Bien que nous aurions souhaité voir une amélioration des performances au cours des sessions, il est intéressant de noter que le fait d'introduire de nouveaux dispositifs aux sujets (la prothèse modifiée puis le dispositif de retour sensoriel) n'a pas causé de baisse de performance. Concernant la métrique de « class distinctiveness » (provenant de Lotte and Jeunet, 2018), bien que nous n'ayons pas d'amélioration significative, nous observons une tendance de hausse de cette valeur au fil des sessions. Enfin, la dernière partie de résultats pour cette étude s'est intéressée à la comparaison des performances de classification en utilisant différentes combinaisons d'électrodes pour le système à 64 électrodes. Nous avons ainsi testé plusieurs combinaisons allant de 64 électrodes jusqu'à 2 électrodes en nous concentrant sur différentes régions du cortex. Nous avons ensuite observé la différence de performance entre la combinaison originale de 64 électrodes et les autres avec nos deux méthodes d'extractions des caractéristiques. Cela nous a permis de mettre en évidence que retirer la moitié des électrodes sur le casque engendrait une perte d'environ 1 ou 3% suivant la méthode de traitement. De même, en retirant le $\frac{3}{4}$ des électrodes pour se concentrer sur une zone du cortex moteur nous avons obtenu une perte entre 3 et 5%. Il est donc intéressant et crucial pour ce projet de définir un seuil de perte acceptable pour le système d'ICM

nous permettant de limiter au mieux le nombre d'électrodes.

En parallèle de ces expériences, nous nous sommes intéressés aux modifications du matériel de base afin de l'adapter pour une utilisation avec une interface cerveau-machine. Il nous a donc fallu remplacer le système myoélectrique classique par un système contrôlant l'ouverture et la fermeture de la prothèse suivant les décisions prises par les algorithmes de classification. Un autre challenge fut de développer des dispositifs et emboitures permettant d'utiliser cette prothèse modifiée à la fois par les sujets amputés, en venant greffer cette emboiture par-dessus leur emboiture actuelle, mais aussi par les sujets sains, en développant un système qui leur permet de tenir la prothèse lors des expériences. Pour ces différents challenges nous avons conçu et imprimé en 3D différents dispositifs qui ont été utilisés avec succès par les sujets lors des expériences. Lors de la deuxième et de la troisième session nous avons aussi procédé à des tests de contrôle en temps réel, en utilisant les paramètres et algorithmes entraînés avec les données d'enregistrement et en répétant plusieurs fois la séquence de mouvements. Ici le sujet doit contrôler l'ICM lors de deux phases, lorsque ce dernier attrape l'objet et lorsqu'il doit le relâcher. Lors de ces tests l'activité cérébrale est enregistrée et traitée en temps réel par l'interface et la sortie des algorithmes de classification est envoyée directement à la prothèse qui effectue un mouvement correct ou non. Nous présentons ici les résultats obtenus avec les données issues de ces tests en temps réel et nous montrons que les résultats sont biaisés par rapport à l'un des mouvements, les sujets présentant soit des bonnes performances lors de la prise de l'objet soit des bonnes performances lorsqu'ils le relâchent. Nous avons donc cherché à trouver différentes explications pour ces résultats et nous avons trouvé l'application de différentes méthodes qui permettent d'améliorer légèrement les résultats de classification, que ce soit en utilisant la géométrie Riemannienne ou en utilisant des méthodes de mises à jour des paramètres. Ensuite, afin d'apporter plus d'éléments pour la mise en place d'un système utilisable dans la vie quotidienne, nous nous sommes intéressés aux résultats en appliquant le concept d'automate avec un nombre fini d'états (finite state machine) à notre système. Il permet de définir les différents états que peut prendre le système (ici la prothèse) suivant l'état dans lequel il se trouve à un instant t . En appliquant cette stratégie de contrôle il nous a donc été possible de grandement améliorer les performances de contrôle lors des deux phases d'intérêt de la séquence. Enfin nous avons commencé à étudier la possibilité d'implémenter un brain-switch au sein de notre système, dont le but serait de pouvoir activer et désactiver l'ICM et notamment la classification de l'activité cérébrale.

Dans la dernière partie du manuscrit nous avons étudié le troisième axe de développement du projet concernant le retour sensoriel et plus particulièrement sur son utilisation dans le contrôle des prothèses. Ce retour sensoriel, du moins son absence, constitue l'un des principaux facteurs d'abandon des prothèses chez les personnes amputées. En effet, elles préfèrent parfois utiliser dans certains cas leurs moignons afin de faire des tâches normalement bi-manuelles. Bien qu'une partie des prothèses myoélectriques actuelles embarquent une série de capteurs de différentes sortes,

les informations qu'ils récupèrent sont peu, voire pas, accessibles aux utilisateurs. De plus, de telles informations doivent ensuite être encodées afin que la personne amputée puisse comprendre l'information sensorielle qui lui est envoyée. En effet, suite à l'amputation, l'envoi de l'information tactile ou proprioceptive du système nerveux périphérique (SNP) au système nerveux central (SNC) est rendu impossible. La recherche est donc dédiée à trouver un moyen optimal de provoquer des sensations chez les utilisateurs. Dans l'idéal ce retour sensoriel perçu doit correspondre à la fois dans la façon dont celui est transmis (modality-matched), c'est-à-dire qu'une pression sur un objet ou une surface doit faire ressentir une sensation de pression, mais il doit aussi correspondre de façon somatotopique (somatotopically-matched), c'est-à-dire qu'une pression sur l'index de la prothèse doit provoquer une sensation sur le même doigt dans le membre fantôme de l'amputé. Comme pour l'enregistrement de l'activité corticale il est possible d'encoder l'information sensorielle de façon invasive ou non-invasive.

Dans les techniques invasives, il est possible de faire la distinction entre des méthodes stimulant le SNP ou bien stimulant le SNC. Les premières vont se baser sur des électrodes qui vont venir se placer soit à la surface des nerfs soit s'implanter à l'intérieur de ces derniers. Différentes études ont montré que ce type d'interface permettait de faire ressentir des sensations à la fois tactiles et proprioceptives (Tan et al., 2014 ; Wendelken et al., 2017, Zollo et al., 2019) avec pour les sujets la possibilité de moduler plus finement la force lors de la prise d'objet (Raspopovic et al., 2014) ou bien de pouvoir reconnaître différentes formes d'objets et surfaces (Oddo et al., 2016, Valle et al., 2020). Les méthodes stimulant le SNC vont se baser sur l'utilisation de matrices d'électrodes (comme pour l'enregistrement des potentiels d'actions dans le cortex) permettant une stimulation du cortex somatosensoriel. Destiné plus précisément à des patients tétraplégiques, ce type de stimulation permet notamment de faire ressentir dans les doigts et la paume de la main tout en augmentant le contrôle d'un bras robotique par rapport à un seul retour visuel (Flesher et al., 2016 ; Flesher et al., 2021). Il est notamment possible de modifier les sensations évoquées en modulant la fréquence de stimulation (Hughes et al., 2020). La littérature montre qu'il est possible de faire ressentir à la fois des sensations tactiles mais aussi proprioceptives (Armenta Salas et al., 2018).

Dans les techniques non-invasives, nous avons fait le choix de présenter trois techniques différentes. La première se base sur une stimulation électro-tactile où les niveaux superficiels de la peau vont être stimulés grâce à un courant électrique dont il est possible de modifier les paramètres. La largeur et l'amplitude de l'impulsion permettent de moduler l'intensité perçue alors que la fréquence permet de moduler les sensations perçues. Les électrodes peuvent être placées sur le moignon du sujet de façon à correspondre à la cartographie du membre fantôme afin d'améliorer les sensations (Zhang et al., 2015). De plus, certaines études montrent des résultats prometteurs pour le contrôle de prothèses chez des sujets amputés, avec une amélioration des résultats avec l'apprentissage de ce retour sensoriel (Strbac et al., 2017 ; Chang et

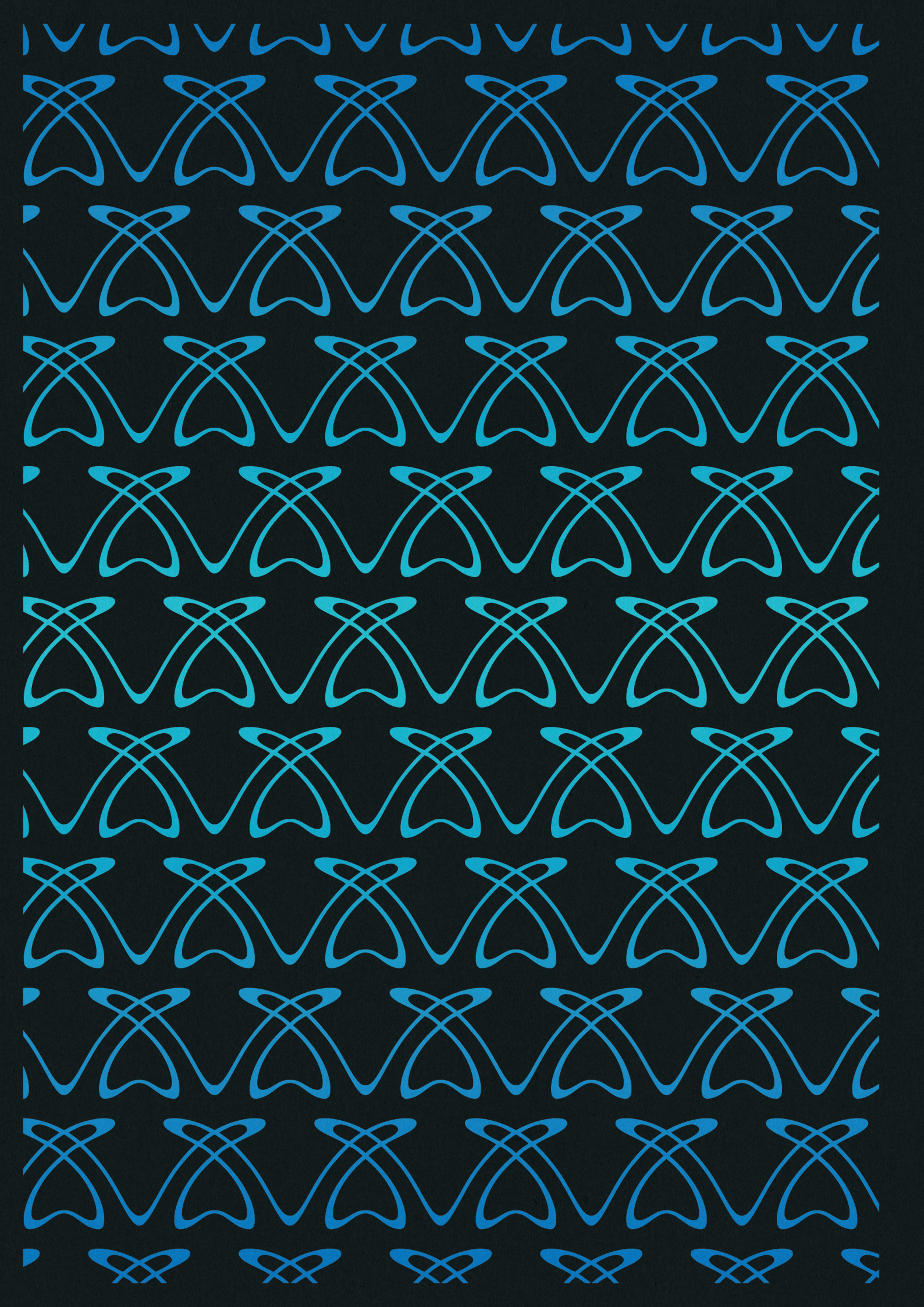
al., 2018). La deuxième technique non-invasive utilise une stimulation mécano-tactile avec différents dispositifs qui vont faire pression sur la peau via des poches pouvant se remplir ou bien un servomoteur relié à un actionneur. Ce type de retour sensoriel peut donc être « modality-matched » car une pression avec la prothèse va déclencher une pression sur la peau. Il peut aussi correspondre de façon somatotopique mais peu d'études ont montré de résultats avec des sujets amputés. On trouve en effet dans la littérature des résultats chez des sujets non amputés montrant que ce retour sensoriel pouvait permettre d'ajuster le niveau de force appliqué en contrôlant une prothèse myoélectrique (Borkowska et al., 2022). Une autre étude, toujours chez des sujets non amputés, a notamment montré que ce type de retour sensoriel pourrait moduler certains aspects de l'appropriation (embodiment) de la prothèse (Shehata et al., 2020). La troisième technique non-invasive que nous présentons est celle que nous avons choisie pendant ce travail de thèse et se base sur la stimulation de la peau via des vibrations grâce à de petits moteurs vibreurs. Ce retour sensoriel vibro-tactile a été utilisé chez des sujets amputés leur permettant de discriminer à la fois des niveaux d'ouverture d'une prothèse mais aussi la force appliquée par cette dernière lors de prises d'objets (Witteveen et al., 2015). L'utilisation de ce type de feedback permet aussi à des sujets sains de pouvoir différencier des objets plus ou moins rigides tout en réduisant la charge cognitive nécessaire comparé à une condition sans retour sensoriel. Enfin, le retour vibro-tactile présente aussi un intérêt dans l'exécution de tâches complexes pour des sujets amputés et, même si ce retour n'améliore pas de façon significative le contrôle de la prothèse, les sujets le considèrent néanmoins comme important lors des tâches (Markovic et al., 2018).

Dans la suite de cette partie, nous présentons les différentes itérations dans la conception du dispositif de retour sensoriel en expliquant les choix nous amenant à la version qui a été utilisée lors des expérimentations. Ce dispositif est constitué de deux parties, la première va se situer au niveau de la prothèse et est composé de capteurs de force FSR (Force-Sensing Resistors) connectés à un microcontrôleur programmé via Arduino. Les capteurs de forces permettent d'accéder à la pression appliquée sur un objet par la prothèse (plus précisément la pression appliquée par le pouce et la combinaison de l'index et du majeur). Cette information est envoyée à la deuxième partie du dispositif qui est située sur le bras du sujet. Elle se compose là encore d'un microcontrôleur, qui va communiquer en bluetooth avec le premier, et de plusieurs moteurs vibreurs dont la fréquence de vibration va être liée aux informations de forces enregistrées par les capteurs des doigts. Nous évoquons aussi les différentes améliorations que nous allons faire par la suite sur ce prototype afin d'augmenter le nombre de moteurs pouvant être utilisés, la qualité du retour sensoriel mais aussi l'aspect esthétique du dispositif. Enfin nous présentons les résultats préliminaires obtenus lors des sessions avec les sujets amputés et les sujets sains mais cette fois-ci sous le prisme du retour sensoriel. Chez les sujets sains, l'ajout du retour sensoriel ne semble pas avoir d'impact sur les performances de classifications, ce qui peut s'expliquer par une période d'apprentissage possiblement trop courte pour les sujets mais aussi par la dominance du retour visuel lors de l'exécution de la tâche. Chez les

sujets amputés on observe une amélioration de la performance entre la deuxième et la troisième session qui pourrait indiquer un effet positif du retour vibro-tactile par rapport au simple retour visuel lors des mouvements avec la prothèse modifiée. Néanmoins ces résultats sont encore à confirmer en faisant passer l'expérience à plus de sujets amputés. Nous tenons cependant à souligner que les patients notaient que le retour sensoriel ajoutait une autre dimension pendant l'exécution des mouvements et qu'il était facile pour eux de faire le lien entre les différentes vibrations et les mouvements effectués avec les objets. Enfin, en regardant les résultats obtenus lors des tests en temps lors de la deuxième et troisième session chez les sujets sains, nous observons une amélioration des performances dans la troisième session, pour certains concernant deux des objets (le cube et le verre) dans la phase de prise d'objet et seulement pour un objet (le verre) lorsque l'objet est relâché. Chez le sujet amputé, on observe une amélioration seulement pour le verre dans les deux phases. Ces résultats préliminaires ne nous permettent donc pas de statuer sur un bénéfice du retour sensoriel dans les performances de contrôle mais les conclusions seront possiblement amenées à changer après avoir fait passer l'expérience à plus de sujets amputés.

Ensemble, les résultats provenant des différentes parties de ce projet de thèse supportent l'intérêt qui réside dans le développement d'une interface cerveau-machine permettant le contrôle de prothèse en utilisant les signaux EEG. Plus de résultats sont néanmoins nécessaires afin d'évaluer précisément les performances de contrôle ainsi que l'intérêt du retour sensoriel dans ce dernier.

L'établissement du cahier des charges associé à cette interface cerveau-machine a permis de guider nos travaux de recherches et nous avons donc présenté les challenges associés à la fois à la modification du matériel existant mais aussi à la conception de nouveaux dispositifs pouvant s'intégrer efficacement et être utilisables facilement. De plus, nous avons d'une part montré les différentes méthodes et algorithmes qui peuvent être utilisés afin de différencier plusieurs mouvements réalisables sur une prothèse myoélectrique. D'autre part, nous nous sommes intéressés à la problématique de réduction du nombre d'électrodes sur le système EEG afin de respecter les critères imposés pour le développement d'un système utilisable dans la vie quotidienne. Nous avons ensuite eu l'occasion d'évaluer notre système lors de tests en temps réel à la fois avec des sujets amputés et des sujets sains. En optimisant la stratégie de contrôle, nous sommes ainsi parvenus à grandement améliorer les performances tout en simplifiant le schéma de décision des algorithmes de classification. Enfin, la suite de ce projet sera consacrée à l'obtention de résultats plus approfondis permettant d'apporter une réponse quant à l'intérêt du retour sensoriel ; mais nous nous intéresserons aussi à la miniaturisation du système afin qu'il soit utilisable par les sujets amputés en dehors du laboratoire. Nous avons en effet encore à faire que ce soit du côté de l'interface en elle-même, qui devra être intégrée directement dans un smartphone, que du côté de la prothèse où il nous faudra là aussi intégrer les différents composants dans l'emboîture ou bien dans le revêtement en silicone.



**“ ‘Cause lately I’ve been
Far more uninclined
To look you in the eye
And tell you we’ll be fine ”**

Evening Light - Vansire & Floor Cry

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Conclusion

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List of abbreviations

ADL : Activities of Daily Living.
ALS : Amyotrophic Lateral Sclerosis.
ANN : Artificial Neural Network.
BCI/BMI : Brain-Computer Interface/Brain-Machine Interface.
BSS : Blind Source Separation.
CAD : Computer-Assisted Design.
CNS : Central Nervous System.
CSP : Common Spatial Patterns.
CV : Cross Validation.
DAC : Digital Analog Converter.
DBS : Deep Brain Stimulation.
DOF : Degree-of-freedom.
ECoG: Electrocorticography.
EEG: Electroencephalography.
EMG : Electromyography.
EOG : ElectroOculoGraphy.
ERD/ERS : Event-Related Desynchronization/Synchronization.
ERP: Event-Related Potentials.
FE : Feature Extraction.
FFT: Fast Fourier Transform.
FINE : Flat Interface Nerve Electrode.
FMA : Floating Microelectrode Array.
FP/FN : False Positive / False Negative.
FSM : Finite-State Machine.
FSR : Force-Sensing Resistor.
GSO : Gram-Schmidt Orthonormalization.
HIC : High-Income Country.
I2C : Inter Integrated Circuit.
ICA: Independent Component Analysis.
ICMS : Intracortical Microstimulation.
LDA : Linear Discriminant Analysis.
LFP : Local Field Potential.
LIFE : Longitudinal Intrafascicular Electrode.
LMIC : Low and Middle-Income Country.
LPF/HPF : Lowpass Filter/ Highpass Filter.
MDM : Minimal Distance to Mean.
ME/MI : Motor Execution / Motor Imagery.
MEA : Microelectrode Array.
MT : Mirror Therapy.
MUAP : Motor Unit Action Potential.

(f)NIRS : (functional) Near Infrared Spectroscopy.
PCA : Principal Component Analysis.
PCB : Printed Circuit Board.
PG : Pathologic Grief.
PLP : Phantom Limb Pain.
PNS : Peripheral Nervous System.
PR : Pattern Recognition.
PTSD : Post-Traumatic Stress Disorder.
PWM : Pulse Width Modulation.
RBF : Radial Basis Function.
RCT : Randomized Controlled Trial.
RDA : Remote Data Access.
RHI : Rubber Hand Illusion.
SCL/SDA : Serial Clock / Serial Data.
SELINE : Self-Opening Intrafascicular Neural Interface.
SNR : Signal-to-Noise Ratio.
SPD : Symmetric Positive-Definite.
SSVEP : Steady-State Visually Evoked Potential.
STFT : Short-Time Fourier Transform.
(TS)SVM : (Tangent Space) Support Vector Machine.
TENS : Transcutaneous Electrical Nerve Stimulation.
TIME : Transverse Intrafascicle Multichannel Electrode.
TMR : Targeted Muscle Reinnervation.
TP/TN : True Positive/True Negative.
TULA : Traumatic Upper-Limb Amputation.
(r)TMS : (repetitive) Transcranial Magnetic Stimulation.
UESA : Utah Slanted Electrode Array.
VC/VO : Voluntary-Closing / Voluntary-Opening.
VR : Virtual Reality.
WD : Wavelet Decomposition.

Introduction

1. Context

Growing up surrounded by science-fiction, either from books, movies or even video games probably shaped careers for a good portion of researchers throughout the world. What a thrilling and exciting moment to see things that you would not think to be possible in the real world: the human-like androids from Blade Runner, the time travels in Back to The Future or the lightsabers from the Star Wars saga. While some of these technologies have not (yet) seen the light of day, seeing some finally being made are probably the most exhilarating moments in a young researcher's life. This quest driven by curiosity led me to be interested in the topic of prosthetics but the realm of possibility stretched when I encountered neuroscience and the stimulating questions raised regarding upper-limb prostheses.

Coming together on a thesis project proved to be a long and winding road but we were all determined that something could be done regarding hand prostheses and it would be worth trying for it. Although upper-limb amputees account for a relatively small part of the total population of amputees (around 20% to 30% of the 65 million people with an amputation, based on the 2020 report from ATScale [1]) the need for progress is still present and although neuroscience will not be able to address all the questions and issues, its promises are sufficient to explore the possibilities. To summarize quickly the roots of the project (before seeing a more thoroughly detailed justification in the following parts of this manuscript), there exist some limitations that lower the level of performance offered on myoelectric prostheses, whether it is the signal recorded on the residual muscles of the user or anatomical issues caused by the prosthesis itself. And by using the original signal from which the muscle contractions are derived, one could be free from those limitations and increase the control of the device, which is exactly where Brain-Machine Interfaces (BMIs) come into play.

BMIs are a subpart of the Artificial Intelligence branch where researchers, developers and all the various people working in this field are trying to build smart machines which could perform tasks as a human would perform them, by breathing human intelligence into the machines. Originating in 1973, Jacques Vidal was the first to put the words "Brain-Computer Interface" on paper [2] and laid the foundation of what are currently around 50 years of research on the subject. A BMI or BCI is a system allowing a user to control different devices (from a computer to various end effectors on robotic arms) through the recording and decoding of the user's brain activity. While Vidal only mentioned the use of ElectroEncephaloGram (EEG) signals, a measure of the electrical activity on the scalp of a person, other techniques exist if one wishes to record the brain activity via more invasive ways yet EEG is probably the most conveniently used technique for BMI research. So far, the use of BCI has been driven by potential promising clinical applications; this thesis project is no exception and therefore explores the development of an EEG-based BMI system dedicated to the control of upper-limb prostheses for amputees.

This PhD project having been realized in the framework of a CIFRE thesis - a collaboration between a company (Otto Bock) and a research laboratory (INCC) - the interdisciplinarity lying behind the project was essential as we did not have, in the laboratory, the pretension to have answers to everything and we had to remain humble in front of what was unknown to us. The great support offered by Otto Bock (financial and technical) throughout those 3 years proved to be both stimulating and challenging, pushing the project further and refocusing our effort on what truly mattered. Moreover, the presence of the Institut Robert Merle d'Aubigné (IRMA) among the partners of the project, a rehabilitation centre located in Valenton close to Paris, has been infinitely beneficial to us for this project. Not only because of the access to a great list of patients with whom we collaborated to develop the system but also because of their undeniable expertise and interest in front of what was, for them, a wholly new world. It is always easy to work on a project while keeping quiet and locking ourselves in the laboratory, but it is also easy to lose track of what is important for the project. Being confronted with the needs of the potential users of the system we worked on during this PhD has been extremely rewarding, broadening and offering new perspectives while pointing out unexpected issues otherwise left unnoticed.

It is possible to adopt two points of view to put into perspective the work done during this project, those points of view will especially cross paths and bump into each other, like the two faces of the same coin. On one hand, we have a more industrial-oriented point of view which would consider the use of BMIs as an alternative solution for the control of prostheses. On the other hand, the control of prostheses is only a potential application of the field of BMIs. As a PhD student doing a CIFRE, it is difficult to stand a position as I had a foot in each of those points of view, yet as the work was mainly conducted in the laboratory environment, the second point of view seemed to be the logical choice to which we would lean towards. Nonetheless, considering the outcome of the project we had to also keep our objectives brought from the first point of view.

2. Thesis objectives and challenges

As this project was carried out through a collaboration between a company and a research laboratory, the outcomes were multiple. On one hand, this project aimed at investigating relevant and efficient EEG processing and decoding techniques for the control of hand prostheses, on the other hand, the project is meant to become a potential commercial application with a system that could be used daily by prosthesis users. We were thus interested in developing a system that would be giving at least equal results if not better than the commonly used myoelectric prosthesis while providing an easy-to-use interface and device. For this project, we tackled the following objectives:

- **Developing a BMI dedicated to the control of upper-limb prostheses.** This project serves as a proof of concept for a BCI system that can identify several mental states associated with motor tasks related to hand movements, starting with a synchronous control (where the subject is instructed of the needed mental state) and evolving into an asynchronous control (where the subject is left on its own to control the system). This BMI is using Motor Imagery of the hand, the imagination of movement on the limb, as the type of signal to control the prosthesis. This objective is thus to look at the best techniques to process the EEG signal and control a prosthesis with few movements.
- **Quantify the contribution of sensory feedback to the control of the prosthesis.** In parallel to the development of the BMI system, we were interested in exploring the changes obtained in the performance of a subject when sensory feedback was added to the system. Little to no sensory feedback devices are currently available for amputees yet the literature on this specific topic is offering different solutions to implement sensory information in the control loop. The feedback system relies on the use of vibrotactile motors used in conjunction with force sensors, providing basic yet useful information to the user regarding the movement done with the prosthesis.
- **Study the possibilities of a daily-life usable system.** BMIs are difficultly but slowly escaping the laboratory environment to be accessible to larger audiences, thanks to video games or other devices monitoring sleep or attention for example. As this project is meant to be a commercial application, one of the objectives of the PhD work was thus to propose solutions to use a BMI daily, without being too cumbersome or unreliable. The project is thus offering leads on how to implement as simply as possible a BMI for the control of a prosthesis, from the selection of relevant electrodes to the hardware necessary to modify current prostheses for them to respond to brain activity. While there is more to be done on the matter, the obtained results are suggesting guidelines and ways to explore a ready-to-use system.

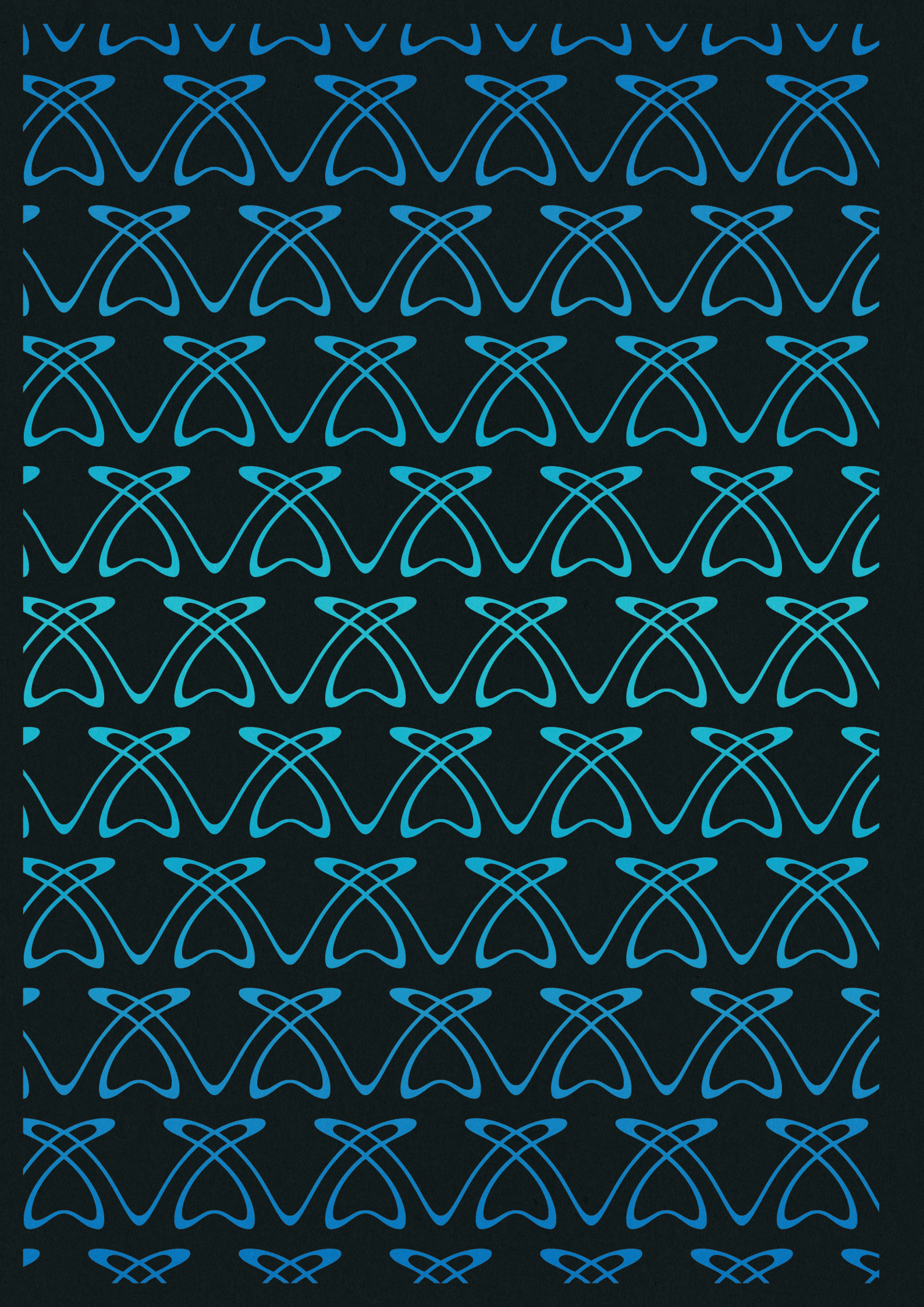
3. Manuscript organization

The first part of this manuscript is dedicated to the state-of-the-art; and in its two chapters, it gives a review of the topics of upper-limb prostheses and brain-machine interfaces. The first chapter will lead the readers from the amputation to the control of a prosthesis, giving insights into the limitations of the prosthesis and the different singularities noticed in amputees as well as offering an explanation of the different prostheses currently available and the different ways of controlling them. The second chapter provides a review of BMIs and their applications with a focus on EEG-based brain-machine interfaces. In this chapter, we also give a summary of the different

processing and classification techniques that are used to decode one's brain activity.

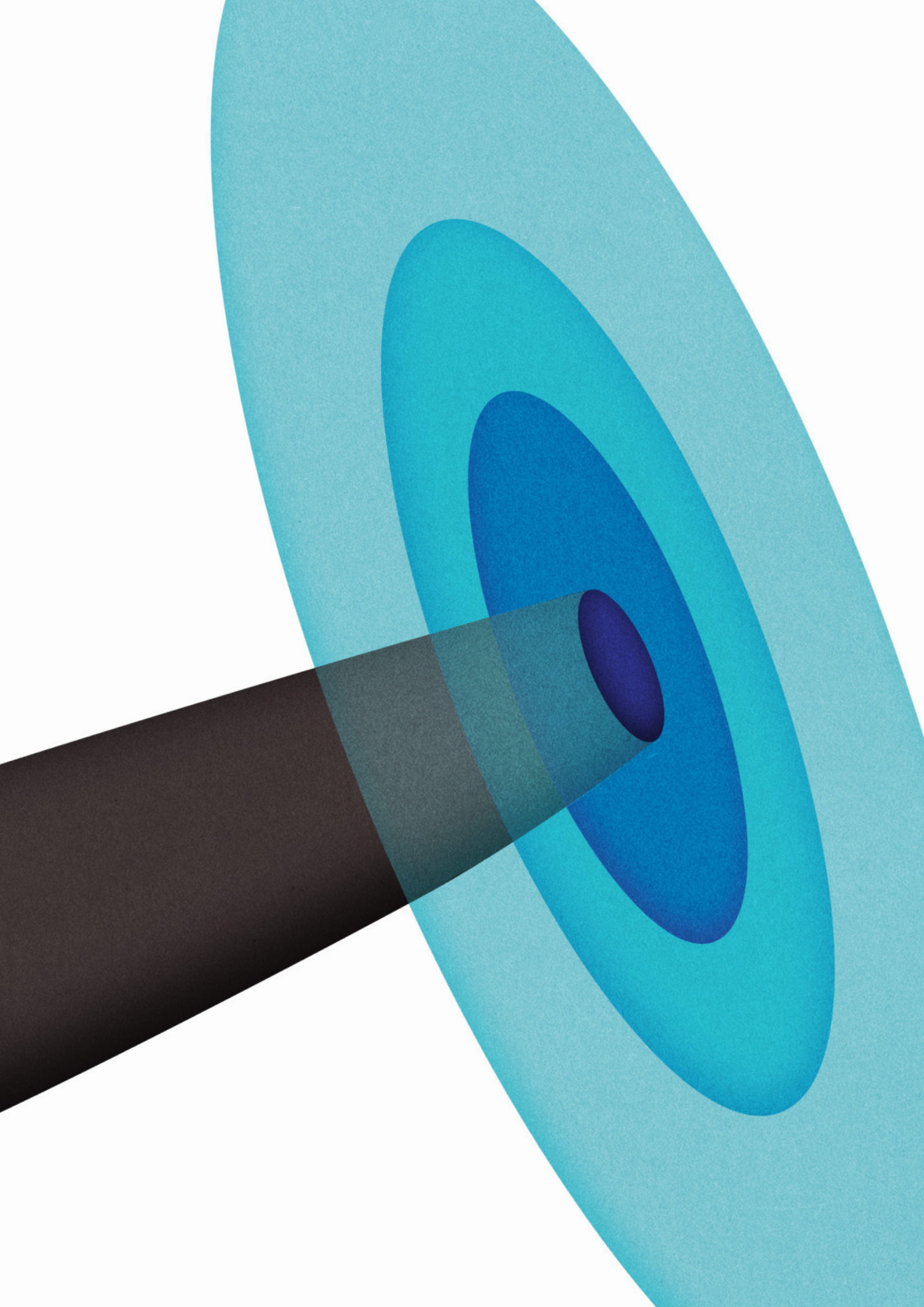
The chapters of the second part of the manuscript present the work done during this PhD project. The third chapter will introduce the specifications of the BMI that was developed for the control of a prosthesis and will present the experiments that were carried out with amputees and healthy subjects during the thesis. The fourth chapter will deal with the work done on the feature extraction and decoding methods by discussing the results presented by the team in already published and submitted articles. This chapter will also present the modifications done to the prosthesis. The fifth chapter concerns the work on the offline performance analysis of the proposed BMI system while the sixth chapter presents the results of the analysis of the real-time performance of the BMI. We will also see how the prosthesis is used by able-bodied subjects. In the seventh chapter, we will review the various possibilities of sensory feedback devices that are used for the control of prostheses or robotic arms, then we will present the sensory feedback system that was developed in conjunction with the BMI and the control performances will be compared between the different modalities.

Finally, the last part will consist in discussing the various results obtained during this project as well as offering perspectives on the work.



Part I

Literature Review





**From the amputation to the
control of a prosthesis**

We find reports of amputations from Antiquity through the Renaissance up until our day and age. In recent times its prevalence was linked to the increase in armed conflicts, and as one can easily imagine the number of amputations increased drastically after the First and Second World Wars. Indeed, tens or hundreds of thousands of amputees can be counted among each of the belligerents, these ex-soldiers quickly became an important social and economic challenge all the more critical in France for example, as the country needed an important workforce to be rebuilt. Nowadays, while the challenge with amputations is still salient with the 65 million amputees globally, it can be reconsidered mainly as a health problem.

1. Context

a. Causes of amputation

By definition, an amputation refers to the removal of a part of a body and, as the name suggests, an upper-limb amputation implies the removal of a part of the upper extremity: digits, hand, forearm, or arm. The causes of amputation are diverse but the most frequent ones are:

- *Dysvascular disease*: a defective blood supply in the limb caused by diseases such as diabetes. Diabetes affects predominantly lower-limb extremities and rarely upper-limb (2/3 – 1/3 ratio approximately [3])
- *Traumatic*: Probably the most frequent cause of upper-limb amputations, mainly due to work-related accidents (with machines) or vehicle accidents (such as car crashes or collisions)
- *Oncologic*: Appearance of cancers or tumours in the bones of the limb such as osteosarcoma. If cancer spreads to the nerves or blood vessels near the bone, amputation remains the only treatment.
- *Congenital*: It is truly difficult to consider them as amputation as we can note two different scenarios: it could refer to the absence of formation of the limb or an anomaly in its formation while the baby is developing in the womb.

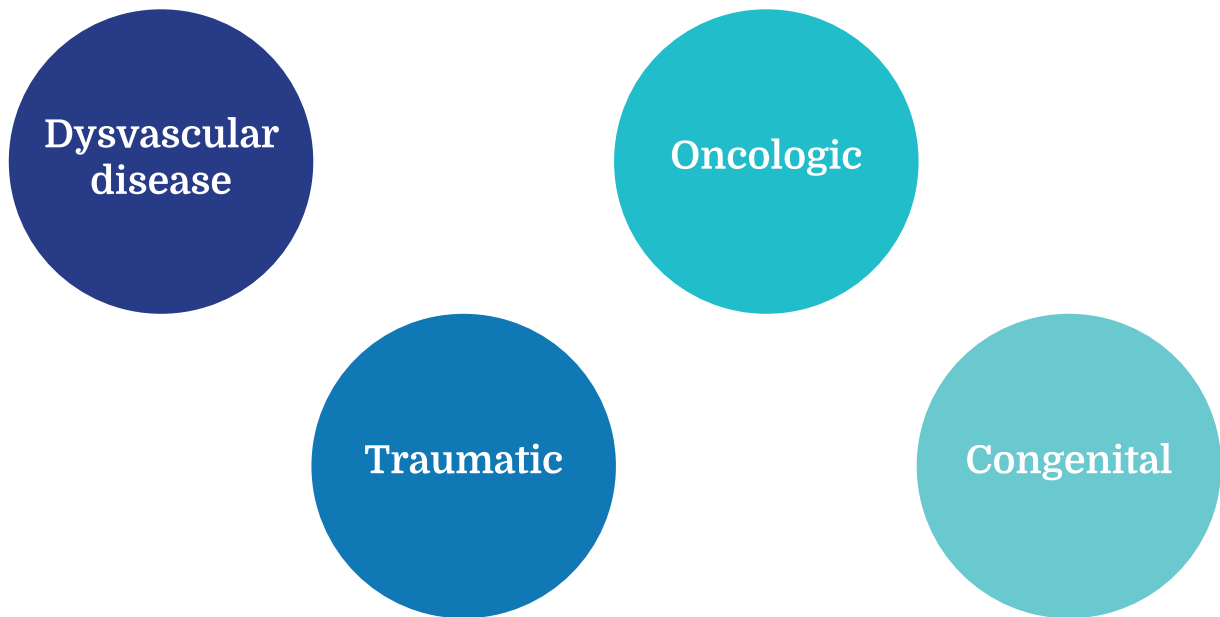


Figure 1.1. Main causes of upper-limb amputation or absence.

b. Types of upper-limb amputation

Because of the diverse etiology behind upper-limb amputations, we can define several levels of amputations on the upper extremity: (see Fig. 1.2.) :

- *Hand amputation*: includes transphalangeal (digits amputation), transmetacarpal, and transcarpal (removal of the hand while keeping the wrist) amputations. It is thus important to take extra care, in that case, to make sure that the patients will be able to use a prosthesis.
- *Wrist disarticulation*: refers to an amputation removing both the hand and the wrist joint while keeping full pronation and supination movements.
- *Transradial (below elbow)*: Indicates an amputation removing a certain portion of the forearm below the elbow joint.
- *Elbow disarticulation*: similar to the wrist disarticulation but this time the amputation occurs at the elbow level.
- *Transhumeral (above elbow)*: Indicates the removal of a certain portion of the arm above the elbow.
- *Shoulder disarticulation and above*: amputation that removes the entire arm and, if above, the collarbone and shoulder blade.

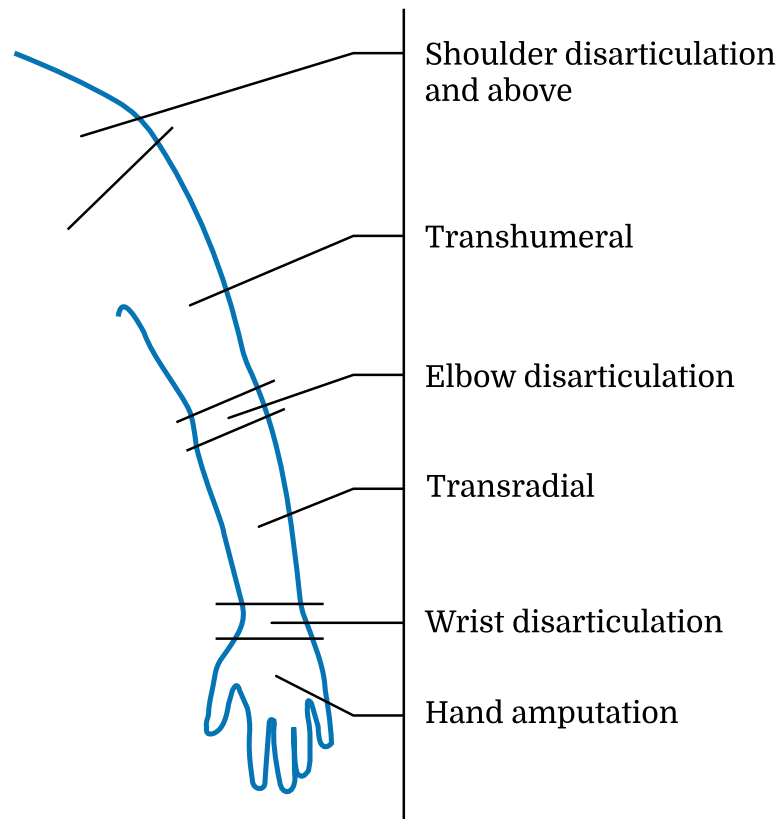


Figure 1.2. Names of the amputations depending on their level.

2. What are the changes after the amputation?

a. Psychological consequences of a limb loss

As one can imagine, the loss of limb results not only in a traumatic physical change for the patients but also in both emotional and psychological changes. Indeed, in their 2014 review, Mckechnie and John [4] showed that post-traumatic amputees suffer from higher levels of anxiety and depression compared to the general population. On par with these findings, Roşca et al. [5] conducted interviews with several patients suffering from lower and upper limb amputations and brought several themes to light regarding psychological changes linked to limb loss. The *emotional shock* caused by the amputation often leads to an alternation between anxiety and depression; Roşca mentioned that “the wish for death, as an expression of extreme dread” is present in many participants’ interviews. Following the shock, the patients are also subject to the classic stages of grief (here known as Pathological Grief) other than depression, in particular:

- Anger that links to the frustration of not being able to perform all the movements that they could do thus far, the anger can also come from the disruption of the person’s body image and could thus trigger bitterness toward others who are not suffering from limb losses.
- Guilt where patients are trying to find explanations behind their amputations, finding legitimate reasons for what could have caused the loss of the limb.

This explains a *tendency toward isolation*, which makes the patients more prone to a decrease in social interactions. Indeed, the amputation is seen not only as the source of the loss of a certain body function or image but is also explaining the losses of their professional careers and their relationships with friends or colleagues which block the return to a “normal” life. In [6] Cassandra Crawford mentions, through interviews with patients, the changes affecting one’s body following amputation and prosthetization; In particular, she tells that for one patient the reactions of her relatives or strangers regarding his prosthesis led him to constantly reconsider if he was himself anymore as if the amputation prosthesis made him lose his “me-ness”.

In a 2020 study Pomares et al. [7] note that the psychological consequences are more present when patients suffered from traumatic upper-limb amputation (TULA), indeed being mentally and physically prepared to face an amputation (because of a chronic illness for example) reduces the prevalence of Post-Traumatic Stress Disorders (PTSD) in patients [8][9]. Pomares & colleagues also highlight that patients showing Pathological Grief (PG) did not cope with the accident, interestingly only a third of the patients without PG assessed that they coped. While the factors were psychological, functional, and social as defined above, showing a high level of pain is linked to PTSD and PG.

Despite a broad range of negative points, patients accepting their limb losses could come up naturally with an acceptance of their state. Roşca [5] notes that the patients can see the use of prostheses as a positive factor because of the added functionality the device is supposed to bring, helping the patients to come closer to their self before the amputation. Yet, Pomares [7] show no significant impact on the patient’s progression and that coping with the amputation was coming from self-acceptance, noting, “Cure is not just a matter of stump healing, but of acceptance of a changed identity”.

Moreover, Crawford [6] highlights that patients are at first in need of masking their amputation and appearing as normal to the general population then, as the patients are forming a special relationship with their prosthesis, it helps them “to fundamentally restore, ‘reconstruct’, or even entirely ‘transform’ [their] dismembered bodies”, rebuilding in a way their previous body schema (see 2.c.). Functional prostheses are achieving this reconstruction, while cosmetic prostheses are used first for the aesthetic qualities they are often disregarded, as they feel “fake” to the users, who prefer to affirm their distinctiveness using artificial limbs. With the help of their prosthesis, Crawford explains that the patients are more likely to “become public” rather than “go public”, meaning that they transform their bodies “into voyeuristic objects” to provoke, reveal and make people look at them. Finally, becoming public is also an opportunity for the amputees to embrace their new bodies, not necessarily get rid of the past but more that, in Crawford’s words, “the body that inhabits the present is never the same body that inhabited the past.”

b. Phantom limb and phantom sensations

Ambroise Paré was the first person in 1545 to document the phantom pain occurring in certain patients after the amputation of a limb, noting “Patients who, months after the amputation of their leg, complained cruelly that they still felt great pain from their severed leg” [10].

Nonetheless, the first appearance of the term “Phantom limb” is due to the physician and novelist Silas Weir Mitchell who was in charge of treating soldiers injured during the American Civil War in the 19th Century. He writes: “Nearly every man who loses a limb carries about with him a constant or inconstant phantom of the missing member, a sensory ghost of that much of himself, and sometimes a most inconvenient presence, faintly felt at times, but ready to be called up to his perception by a blow, a touch, or a change of wind” [11]. From a cohort of ninety patients, he highlights that approximately 95% experience such a phenomenon. These results are on par with studies published close to a century later [12], in particular, in an epidemiological study by Kooijman et al. [13], 76% of the responders of the study mentioned phantom sensations of their lost limbs. Moreover, a systematic review by Stankevicius et al. [14] showed a lifetime prevalence of phantom limb sensations (PLS) of 87%, showing that the presence of the phantom does not decay in time.

As reported by Giumarra and Moseley in [15], while a majority of patients reported that the phantom limb they experience is of normal size, around 20% of them mentioned a case of “telescoping”, where the limb is felt as shorter than it used to be. Moreover, some cases show that the phantom limb can take unnatural/impossible positions (see Fig. 1.3), in particular Moseley and Brugger [16] showed that upper-limb amputees could train to perform impossible movements with their phantom limb.

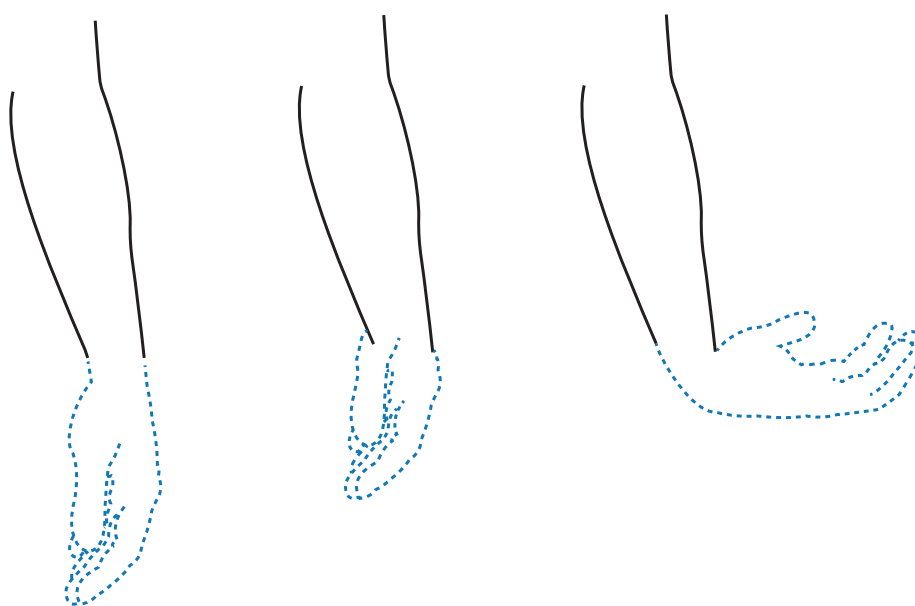


Figure 1.3. Description of different cases of phantom limbs. From left to right : normal phantom, telescoped limb and limb in unnatural position

The sensation of the phantom limb is often coming with pain, commonly known as “Phantom Limb Pain” (PLP). In [14], the authors note a lifetime prevalence of PLP varying in studies between 76 to 87%. This review contrasts with [12] where 50% of the 58 patients “reported that pains were decreasing” with time. This shows that phantom limb pain is a complex issue and its causes are difficult to pinpoint, studies show [17] [18][12][19] a link between pre-operative pain and phantom pain with a decay of the pain along the healing of the stump [20]. Yet surgical revisions are sometimes needed to remove potential neuromas (a thickening of the distal part of a nerve at the base of the stump) [21][22] and remove pain sensations. The presence of phantom limb pain also differs from the etiology of amputation, traumatic amputees being less subject to PLP than vascular amputees [23].

Physiological factors on the peripheral nerves such as stump pain caused by neuromas are one explanation behind the presence of PLP but, because they are not widely present in the population of amputees, there should exist more factors that are associated with phantom pain. In [23] Richardson note that for a mechanism about PLP to be accepted it necessarily requires the joint presence of the peripheral system, the spinal cord and the brain. As Hill suggests in [25], “Phantom pain can occur in the absence of nerve damage” which is indeed the case for certain patients with congenital limb deficiency reporting pain, meaning that the cause of the pain not only can get explained by the peripheral system but probably requires to go back up from it. The response of the spinal cord after a peripheral nerve section has been studied by Wall in [26], he reports changes in the dorsal horn cells caused by the loss of afferent inputs coming from peripheral stimuli, mainly an increased response from the deafferented cells because of a missing “part of their normal inhibitory mechanism”. Nonetheless, Richardson [23] recalls that although we observe those changes on both the peripheral and spinal levels it does not explain why some “patients do not experience PLP after amputation”, hinting that changes should occur in higher levels as well.

It is easy to think that if we look closely at the somatotopic arrangement of the body on the cortex, a correspondence of areas of the body in the sensorimotor cortex (see Fig 1.4.), something must be happening on this level after the loss of a limb. Various studies are indeed showing that a reorganization is found on the cortical level, referred to as maladaptive plasticity, where adjacent areas of the deprived part of the cortex are expanding and “invading” the representation of the missing limb [27][28]. In particular, Flor et al. [28] highlight a significant correlation between PLP and cortical reorganization, noting that patients presenting congenital limb deficiency or non-painful phantom sensations were not showing reorganization. On the other side, Makin et al. [29] suggested the cortex is keeping the local structural and functional representations of the limb maintained (also found in [30]). The loss of sensory input leads to a structural degeneration in the phantom area yet the activation during phantom movements was no different from that of the intact limb for unilateral upper-limb amputees. He also notes that the activation “was greater in amputees suffering from worse phantom pain” with a correlation of the PLP to the reduction of the functional connectivity of

the phantom cortex, translating into an “isolation of the phantom cortex from the sensorimotor system”. Nonetheless, those findings are contrasted with more recent studies in favour of maladaptive plasticity that, while acknowledging a degeneration of the structure of the phantom area [31][32]. It shows that reorganization happens on the cortical with a small shift of the lip and elbow towards the hand area which shows few signs of reorganization, creating an overlap of the different area [33][34]. Anderson in [35] adds that, if we feel sensations in the face and consider that they are referred to as the arm, it is at the same time a sign of cortical plasticity for the first part and a sign of cortical stability, precisely a stability of the “underlying somatosensory schema”.

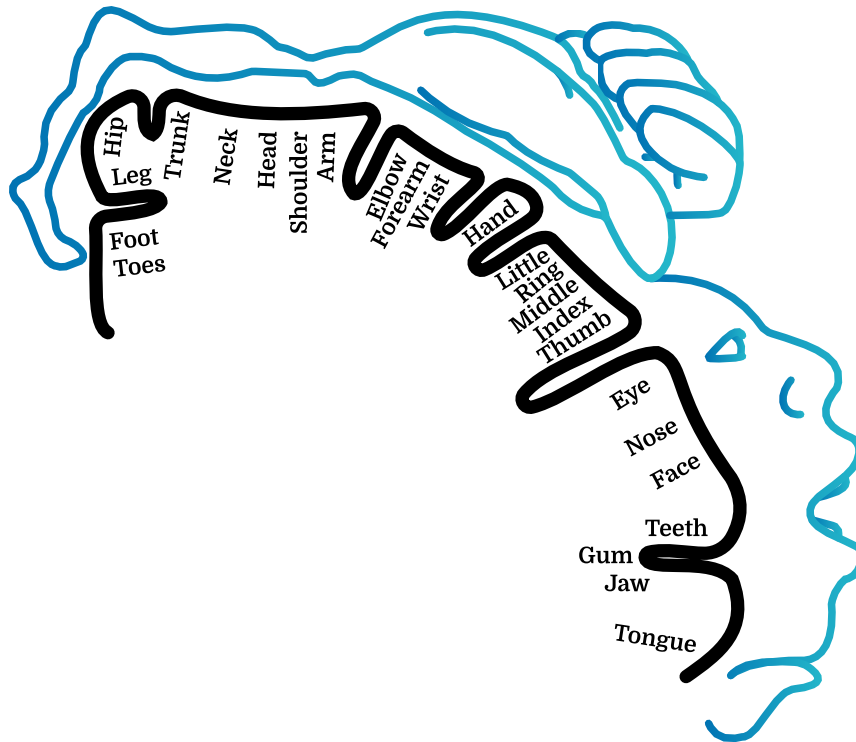


Figure 1.4. Schematic representation of the somatotopic arrangement and of the motor homunculus in the motor cortex.

c. The body representations in prosthesis users

One question that occurs when talking about our body can be: how do we become aware of the body? To attempt to give an explanation we first have to define a few notions concerning one's body. We can observe in the literature differences between *body image*, *body schema*, and *body awareness*. The *body image* refers to the conscious visual representation of our body, both in terms of physical characteristics (like our size for example) and psychological experience (like our emotions). The *body schema* can be distinguished in that it does not necessarily reach consciousness; it represents spatial characteristics of our body parts and is mainly used for performing movements. It is thus updated continuously during motions, as we are changing the properties of our bodies. *Body awareness* is closely related to *body image*, in particular, Kudar [36] define it as the conceptualization of *body image* on which individuals will chose to give more or less focus on certain body parts, the *body awareness* is

shaped consciously and unconsciously through experiences. A clear example of *body awareness* can be seen in athletes, especially high-level ones, where they can show a greater focus on the body parts that are related to the activity they are doing, being able to kinaesthetically feel imagined movements [37][38]. Nonetheless, [6][35] bring more nuance to those definitions and advocate for a much-needed consensus on the various body representations, in particular, Anderson [35] proposes at least five different representations: “a lexico-semantic representation of the body and its parts; the bodily structural description; the body image; the somatosensory schema; and the motor schema.”

One can thus wonder about the changes created by a limb loss on those notions. An amputation disrupts the body image and body awareness of an individual. The person is well aware that the limb is not there anymore, yet, as we have seen previously, phantom limb sensations can still be present with some patients being able to move it: we can thus note an alteration of both *body awareness* of that person and its *body schema*. In [39], Mayer and colleagues explore those changes in *body schema* and *body awareness* of amputees; they especially try to explain the differences between prosthesis wearers and non-wearers for upper and lower limb amputations. First, he reports no significant differences in limb awareness between the patients wearing a prosthesis, those who started to wear one, and those who are not using any devices. He adds that, regardless of the categories of patients, the structure of the *body awareness* is rather stable and does not change before a few months when it will slowly decrease. The use of a prosthesis is thus not “tricking” the person into believing the missing limb is still present in his /her body image.

Moreover, Mayer highlights that the use of a prosthesis is crucial for the conservation of the body schema, arguing we can see that “a strong, complete body schema is created due to regular prosthesis use” while patients not using prosthesis will be more prone to a rearrangement of the body schema with experiences of shortened or “telescoped” body parts. These findings go along [40] where Giummara and colleagues explain that most amputees “try not to allow their phantom limb to enter into conscious awareness because it is usually annoying or painful”. They add that about 1/3 of the interviewed amputees report an “embodiment” of the prosthesis, meaning that the device was now forming a whole with their body by merging with the phantom limb. They also note that the embodiment of the prosthesis is probably correlated with the sensations felt by the patients on their stump. In their chapter [41], Eskiizmirli and Goffette add that prostheses are “raising questions about both embodiment and ownership” in that, when they are used, they will appear in the body schema “with its different possible facets” such as various sensations, affective investment or motor skills, but this immediately disappears when they are removed, going back to them being just “objects”. Alongside the team of Mayer and Giummara, Eskiizmirli and Goffette explain that if the prosthesis is a “source of sensations and motor expression” then it will appear as “affectively invested, embodied and associated with a sense of ownership” by the users.

In [42], Haggard and Wolpert show how several pathologies are affecting the body schema, devoting a couple of paragraphs to differentiation and phantom limbs. In particular, they point out the importance of proprioceptive and tactile inputs for the maintenance of a stable body schema, adding that visual information can difficultly keep the body schema intact. Feeling aware of our body and that we own it can be explained by sensory events that happen most frequently together in time and place, particularly combinations of exteroceptive information (such as vision, audition, or touch), interoceptive information (like hunger, pain, temperature or itch) and proprioceptive information (position of body parts in space for example). It is indeed reminded by [39][40] that good learning of how to use a prosthesis will also come from a proper integration of information coming from the stump. They also point out that, for the user to embody its prosthesis, the phantom limb must not be in an unnatural position, particularly, the patients in [40] “described a distinct perception of a mismatch between the phantom limb and the prosthesis”. These findings are also coherent with the results obtained using the Rubber Hand Illusion (RHI) which was first introduced by Botvinick & Cohen in 1988 [43]. In this experiment, subjects are seated with one of their arm resting on a table, a screen is hiding the arm from the subject and a rubber hand is set on the table in front of the subject. In one group of subjects, the rubber hand and the real hand are stroked synchronously while in the other group, the control group, the rubber, and real hands are stroked asynchronously. After the experiment, the subjects completed a questionnaire asking them to report on the sensations they felt, eight of the ten subjects in the first group felt as if the rubber hand was their own. Anderson [35] explains that this illusion “is multi-layered effect: it causes the mislocation of the conscious position of one’s arm, and the spatial mislocation of the bodily stimulus, but does not affect the estimation of arm location as used in movement”, leading to a clear distinction between *body image* and *body schema*.

A similar experience using illusions has been proposed by Ramachandran in 1996 [44], the subjects, ten unilateral upper-limb amputees, were asked to put both their intact hand and phantom hand in a mirror-box and, once the hands were inside, the mirror is giving the illusion of having two intact limbs. First, the patients had to put their intact hand in the same position as the phantom hand, so that the two match. Then they were asked to perform symmetric movements with their eyes closed, all except one subject reported that the phantom was frozen. Finally, the patients had to do symmetric movements but this time while looking at the mirror. Out of the ten subjects, six reported kinaesthetic sensations coming from the phantom and were able to move it freely, relieving phantom limb pain for four of the ten patients. Ramachandran also reports that, for the sensations to appear, the subjects had to have their intact limb in the mirror-box, substituting their hand with one of the experimenters elicited no sensations in the phantom. This supports the hypothesis that the multisensory integration of information that is happening at the same moment in time and place is explaining *body awareness*.

Finally, Anderson [35] concludes that the phantom limb is “the experience, via the body image, of one’s body schema unaltered by amputation.” This means that, based on the various results presented earlier, the phantom is dependent on the pre-amputation period: when the patient has the time to experience, following Anderson’s word, his “limb in its new reality” then he/she will be able to keep a harmony between *body image* and *body schema*. There is a consistency between the possibilities of the limb in the pre-amputation state and the sensations/feelings of the phantom limb: if the hand of the patient was paralyzed then the phantom will most likely appear as paralyzed at first, as there were no updates of the patient’s body schema. In particular, as we have seen before, Anderson makes the distinction between the *somatosensory schema* and the *motor schema*, arguing that the first one needs to synchronize with the motor schema reinforcing the other in “maintaining the bodily-spatial structure of somatosensory experience”. This partly explains why Ramachandran’s experiment works so well, because not only it gives the patient the possibility to change his body image but also because the patient can update the missing limb, changing the experience the patient has of its phantom.

d. Available treatments for pain management

So far, throughout this chapter we have seen that amputees are experiencing pain in various shapes, it can be pre and post-operative pain, pain occurring because of issues with the stump or issues with nerves, and we mentioned quite extensively the notion of phantom limb pain. While pre/post-operative pain can be treated using various drugs (to attenuate the effect of a certain condition and then the surgical consequences of amputation) and pain linked with the stump or the nerves can be solved surgically, it is difficult to track down solutions, which could bring relief for phantom limb pain. The literature about the subject commonly reports two categories of treatment for PLP [15][45][46]:

- *Pharmacological*
- *Physical, behavioural and psychological*

The Pharmacological category consists in the different drugs that can be administered to patients; they are mainly of three types: antidepressants, anticonvulsants, and opioids. These drugs are often used to relieve pain in other neuropathic conditions [47].

The second category is partly based on the various cortical processes taking place after the amputation. First, we have seen with Ramachandran and his mirror-box that mirror therapy (MT) was commonly used on amputees for helping to control their phantom and additionally relieving the pain for some of them. This therapy is targeting the cortical reorganization that is occurring in the motor cortex of the amputees. Graded Motor Imagery [48], a combination of limb laterality recognition (left/right), imagined movements, and mirror therapy, is also one treatment for PLP. Recently, virtual reality is also a tool used for treating pain, functioning as an alternative to conventional mirror

therapy. This technique presents the advantage of offering patients an immersive experience all the while expanding the possibilities brought by MT [49][50]. As we have seen above, the use of a prosthesis is essential as the user can embody the device and merge it with the phantom limb. Some studies showed that the frequent use of functional prostheses was positively correlated to a reduction in phantom limb pain [51], suggesting that the visual information and the training of the muscles from the stump could diminish the cortical reorganization, which as we explained was shown to be correlated to PLP [29]. Finally, other possible non-pharmacological treatments include different types of non-invasive neuromodulation, which consists in applying electrical stimulation to the peripheral or central nervous system to treat neuropathic pain [52]. Among those techniques, one called Transcutaneous Electrical Nerve Stimulation (TENS) has been applied in a certain number of studies for the treatment of PLP [53][54][55]. Repetitive Transcranial Magnetic Stimulation (rTMS) is also a technique used in studies for PLP, an electromagnet is used to stimulate a brain region with a magnetic pulse, which, by targeting the primary somatosensory and motor cortices, is used to slow down/prevent the cortical reorganization happening in those regions.

Far from being exhaustive, this list allows us to embrace the diversity of treatments present to patients suffering from Phantom Limb Pain. Yet, having a multitude of options does not necessarily imply that those options are giving significant results on such a specific type of pain. While many studies over the years highlighted the positive results of PLP, recent articles commend more rigorous studies. In 2021, a study conducted with 27 experts in PLP by Limakatso and Parker [56] was aimed at finding a consensus regarding thirty-seven different treatments. They considered consensus once at least 50% of the experts were agreeing on a treatment. On those thirty-seven proposals, the consensus was reached on seven of them, with 6 out of 7 being non-pharmacological treatments (mirror therapy, graded motor imagery, cognitive behavioural therapy, use of a functional prosthesis, sensory discrimination training, and virtual reality). The consensus was found not only because there is scientific evidence that supports the efficacy of those treatments but also because those techniques are working in clinical practice. Yet the authors note at the end that “proving that a treatment has active efficacy (efficacy beyond meaning) requires the use of valid shams, which are often expensive and sometimes impossible”, this supports that there are no results yet that could help validate one method compared to others. Indeed, in 2019, Aternali and Katz [57] reviewed randomized controlled trials (RCTs) from the past 5 years that were interested in different treatments for PLP; in particular, they examined both the efficacy of the treatments and the risk of bias in different domains of the studies (following the Cochrane risk-of-bias tool for randomized trials [58]). They point out that there is no treatment yet that is targeting the multiple mechanisms of PLP, underlying that we still know very little about PLP. Moreover, they add that other explanations lie behind the small sample sizes of the studies or the fact that researchers are not specifically looking for which PLP mechanisms the subjects are suffering from. All of that led them to argue that there are no differences, in terms of PLP, between the group treated (with rTMS, motor imagery, mirror therapy, or virtual reality) and the control group.

Finally, Makin attempts to explain in [59] that if there are no efficient treatments available might be because the maladaptive plasticity theory is predominant in research, which led to the development of treatments that are targeting the mechanisms, seen in this theory. Nonetheless, the absence of evidence supporting those treatments should be enough to question researchers in finding other ways. Moreover, and similarly to Aternali and Katz, the studies in the literature are mostly based on interviews and questionnaires with amputees, the results presented in the articles are thus subject to biases. She thus advocates for more double-blind placebo-controlled studies, something that is not that visible in PLP research. Following her words, this lack of efficient treatment challenges PLP research and clinical practice. Indeed, because of a focus on mirror therapy, it is difficult to develop innovative solutions although they are a need. Moreover, she argues that both the patient and the clinical team need to be aware that the treatments offered are “not more effective than a placebo”. Moreover, while there is nothing necessarily wrong in offering a placebo given its potential effects, they should have the option to refuse such treatment, especially if it reveals to be “expensive or time consuming for the patient”.

Despite more than 50 years of extensive research, it seems that our knowledge about phantom limb pain is still in the same state meaning that, as Makin suggests, there is a need to be more critical in trying to understand this condition, which in turn will help researchers in finding an appropriate treatment. As we have seen that the use of a functional prosthesis appears to relieve phantom limb pain, we can now interest ourselves in the differences between the types of prostheses, and attempt to shed some light on their specificities.

3. The different types of prostheses

It is widely accepted that we can differentiate between three types of upper-limb prostheses, commonly referred to as passive, body-powered and externally-powered. Here we will mainly present those prostheses in the case of upper-limb amputations.

a. Passive prosthesis

Maat and colleagues [60] propose to refine more thoroughly and for clarity's sake, the devices found in the passive category. First, one should make the difference between prosthetic hands and prosthetic tools: in those two sub-categories, we find static and adjustable devices. If we start with the prosthetic hands, a static device would mostly correspond to a cosmetic prosthesis which has no real functional use and its only purpose is to look as close as possible to a real hand. We saw earlier that it was the preferred choice for new amputees before moving to a functional device, it is also found in the literature that older persons often go back to passive prostheses [61] but this result might change in time due to progress in prosthesis technologies. The adjustable devices contain a mechanism that allows the user to operate the hand

thanks to its intact limb or with support.

The second sub-category is composed of prosthetic tools, as the name suggests they are intended to perform specific tasks like activities of daily living (ADL) where the user needs to do a specific movement with two hands. It can go from biking and other sports to playing instruments, driving vehicles or using kitchen utensils. In [62], Woldendorp and Van Gils highlight that in music (and this can expand to other fields as well) the prosthetic tools must be created using an interdisciplinary approach combining the prosthesis user, the therapist and the doctor as well as the instrument maker. Nonetheless, most of the time there are difficulties to find appropriate solutions and information. Yet this type of device is sometimes preferred over functional prostheses because they are less fragile and mainly dedicated to tasks that do not require advanced technologies.

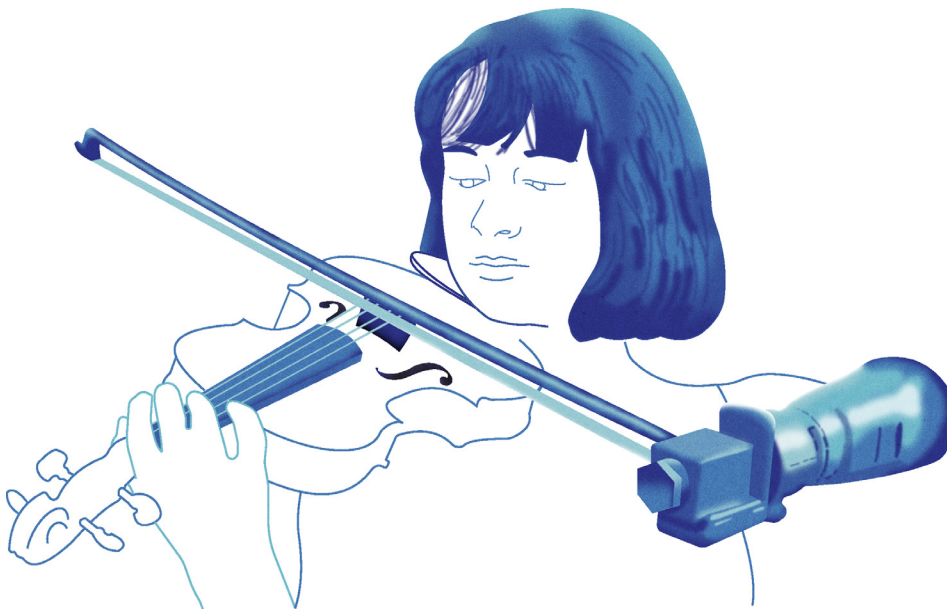


Figure 1.5. Example of passive prosthetic tool, here designed to hold a violin bow.

b. Body-powered prosthesis

As implied by its name, this type of prosthesis requires a combination of parts for the user to perform a movement. The first part needed is referred to as the end effector or terminal device, it can either be a body-powered hook or a body-powered hand. With a hook, the user can perform different grip types like the side grip (lateral grip) or the precision grip (tip pinch) while with a hand the movement is a grip involving the thumb, index and middle fingers (also called three-jaw chuck grip). In [63] Jack Uellendahl explains that hooks present the advantages of being “simple in design” compared to hands, meaning a reduction of their cost as well as their weight. Alongside those benefits, patients are also using them for heavy-duty activities, as they are resilient in various work environments (where you can find dirt or water for example). Nonetheless, the fact that hooks do not resemble real hands can be an obstacle for many prosthesis

users who would move towards body-powered hands although those are heavier and more difficult to control than hooks for activities of daily living [64].

Uustal and colleagues [3] then compare two different types of control for the end effectors: voluntary-opening (VO) and voluntary-closing (VC). The voluntary-opening is the most commonly used type of terminal device, with this control, the prosthesis is kept closed using various rubber bands and the user can control the opening using a harness which is powered by the motions of the upper arm and shoulder. Then, when grasping an object, the user can adjust the level of force by releasing the tension on the muscles of the upper arm, the device going back to the closed position. With the voluntary-opening closing type, the prosthesis is open at all times and the user has to close it using the harness, pulling a cable. This time the level of grip force is congruent with the level of strength the user is applying to the cable. Uustal and colleagues note also two disadvantages for the VC over the VO: first, the device is always open which can reveal awkward when the user is not using his device; secondly as we have seen, a continuous grip on an object requires continuously pulling the cable which can be tiring over long periods. Yet the opening/closing function presents the advantage of being more physiological than the VO type.

The second part refers to the wrist unit; its main purpose is to attach the end effectors to the prosthesis and allows the user to place the terminal device in the desired position before doing any movement. Indeed, with a trans-radial amputation, people are losing the ability to perform pronation and supination of the wrist, they thus need a device that substitutes their wrist and allows for the rotation (and less frequently the flexion) of the terminal device. Friction wrists are the first type of wrist unit, for which a user has to perform the pronation/supination with his intact limb; a rubber washer providing friction helps to keep the position. The second type is called locking wrists and, as the name suggests, is more secure in that the user can lock the terminal device in the needed position with no risk of unwanted rotation when grasping heavy objects. To perform flexion, the users can either replace the rotation unit with a flexion wrist that allows them to bend the terminal device at different degrees of flexion. They can also combine the wrist and flexion units to offer a wider range of positions but at the cost of added weight on the prosthesis.

The third part of the body-powered prosthesis is the socket, which makes the interface between the stump on the residual limb and the prosthesis. For trans-radial amputations, we find mainly different sockets, dependent on the level of amputation on the forearm. We also note some special designs when the user has a short residual limb. In particular, the split socket presents two parts connected with hinges. We find a combination of the wrist unit and terminal device in the first part and the second part is the socket that fits on the stump.

The fourth part is a combination of hinges and cuffs/pads: the hinges are connecting the socket to a cuff located on the upper arm of a user. The hinges can be flexible if the

user can perform voluntary pronation and supination of the forearm. If those motions are not possible (because the residual limb is short for example) then rigid hinges are used which also present the advantage of being more stable. The cuffs/pads are connecting the socket to the harness while also giving stability to the prosthesis.

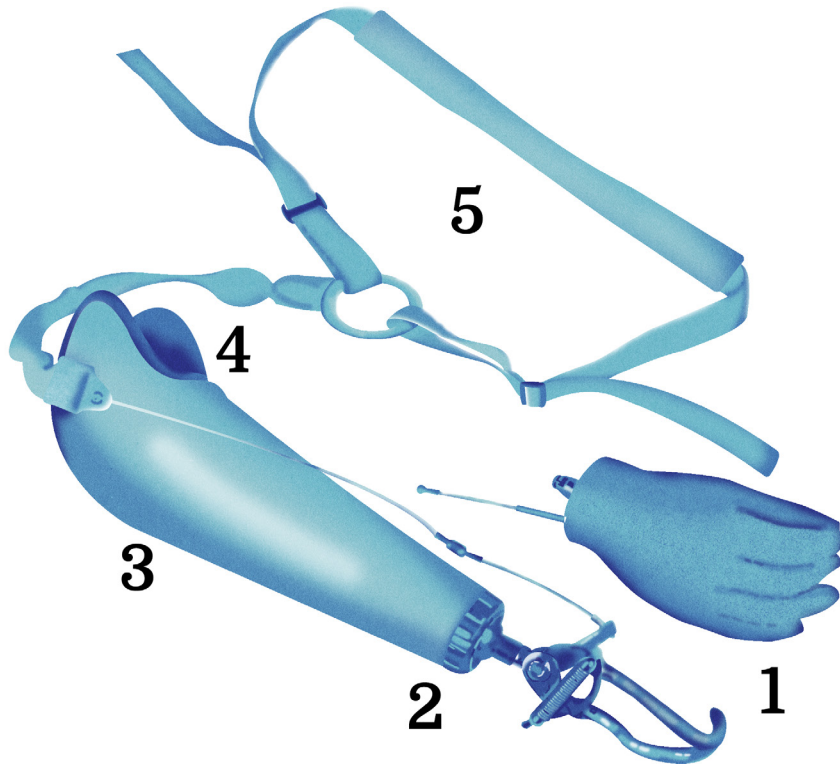


Figure 1.6. Example of body-powered prosthesis. 1. Hook or prosthetic hand. 2. Wrist unit. 3. Socket. 4. Hinges and cuffs/pads. 5. Control mechanism with harness and cable system.

Finally, the last part of the body-powered prosthesis is the control mechanism which is composed of a harness and a cable system. The harness is holding the prosthesis securely in place as well as supplying power to control the device by the means of body motions. The most commonly used type of harness is the figure-8 and consists in a strap which goes from the cuff on the upper arm to the axilla on the contralateral side, which is the area responsible for capturing the motion transmitted to the terminal device. The cable system is made of a stainless steel cable that attaches to the harness and the terminal device. The system uses the Bowden principle that transmits tension forces from one end of the cable to the other; the cable is here located in a flexible housing attached both on the forearm and on the triceps pad [65]. Uellendahl et.al. [63] explain that the use of the control system can provide some sort of proprioceptive feedback to the user “regarding force, position, and velocity of the prosthetic component”. Nonetheless, the harness can be a source of discomfort for the users. First because of the potential high forces needed to use the prosthesis but also because of pain that can appear around the contralateral axilla where the harness is located, moreover the fact of having to put the harness on is also an obstacle to the use of this kind of prostheses.

c. Externally powered prosthesis

Compared to a body-powered prosthesis, an externally powered device is composed of fewer parts while offering a similar and often higher level of control. For this kind of prosthesis, we can note two different control systems: using an electric switch or myoelectric. The first system consists in using push or pull switches to activate movements on the terminal device. The location of the switches is adjustable to the needs of the amputees so that the users can activate the prosthesis with their intact limb or using body movements. On myoelectric prostheses, which we will detail further in the next paragraphs, we find surface electrodes on the residual limb of the amputee, specifically above the flexor and extensor muscles of the forearm for trans-radial amputees.



Figure 1.7. Example of polydigital myoelectric prosthesis.

The myoelectric prostheses can work in two control modes: the first is called *analogue control* or *proportional control* and the second mode is called *digital control*. *Analogue control* means that the speed of movement is proportional to the muscle contraction, the more the muscle contracts and the faster the terminal device is doing the movement (closing of the hand for example). In the *digital control*, the strength of the contraction is not critical, the terminal device is turned on or off following if there is muscle activity or not. As for the body-powered prostheses, we can find both hooks and hands as well as grippers in commercially –available terminal devices and models that are more recent are now presenting poly-digital effectors. Nonetheless, and contrary to the previous type of prostheses,

myoelectric prostheses for trans-radial amputations do not require a harness as all the parts (terminal device, wrist unit, socket and control system) are contained in the shell case on the forearm. As they contain electronic parts, myoelectric prostheses should be used with caution in environments where there is a risk of liquid intrusion or ingress of foreign objects (like dust) although those types of damage are reduced with new models of prostheses. Moreover, the addition of electronic parts means that the user has to charge the battery if he/she wants to use his/her device daily; it also means that the weight of the device will be higher which could constitute an obstacle to its use.

d. The access and costs to these prostheses

Accessing the precise information regarding upper-limb amputations is quite difficult as most of the reports available are based on estimations and projections. McDonald and colleagues published a report [66] on the global prevalence of traumatic limb amputation, they estimated this number to be of about 57.7 million people in 2017. They also added that around 7.3 million people were living with an amputation caused by diabetes (the source of this number is present in the 2015 report from the Global Burden of Diseases, Injuries and Risk Factors Study [67]), which makes the total number of amputations at more than 65 million, with approximately 1.5 million amputations per year. Moreover, in the report, McDonald et. al. note that the prevalence of traumatic amputations was higher in low and middle-income countries (LMIC) compared to higher-income countries (HIC) where the main cause of amputation is diabetes. Furthermore, the AT2030 report from the Clinton Health Access Initiative about prostheses highlights that, although access to prostheses should be considered critical and essential, only 5 to 15% of people in LMICs have access to such devices. One explanation behind this low estimate is the lack of budget allocated by governments in LMICs for prosthesis access. In particular, McDonald et al. underline that prevention (of falls and road accidents), the training of prosthetic personnel and a more developed prosthetist education are key points to improve amputation care globally.

Another obstacle to prostheses access is the cost of such devices; this is especially an issue for LMIC as people in HIC benefit from coverage in part or fully by their national health insurance. As it is difficult to evaluate the total number of amputees worldwide, it is also quite difficult to evaluate the cost of a prosthesis and its maintenance for a prosthesis user, as it combines several aspects that are changing from person to person. First, the cost of the prosthesis in itself ranges from approximately 2 000€ to 4 000€ for passive prostheses, 5 000€ to 9 000€ for body-powered prostheses and 10 000€ up to 50 000€ for myoelectric prostheses, depending on the level of technology in the robotic hand [68]. We also have to take into account the costs of the occupational and physical therapies to improve the recovery and mobility after the amputation, as well as the cost of the stump casting to fit perfectly the prosthesis. Moreover, the devices are potentially subject to various damage over time for which they need maintenance and repairs. The prosthesis also needs to be changed periodically depending on the person, with several patients receiving 10 or more prostheses throughout their lifetime. This issue of cost is pushing innovators and companies to put on the market low-cost prostheses (using 3D printing techniques for example) for low and middle-income countries, with a cost reduced to less than 500€ for a myoelectric prosthesis while still offering sufficient dexterity for daily use.

4. The control of myoelectric prostheses

Now that we have seen the differences between the types of prostheses, we can interest ourselves in myoelectric prostheses, which were the prostheses used during this thesis work as they are the devices that are the most commonly used by upper-limb amputees. Although we have mentioned roughly how they function previously, this paragraph will be the occasion for digging deeper into myoelectric devices and the different ways of controlling them.

a. Classic myoelectric control

We find the first trace of myoelectric control around the beginning of the 1940s when Reinhold Reiter, a student at Munich University developed a prototype that was intended to be used by a factory worker [69]. The device could not be moved around as it was composed of a large vacuum tube amplifier, but it would have been perfect as a factory tool. Nonetheless, the difficulties of finding funds in Germany after the Second World War prevented Reiter and others to pursue their research on myoelectric control, the British, Americans and Soviets taking over in this regard during the 50s and 60s [70][71][72]. The progress on that subject was also made possible with the invention of the transistor in 1947, which facilitated the development of smaller and more efficient devices, particularly batteries and magnets that were and still are key components in myoelectric prostheses. Most of the research on myoelectric devices at the time hardly escaped laboratories as they were purely for experimental purposes, but things changed in the 70s with advances in signal processing techniques and the development of electric hands for both adults and then for children at the end of the 70s and during the 80s. The development of computers allowed for more functions on the prosthesis, with currently certain models offering an impressive level of control.

To further understand myoelectric prosthesis, we first need to review the basis of the myoelectric signal. As the name implies, the word *myoelectric* is a combination of *myo*, derived from the Greek word for muscle, and *electric*. Myoelectric refers thus to some electrical activity produced by a muscle when it contracts. The source of the contraction originates from the Central Nervous System (CNS), where a motor command is sent from the brain down to the spinal cord; an impulse is then transmitted to one or several motor units, a combination of motor neurons whose axons are projecting in muscle fibres. If we were to look closely at the muscle fibres, we would see a multitude of rod-like structures called myofibrils that are mainly composed of long protein filaments of actin and myosin (see Fig 1.8).

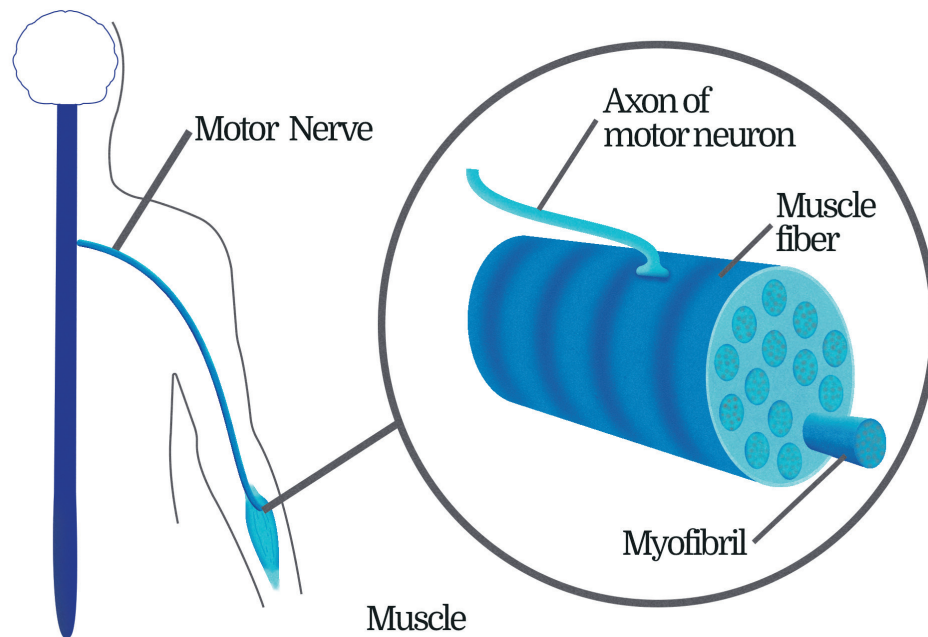


Figure 1.8. Muscle contraction pathway from the CNS down to the muscle fibers.

During the contraction of a muscle, a chemical interaction happens between the actin and myosin filaments. The actin filaments, which are thinner than the myosin filaments and overlap them, are sliding over the myosin filaments, which accentuate the overlap, and an electrical potential appears at the level of the muscle fibres with a polarization of the membrane. When the muscle receives the nerve impulse from the CNS, another chemical reaction causes the depolarization of the membrane, which is then subsequently re-polarized, turning back to its original state. This sudden shift in membrane potential is also known as an action potential or a spike. Because the impulse is sent to a motor unit that is connected to many muscle fibres, the spike signals are happening (firing) synchronously leading to what is called a Motor Unit Action Potential (MUAP) which is the sum of all the firing of the motor unit along the muscle. Then, as explained by D.F. Lovely in [73] the force of contraction can be controlled by two modalities: first, more motor units can be recruited, which increases the MUAPs on the muscle, and the spatial summation of MUAPs corresponds to the myoelectric signal we are interested in. Second, the frequency of spikes, also called the firing rate, can be modulated and therefore increased. Lovely reminds us in [74] that those two modalities are controlled voluntarily by a person; if we need to grasp a heavy object with our hand we need a higher level of force, thus more motor units are needed .

To record this myoelectric signal and particularly for the control of prostheses, surface electrodes are used and placed above the residual muscles on the stump of the amputee. These surface electrodes are using what is called a differential amplifier that amplifies the difference between two electrodes (over the same muscle) while eliminating the signal that is common to both (see Fig 1.9), thus rejecting potential noise and interference coming from the environment. As explained by Lovely [74] a further reduction of the interference of the myoelectric signal is possible using notch

filters, whose purpose is to get rid of a specific frequency, it is used in surface electrodes to suppress the line frequency that is at either 50Hz or 60Hz. Another technique used to further process the myoelectric signal is the rectification of the signal; it is done by folding the signal over time so that it is only composed of positive values (and not negative and positive values as with the original signal). This rectification is then usually followed by a smoothing of the signal using a low-pass filter, which gives a cleaner signal to be used for the control of prostheses.

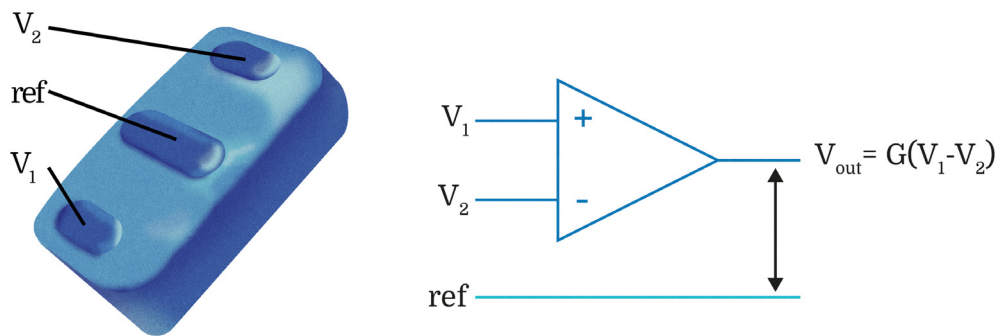


Figure 1.9. Example of EMG electrodes and its schematic representation .

Depending on the numbers and qualities of the muscles on the stump of the amputee different numbers of surface electrodes can be used for the traditional control of a prosthesis. If only one electrode can be fitted in the socket of the amputee, the control of the terminal device can be done by implementing several thresholds on the recorded signal to differentiate between the movements on the prosthesis. Particularly, a contraction above the first threshold allows the prosthesis to close, while a contraction above the second one is controlling the opening of the hand. Another strategy of control depends on the rate of contraction of the muscle by the user, if the amputee is suddenly doing a high (/low) contraction of the muscle then the slope of the myoelectric signal at the beginning will be steep (/soft), the slope of the signal serves to decide between the different movements on the prosthesis. Once the movement is selected it is performed as long as the myoelectric signal is above the initial threshold, which differentiates between rest and active moments. If two surface electrodes are used in the prosthesis then they are placed above two antagonistic muscles (usually flexors and extensors), which will be controlling different movements. Two thresholds are implemented and the gain of amplification for each electrode can be adjusted based on the contraction capabilities of the amputee in the two muscle groups (see Fig 1.10 for a schematic representation of the control strategies).

Finally, it is also important to remind that an efficient level of control of the myoelectric prosthesis is only feasible with a perfect fitting of the prosthesis on the stump of the amputee. Indeed, when the contact between the stump and the socket of the prosthesis is adequate then there are little to no movements of the surface electrodes at the skin level. This fitting prevents the appearance of artefacts that create noise on the myoelectric signal, which could lead to unwanted movements on the prosthesis.

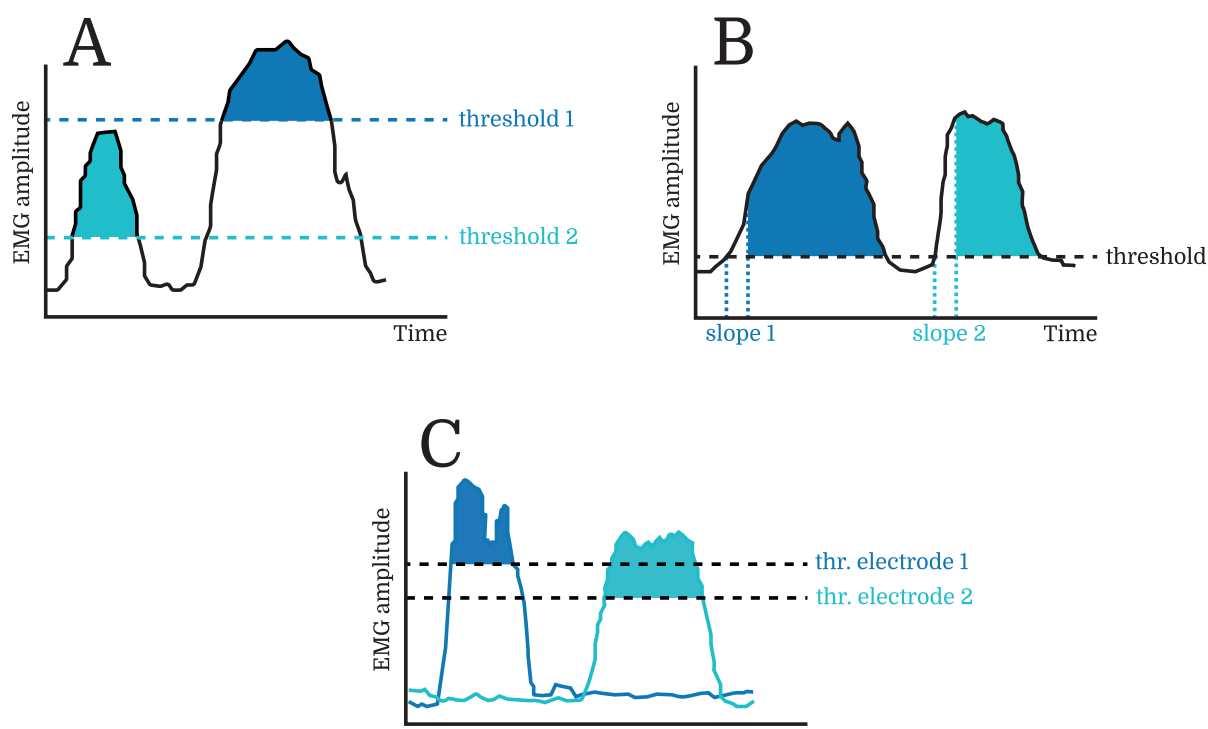


Figure 1.10. Different types of control strategies for the control of myoelectric prostheses. A. Two different movement thresholds for a single electrode. B. Use of the contraction slope to activate different movements from a single electrode. C. Two movement thresholds for two electrode sites.

b. Possible movements on the prosthesis

Most of the commercially-available myoelectric prostheses used by amputees present one or two degrees of freedom (DoF) with the first one being the opening/closing of the hand and the second DoF being the optional wrist rotation module. The switch between the two DOF is obtained using co-contraction of the muscles in the case of a two-electrodes control. One example of this prosthesis is the Ottobock SensorHand we used extensively during this project.

More advanced products possess more than two DoF and the control is based on performing different movements that one could do during daily living. For example, Ottobock's Michelangelo hand offers up to 7 different grip patterns (with different grips in the Lateral and Opposition Modes, as well as a Neutral position), the BeBionic hand once again from Ottobock exhibits 14 grip patterns while other hands such as Ossur's i-Limb or the TASKA hand from Taska prosthetics provide more than 20 different grip types. Nonetheless, a high number of grip patterns does not necessarily mean that each of them will be used daily. Indeed, we find in the literature some studies showing that amputees are using up to 3 grip patterns to achieve all their daily tasks and not exploiting all the possibilities offered by their prosthesis [75][76]. To add more on that subject, Franzke et al. explain that multi-function prostheses are mainly used for tasks where amputees are requiring two hands, with the prosthesis being there to support the sound hand during the execution [77]. The fact that prostheses users are not fully using all the grip types on their device might also be explained by the necessity to rely on switches to have a broader control. This switch is usually

done either through buttons on the prosthesis (like those we find on the BeBionic or TASKA hands) or with co-contractions of the muscles. Based on interviews with users, Franzke and colleagues highlight that some of them find the switch to be non-intuitive and exhausting to perform.

Consequently, the contrast between highly advanced prostheses with extensive possibilities of grip and the relatively archaic and non-intuitive way of using them is compelling, nonetheless solutions have been and are currently being developed (as in this present project) to overcome this obstacle and offer a more natural and physiological control on the prostheses.

c. Alternative methods of control

Over the years several methods have been used to improve the dexterity of prostheses for amputees, here we will present two of them: the first one being a clinical method while the second one is based on the use of multiple surface electrodes.

i. Targeted Muscle Reinnervation (TMR)

Kuiken, Childress and Rymer showed in 1995 [78] on rats that hyper-reinnervation of a muscle, a surgical procedure aimed at rerouting several peripheral nerves on another muscle, was improving muscle recovery. They also hinted that this technique could be used, in the future, “to provide added sources of EMG control signals in some amputees” which they ultimately applied almost a decade later to a patient suffering from a bilateral shoulder disarticulation amputation [79]. The procedure consisted in reinnervating the major and minor muscles of the pectoralis using five of the patient’s residual brachial plexus nerves (see Fig 1.11). After the recovery the patient was able to activate independently three different sites of the pectoralis major by using his phantom limb to bend his elbow, close his hand and extend his arm.

In order to use those contractions for the control of a prosthesis, the patient was fitted with three ElectroMyoGraphy (EMG) surface electrodes on his pectoral. More precisely, one electrode is in charge of the proportional control of the elbow while the other two electrodes control the opening and closing of the hand and with a co-contraction the pronation and supination of the wrist. Kuiken et al. also noticed that sensory reinnervation happened at the chest level simultaneously with the motor reinnervation, the patient was feeling touch sensations of his hand or arm depending on the area stimulated on his chest. Interestingly, as the sites of muscular activities were independent the patient was able to control several DoF on his prosthesis (the elbow and pronation/supination of the wrist), allowing him to perform more complex movements than with the traditional body-powered prosthesis he had been using. The patient was then tasked to perform two tests to evaluate the performance of this new control, both tests showed an improvement over the other control. Moreover, the patient’s subjective reports pointed out that this new control was more intuitive

and seamless while offering him a wider range of daily tasks. The TMR is particularly used to reduce neuroma pain, as the regenerating axons of the severed nerves have a muscle in which they can sprout [80][81].

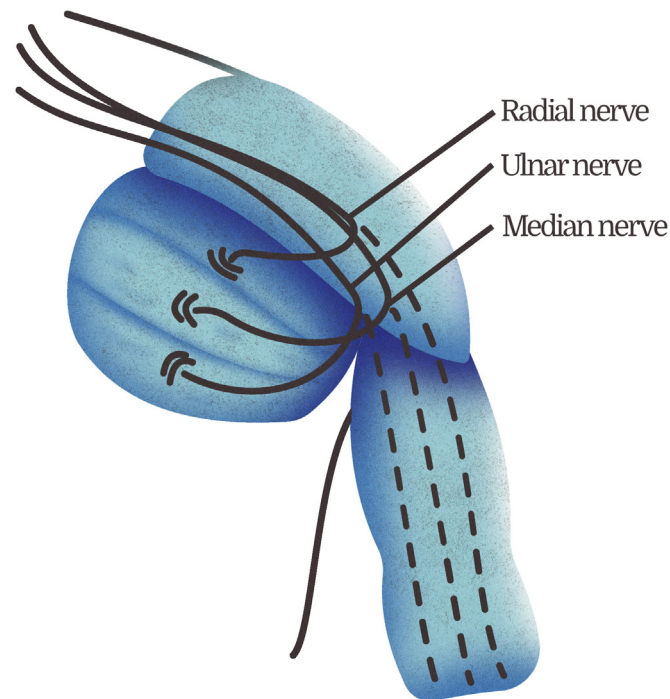


Figure 1.11. Representation of the Targeted Muscle Reinnervation procedure. The three main nerves from the brachial plexus - the radial, ulnar and median nerves - are rerouted and reinnervating muscles on the pectoralis of the patient.

Since this first successful procedure the TMR became a standard procedure for above-elbow amputees [82][83], it is indeed not recommended for below-elbow amputees as they could lose some functionality (especially when they use the method we will be presenting next). Nonetheless, a recent study led by the team behind the TMR is currently trying to explore the use of the technique for transradial amputees to improve the control, by reinnervating median and ulnar nerves of the hand on the forearm. While the TMR offers a great and promising future for the control of prosthesis, it still suffers from the drawbacks of the use of surface electrodes to record muscle activity, in particular, Kuiken et al. [79] reported that the patient was not able to successfully use his prosthesis when there was sweat on the site of the electrodes.

ii. Pattern recognition (PR)

For the control of prosthesis, the pattern recognition technique relies, as the name suggests, on the recognition of patterns in the activation of different muscular sites to control with a higher performance and more intuitively. The first description of pattern recognition occurred during the 70s when research teams noticed that patterns of activation during the execution of certain movements could be classified using EMG signals recorded on different electrodes over regions of the upper arm [84] or on the forearm [85] (see Fig. 1.12).

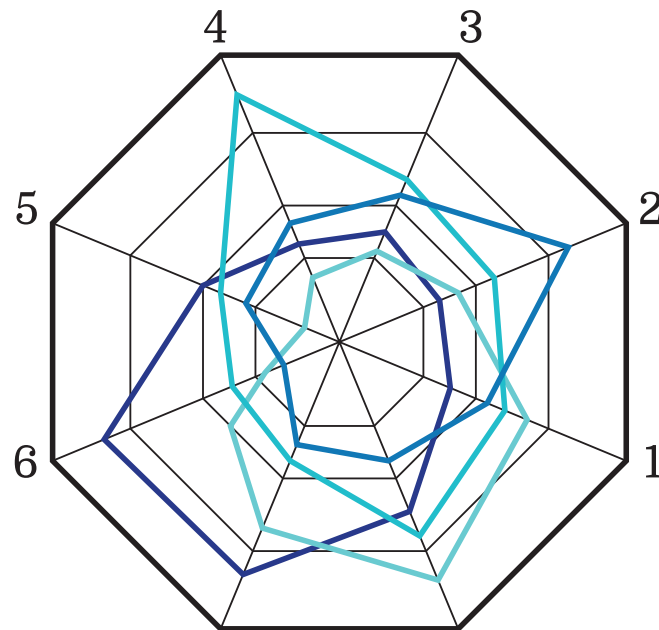


Figure 1.12. Schematic representation of the pattern recognition control. The numbers represent different electrode sites and the colored lines represent the patterns in muscle activities for different movements.

This field of research then constantly developed since the 90s when Hudgins and colleagues [86] showed that the EMG activity obtained from a given movement is reproducible over time and that this activity is different for different movements in amputees and control subjects alike. The team also explains that the appeal behind the use of this technique is that the exhibition of such muscular activities comes with little to no effort as they derive from a natural intent. The EMG activities from several sites are windowed and processed to extract some features, which are then sent to a classifier in charge of recognizing the intended movement.

The research on this topic has mainly been conducted on non-amputated subjects and, while this may be a source of caution, it has been shown in the literature that the difference in the performance of classifiers is consistent between groups of subjects (amputees vs control). Nonetheless, non-amputated subjects can present a lower level of error compared to amputees, see [87] for an example. For a long time, a large part of the research has thus been devoted to finding the most efficient classifiers and not at comparing the results between control and amputees.

Recent research is now more turned toward the evaluation of the PR technique for the control of prostheses which is quite critical, as devices for this type of control are now commercially available such as the MyoPlus system from Ottobock or the Coapt Complete Control from Coapt Engineering. Nonetheless, it is still difficult to have clear results on the use of PR compared to the conventional control. As explained by Roche et al. [88] one of the issues is to translate what is done in the laboratory to a real-life setting, the team is citing results obtained in [89] where the classification accuracy for 10 movements reached approximately 85% while the completion rate of hand movements had a mean of about 54%. This level is insufficient for real-time control of

a prosthesis as a wrong movement could be a danger for the user and its environment. In a study looking at using the movement of the phantom limb as a way to control prostheses Jarrassé et al. [90] hinted that, even though the pattern recognition control performance was lower for amputated subjects, it could be explained by the short training of the subjects to the tasks. Thus, better results should come with proper training. Another potential reason behind the lack of results could reside in the fact that the studies in the literature are based on a very small sample size to conclude on the PR method, with most of them being in the range of 1 to 4 subjects [91][92].

The research is also looking at the combination of both the TMR and PR techniques for above-elbow amputees. While still in a laboratory setting, the results obtained are promising and show the potential behind the combination of the two techniques. In particular, Hargrove and colleagues [93] showed significant improvement in the execution of three different tests when using the TMR+PR compared to the conventional myoelectric control. These results were also accompanied by subjective reports from the subjects praising the intuitiveness and easy-to-use qualities of the system over the conventional one. Yet, it is still difficult to conclude on the best method to use regarding the control of prostheses, which Mereu and colleagues [94] explain by the lack of standard criteria to evaluate the performance, particularly the real-time performance of the systems.

The search for alternative methods of control for prostheses is thus still a work in progress and benefits from clinical (with the osseointegration of prostheses to avoid their suspensions [95]), hardware (through the use of high-density electromyography for example, as seen in [96][97]) and software advancements. Yet a part of the work should be dedicated to the use of such systems outside idealistic environments to truly assess their potential. Finally, and as one can imagine, funding and ethical issues can slow down the appearance of new devices on the market. In an article gathering experts in the research and clinical fields, Farina et al. [98] highlight a need for collaborative efforts between academic and industry to design efficient and relevant clinical studies that would be based on “standardized and ethically considerate animal studies”, allowing to transfer and select appropriate technologies. They also remind us that a breakthrough in the domain of bionic limbs will necessarily be done by putting prostheses users in the discussions, and sharing with clinicians, researchers and manufacturers.

d. The factors behind prosthesis abandonment

Throughout this chapter, we have discussed the different aspects surrounding amputation and the use of a prosthesis. While what we reviewed could be enough to support the importance of using a prosthesis, we also noticed some grey areas that require to be thoroughly investigated, as they are potential explanations behind the rejection of prostheses amongst the amputee population. In the hopes of understanding what is at stake regarding prosthesis use and abandonment for people with an upper-

limb deficit, Biddiss and Chau reviewed 25 years of literature to find some answers [99]. By combining results about rejection rates in research articles, they noticed an overall rejection rate of approximately 20% yet they argue that this percentage might be underestimated, as the non-wearers of prostheses were not the target of the studies in the reviewed articles. To further understand the factors behind prosthesis abandonment, the same authors conducted a survey that included 242 persons with an upper-limb deficit [100]. The survey aimed to highlight reasons explaining the rejection of prostheses following three different categories: predisposing factors, established need and enabling factors.

Among the predisposing factors, the level of limb absence was one of the main reasons for prosthesis rejection which transradial amputees being the more prone to use their prosthesis compared to others. We have indeed seen that compared to the above-elbow prostheses, transradial ones do not need a harness to assure the suspension of the device as they are fitted directly on the stump. Another predisposing factor was the origin of the limb absence, with individuals presenting congenital deficits rejecting devices more than other people living with an amputation. This can be explained by the fact that in the case of congenital limb absence, the individuals are used, since they are infants, to adjust their behaviour and movements based on the limb absence and they do not feel the need to wear a prosthesis compared to those who endured a traumatic or disease-related amputation. One last predisposing factor to note is gender, Biddiss and Chau pointed out that females were more likely to reject prostheses compared to males; particularly females with an acquired above-elbow amputation presented a rejection rate of 80%.

The second category contained answers regarding the need for amputees of using a prosthesis in their daily lives. As one can imagine, prosthesis rejection is higher for people who do not think a prosthesis would be useful to achieve daily tasks (which could include individuals with congenital limb absence as we have seen previously). When matched with their occupations what standd out is that students and stay-at-home individuals are the two highest categories for prosthesis rejection. This result is consistent with what the authors presented in [99] in that prosthesis wear is usually reduced in the home compared to work activities.

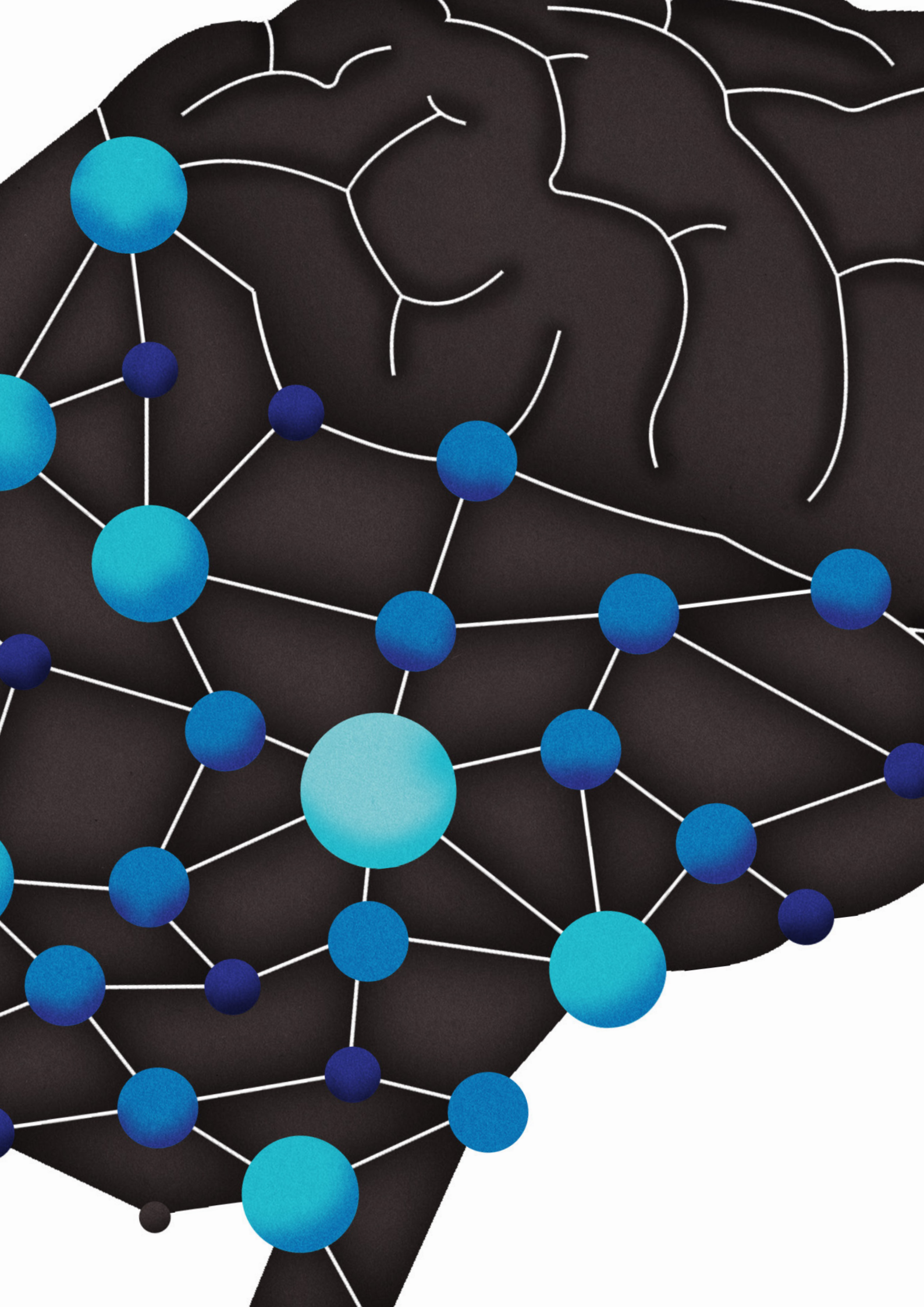
The third category combines the enabling factors, meaning the factors linked to the use of a prosthesis. The two factors underlined by the authors concern health care and the technology of prostheses. Regarding the first factor, prostheses rejecters were significantly less satisfied with all the aspects associated with prosthesis care, whether it is the fitting, training or maintenance of the devices. These results can be associated with a survey conducted on 25 non-wearers of prostheses by Diane Melendez in 1988 [101] where more than half of the interviewees reported they were not provided with enough information regarding available options. To extend further on these findings, Biddiss and Chau add that prostheses rejecters considered that they were not sufficiently involved in the prosthesis selection compared to the frequent

wearers. It was also reported that longer fitting times were likely to induce prosthesis rejection with frequent wearers reporting shorter times leading to the fitting of the prosthesis. The other factor concerns the prosthesis technology for which prosthesis rejecters appear to be dissatisfied with the appearance, comfort, functionality, ease of use, reliability and cost compared to prostheses users.

Nonetheless, as pointed out by a prosthesis user in the article by Jones et al. [102] users are well aware that there is a trade-off between appearance and functionality, as it is known that a more realistic appearance is found usually for cosmetic prostheses whereas functionality is for body-powered/myoelectric prostheses. Regarding the comfort and ease of use, it is often reported that prostheses are too heavy which can make them difficult to use [102], rejecters in [100] and [101] explain that they are more comfortable and as functional or more without the prosthesis. Prosthesis users also report that the use of prostheses generates heat leading to sweat, thus contributing to difficulties to use the devices. Although not a significant factor, we can note that the cost of the prostheses can be an obstacle, as some patients might not have access to the most recent models.

One last factor for prostheses rejecters, and certainly not the least, is the lack of sensory feedback when using a prosthesis and the fact that they have more sensations without it (when using their stumps to perform a movement for example). This need for sensory feedback is also shared by prostheses users as seen in [103] however no commercially available devices showcase sensory feedback although it has an impact on how amputees are using and integrating their prostheses [104][105].

While it is easy to say that the acceptance of prostheses could be improved through a comprehension of the reasons behind prosthesis rejection, solutions to those factors represent challenges for researchers and manufacturers, especially regarding prosthesis technology. The next chapter of this manuscript will be the occasion to introduce the concept of brain-machine interface used in the project that attempts to improve the acceptance of several of those factors.





II

**Brain-Machine Interfaces
and their applications**

We have seen in the introduction that the concept behind Brain Machine Interfaces/Brain-Computer Interfaces (BMIs/BCIs) is not new and has been proposed in 1973 by Vidal [2] where he speculated about the use of one's brain activity to control a computer. Nonetheless, while well aware of the limitations of the technologies at the time, he offered some insights and guidelines regarding the different parts that constitute a BMI. Nothing changed much since the 70s regarding what is composing brain-machine interfaces, we can divide them in five parts:

- Recording of the brain activity
- Processing of the activity to extract relevant features
- Classification of the features to distinguish between patterns of activities
- Control of a device (the Machine in BMI and the Computer in BCI)
- Feedback given to the user

This chapter will be the occasion to tackle the first four parts of BMIs and we will first see how the brain activity is recorded.

1. Recording of the brain activity

There are several ways of recording the electrical activity of a brain, those methods depend on the level at which this activity is recorded, whether it is recorded invasively, semi-invasively or non-invasively. Nevertheless, before naming and reviewing some of those techniques, let us dive into the neuroscience behind the activity of the brain.

a. Basic neuroscience

In a similar fashion to the first chapter where we described what was happening at the level of the muscle, if we were now to look closely at the brain we would see a multitude of interconnected cells (billions of them to be a bit more precise) called neurons forming huge and complex networks. A neuron is composed of three parts: the soma, the dendrites and the axon (see Fig. 2.1). The soma can be considered as the body of a neuron; its role is to maintain the function of the neuron. The dendrites form a structure that can be compared to a tree with multiple branches that come from other neurons to the soma, their role is to receive information from those other neurons and transmit it to the soma of the neuron. Finally, the axon is a fibre whose role is to transmit the information coming out of the neuron to other neurons. The connection between neurons is made by synapses, a structure happening between the axon of a neuron and the dendrite, or between the axon or the soma of another neuron. Even though there exist electrical synapses whose role is rather the regulation of the neuronal networks, the majority of synapses are chemical ones where the transmission of information is

due to the unidirectional transmitting of chemical molecules, and neurotransmitters, from presynaptic neurons to postsynaptic ones if an action potential (spike) occurs on the axon.

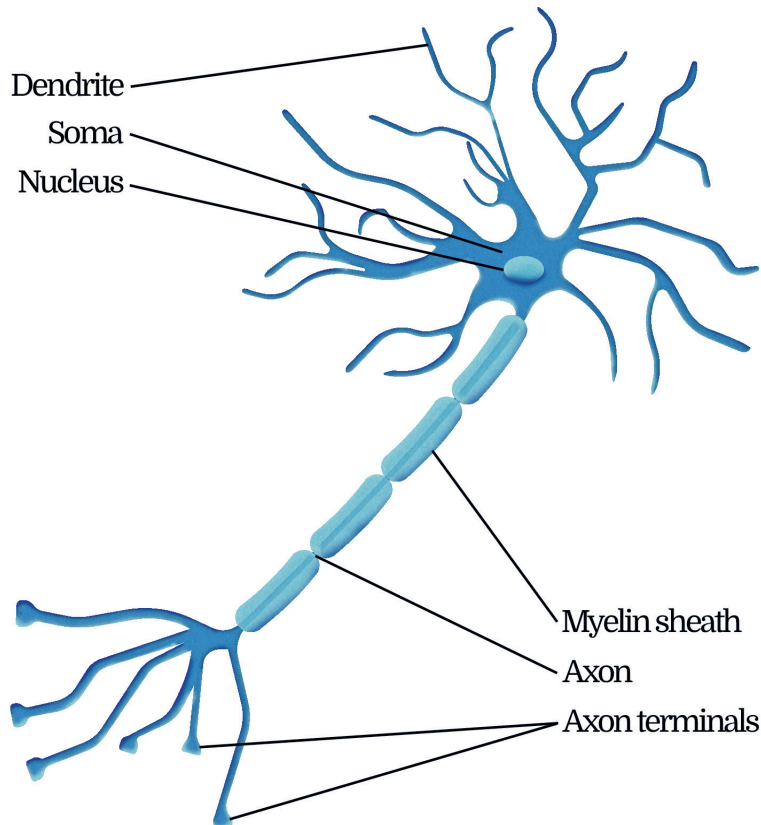


Figure 2.1. Schematic representation of a neuron and its different elements.

For an action potential to appear at the level of the neuron it must receive inputs from several other neurons. If the membrane potential, being the sum of the inputs received from the other neurons, is above a certain threshold (which is neuron-dependent) then a spike is triggered on the neuron, caused by a sudden shift in its membrane potential. This phenomenon is also referred as all-or-none; the obtained spike always presents the same amplitude if the excitation is above the threshold. Several theories exist to explain how the information is coded in those spikes. A large extent of the literature has been dedicated to find how the information is coded in the firing rate of the neurons (frequency coding) while other theories suggest that the spatial distribution of spikes over time (temporal coding) and the interval between them is where the information is coded [106][107][108][109]. Finding a satisfying answer to neural coding is still an ongoing challenge, opposing supporters of the rate (frequency) coding versus supporters of temporal coding. Nonetheless, in a review article [110] Romain Brette suggests that the question is not about finding whether the brain use rate coding or temporal coding but rather finding if firing rates are causal in the way neurons are interacting with each other or if they are correlates of that interaction.

In the first chapter, we talked about the somatotopic map found in the sensorimotor cortex, which corresponds to a mapping of body parts in this region of the brain. This brief introduction is the perfect occasion to talk more about the brain and its functions;

more specifically, we will focus on the cortex, leaving behind the other structures in the brain. As hinted, the cortex can be divided into different areas that are specialized in specific functions. The sensorimotor cortex straddles two areas of the brain: The motor cortex located in the frontal lobe and the somatosensory cortex located in the parietal lobe. On one hand, the frontal lobe is thus involved in the movement, from its planning to its execution, but it also has a role in language and speech. On the other hand, as explained by Chayer and Freedman in [111], the frontal lobe also plays a role in attention, in memory (for working, long-term and prospective memory) and also in personality traits such as emotions or social responses. As for the parietal lobe, we have seen that it was involved in the processing of sensory information, with both the perception and integration of this information, whether it is the sense of touch, pressure or pain. The parietal lobe also comes into play with visuospatial orientation and proprioception, how we can locate ourselves and our environment in space, as well as language processing or mathematical calculations. At the back of the brain, we find the occipital lobe whose principal function is to process visual information, through the primary visual cortex (also known as V1). V1 is sending information to other parts of the occipital lobe that will process several functions such as evaluation of distances, size, depth and colours, objects and face recognition. The occipital lobe is also sending some information to the last areas of the cortex, the temporal lobes that are responsible for processing the visual information by adding meaning to them. The auditory cortex is involved in the processing of auditory information such as speech and its understanding/interpretation. Finally, the temporal lobes are also involved in the formation of memories.

Now that we have a short and clearer understanding of what is happening in the brain at both the level of the neurons and on a larger scale with the functions of the different areas we can take a look at the various methods with which we can record the membrane potential of neurons. Depending on the locations of the electrodes, we will talk of invasive, semi-invasive or non-invasive recordings. We will not review all the techniques but rather those that are mainly found in BMIs research.

b. Invasive recordings

What lies behind invasive recording techniques is the desire to access the electrical activity of a single (and/or of a population of) neuron(s). To access those neurons a surgical procedure has to be initiated where a part of the skull is removed to put electrodes on a specific area of the brain. The electrode used can be designed to record the activity of only one neuron or the activities of several neurons simultaneously, in which case we can use either tetrodes or microelectrode arrays (also known as MEAs) which are grids of electrodes. With invasive electrodes, one of the main advantages is to have a high temporal resolution; the systems can record spikes with a short timescale, in the range of the millisecond. Moreover, when using MEAs the multitude of electrodes also allows for a better spatial resolution: one can then record several neurons from the same area, thus mapping more effectively the activity in that area. As

reminded by Buzsaki and colleagues [112], the recorded activity (during extracellular recordings) is composed not only of the action potentials of the neurons but also of “membrane potential-derived fluctuations” coming from the recorded population of neurons, hence the name Local Field Potentials (LFPs) that is seen in the literature.

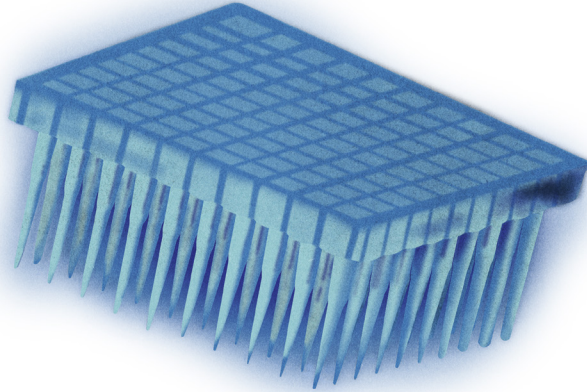


Figure 2.2. Example of a Microelectrode Array (MEA). Here depicted is the Utah Array.

While invasive techniques offer probably, the best quality on the recorded signal they also suffer intrinsically serious disadvantages. Because they require electrodes to be located within the brain, a consequence of that implantation is that cells, called glial cells, will start to stick together around the electrodes or the array. The glial cells are aimed at protecting the neural tissue, and will thus prevent contact between the electrodes and the neurons. This process will cause a rise in the impedance on the electrode, leading to a signal slowly decreasing in quality over time. One of the main challenges in the field of invasive recording is thus to develop electrodes and arrays that can resist or delay this phenomenon by improving the biocompatibility between those devices and the brain [113][114][115].

This makes it difficult for invasive methods to escape the research setting, as Stephan Waldert highlights in [116], those techniques will be acceptable for a majority of patients once “their benefits outweigh concerns”. The author also raises ethical issues that we will be discussing at the end of this chapter.

c. Semi-invasive recordings

Going out from the brain and the invasive techniques, we find the appropriately named semi-invasive recording techniques. As for the invasive recordings, this technique, called ElectroCorticoGraphy (ECoG), requires a surgical procedure to remove a portion of the skull and usually place a grid of electrodes on the brain surface. Two forms of ECoG exist; the recording can be done epidurally or subdurally meaning that the electrodes will be placed over or under the dura mater, the last fibrous membrane that offers protection to the brain before the skull. As reminded by Rao in [117], the use of ECoG electrodes is primarily seen in clinical research to monitor seizure activity for epileptic patients, they can thus be located in grids of electrodes all over the brain to target areas of interest.



Figure 2.3. Example of a flexible ElectroCorticography array of electrodes. The array can be placed either under or over the dura mater.

Because of the localization of the electrodes, the recorded signal does not possess the same spatial resolution as the microelectrode arrays; it consists of the electrical activity coming from large populations of neurons in the superficial layers of the cortex. Recent works are aimed at developing smaller ECoG electrodes, also known as micro-ECoG, with a smaller electrode diameter and a reduced inter-electrode distance. The goal is to obtain a higher spatial resolution of the ECoG and to target localized areas for specific applications.

One advantage of the ECoG technique is that, although it requires a surgical procedure to put the grid of electrodes on the brain's surface, this procedure is safer than the invasive arrays. Indeed, there is no need to implant the electrode and as a correlate to this intervention, the electrodes will suffer less from the response coming from the glial cells. This will offer to the ECoG electrodes a longer lifetime all the while being safer for the patients [118][119]. Of course, the clinical applications are different between invasive and semi-invasive recording, and recent works with ECoG showed promising results regarding the BMI control of end effectors [120]. Nonetheless, most of those studies have to rely on already placed grids for the recording of the signal, with a localization that may be sub-optimal for specific applications [121].

d. Non-invasive recordings

Finally, and after going through invasive and semi-invasive methods we naturally arrive at the domain of non-invasive recordings. There exist several techniques to record the activity from the brain and, as it is the technique used during this thesis, we will focus on ElectroEncephaloGraphy (EEG). The German psychiatrist Hans Berger invented this technique in the 1920s as he was trying to explain a case of telepathy between his sister and himself. While he was not successful in finding a reason for this phenomenon, it led him to record for the first time the electrical activity of the brain using electrodes on the scalp of a patient. He published an article with his findings on brain oscillations in 1929 [122] where also appears for the first time the term ElectroEncephaloGraphy. At first mocked by his colleagues, Berger was in the 1930s recognized by his peers thanks to other studies confirming the importance of EEG.



Figure 2.4. Example of an ElectroEncephaloGraphy cap with 16 electrodes.

As with the ECoG technique, the activity recorded through EEG is the compound electric potentials coming from more than thousands of neurons. Continuing with Rao [117], he adds that the EEG signal corresponds to the electric activity from neurons radial to the scalp, while tangentially oriented currents are not detected by the electrodes. Because of all the different layers between the electrodes and the cortex, the EEG technique is both not able to access the activity from deeper structures in the brain but also suffers from poor spatial resolution, as the layers alter the signal.

Because of the low amplitude of the recorded signal (in the range of several microvolts), the EEG recording system is also composed of an amplifier which primarily amplifies and filters some of the noise. The signal-to-noise ratio (SNR) is de facto one of the main issues with the EEG signal, and to increase this ratio it is first possible to act on the electrodes that are used for the recording. The most common types of electrodes used in EEG setups are also known as wet electrodes: after preparation of the scalp

of the subject with an abrasive gel to remove dead skins, a conductive (electrolytic) gel or a saline solution is put between the scalp and each electrode to further reduce impedance between the two parts. The others, logically called dry electrodes, are directly placed on the scalp and do not necessitate any gel or liquid before recording the activity. As one can easily imagine, this second type will be more subject to noise than wet electrodes but they offer in turn a significantly quicker time to prepare the recording setup. As such, a portion of the research in the field is thus dedicated to the development of easy-to-use electrodes that still offer a good signal for BCI applications [123][124].

The fitting of the EEG caps, containing up to 256 electrodes, usually follows a standardized localization of the electrodes. The main standard is called the 10-20 system and has been created based on the distance from two landmarks on the head: the inion, a bone protuberance at the back of the skull and the nasion, a hollow located between the eyes and at the top of the nose. Following those two points, the radius of the skull of the subject and the distance between the two ears, this standard guarantees a consistent positioning of the electrodes on the scalp for everyone. Another point to consider when fitting the EEG cap is the choice of the Ground and Reference electrodes. The ground electrode, as the name implies, is connected to the ground of the amplifier and is used to pick up the electrical noise in the circuit. Without a reference, the recorded EEG signal is expressed as the difference in the electrical potential between one electrode and the ground. To remove the electrical noise, a reference is added to the circuit whose role is to act as the “baseline for all remaining EEG channels” [125]. In short, it means that instead of being expressed as the difference between one electrode and the ground, the signal from each of the electrodes (including the ground) will be obtained as the difference between the electrode and the reference. The choice of the ground is not crucial as it is only picking up the noise, on the contrary, the choice of the reference is much more important as explained in [125]. There is a trade-off between a desire for the reference electrode to not pick up the signal of interest, as it would reduce the effect especially if the reference is placed close to the region of interest for the study, but also picking up the same noise as the other electrodes. This is why a common placement for the reference is one of the mastoids, located behind the ear. One can also choose a location on the head but it should preferably be in a symmetric position (in the midline between the nasion and the inion) to not bias the signal towards one hemisphere. To satisfy the other part of the trade-off and to improve as much as possible the SNR the reference should also be close to the region of interest and should as such be able to access the same noise. The choice of the reference is thus clearly dependent on the application and on the signal that is to be recorded, which also explains why there is no clear consensus on the perfect reference placement.

Besides the choice of the type of electrodes and the reference, one also needs to pay attention to avoid the appearance of noise on the EEG signal. Usually, subjects are asked to reduce as much as possible their movements during the recordings, this

includes eye movements and muscular movements (like jaw clenching for example), those movements indeed generate artefacts that contaminate the EEG signal. Another type of noise that is usually seen on the EEG signal is the noise coming from the general power line, this noise is visible on the power spectrum of the signal with a peak at 50 or 60Hz depending on the country. We will see later at 3.a. the various ways available to clean the EEG signal to retrieve the relevant brain activity

In his 1929 article, Berger [122] used the terms Alpha and Beta waves to describe two types of oscillations that, according to him, were composing the EEG signal: Alpha waves ranging from around 7 to 13Hz, and Beta Waves happening at a higher frequency. He noticed that the low-frequency waves were appearing when the subjects had their eyes closed while the beta waves appeared when they reopened their eyes. Decades later, it was found that those two oscillations were not the only important components of the EEG signal, the various studies on the subject agree to describe at least 5 frequency bands whose frontiers can change in the literature:

- *Delta waves*, found below 4Hz, are predominantly appearing during sleep, specifically during slow-wave/deep sleep.
- *Theta waves*, between 4 and 7Hz, are usually present when the subject is quietly waking up from or falling into sleep, losing awareness.
- *Alpha waves*, from 7 to 13Hz, present when the subject is relaxed or with their eyes closed. They are also referred to as Mu rhythm when recorded over the sensorimotor cortex when there is movement execution or imagination.
- *Beta waves*, from 13 to 30Hz, are mostly present during active tasks when a subject is concentrated.
- *Gamma waves*, ranging from 30Hz to above, are associated with cognitive functions such as learning, memory or attention.

It is thus quite naturally that we decided to focus mainly on Alpha and Beta waves for this project, as we were interested in performed or imagined movement requiring the concentration of the subject.

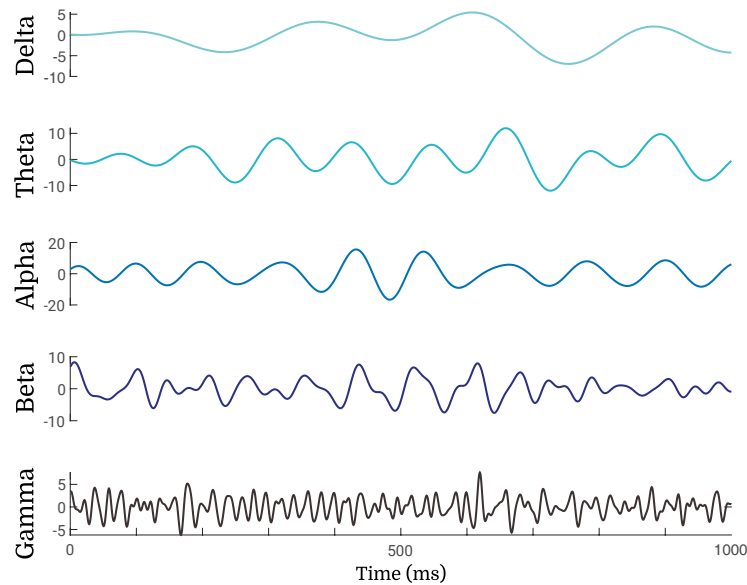


Figure 2.5. Representation of the EEG activity for different frequency bands in the cortex.

2. The specificities of Brain-Machine Interfaces

Now that we have a better understanding of how brain activity is recorded and what are its components, we can look at the brain-machine interfaces and their different types. We have seen in 1.b. that there are several possibilities of recording the brain activity with invasive, semi-invasive or non-invasive methods. As such, the first classification of BMI that we can make would be invasive or non-invasive BMIs. We will see in 5.b. that invasive ones, because of the required surgery, are limited to only specific categories of subjects and are thus difficult to test on larger populations. In this PhD work, we focused on non-invasive recordings and we will thus present the details of BMIs relying on the EEG activity.

a. The different types of BMIs

We can first classify the BMIs into three categories: active, reactive and passive. In the passive category, the control is done without asking the user to perform a task, the brain activity is tracked and an output is given following changes in the activity. Passive BCIs are mostly used to monitor cognitive or mental states and particularly, in [126], Alimardani and Hiraki highlight three directions of passive BCIs in research: 1) detection of attention and mental fatigue, 2) detection of errors, 3) detection of emotions. Those three directions offer large possibilities of use outside the research field such as in marketing (see the review by Pei and Li [127] for applications using EEG), education [128] or healthcare [129].

Reactive BMIs rely on the user focusing his attention on an external stimulus that can be visual, auditory or somatosensory. The most common type of stimuli used in reactive BMIs are the visual ones, they can be found in the SSVEP BMIs paradigm where SSVEP mean Steady-State Visually Evoked Potentials. In this paradigm, the

user is focusing on various lights that are flickering at different frequencies, when the user put his focus on a particular light, a peak on the EEG signal at the flickering frequency can be observed. This peak, if maintained, is then used to trigger control on a machine [130]. As one can imagine, in the auditory or somatosensory paradigms, it is not a flickering light that is used but rather a sound played or a tactile stimulation at a specific frequency [131][132].

Finally, active BMIs - the category of BMIs we used during this project - requires the user to actively perform a task to control a device. As the aim of a BMI/BCI is to be controlled without the user being forced to perform overt movements, the task that is used for BMIs is mainly a mental one. For example, if the user wants to make a robotic arm move to the right he/she could have to imagine performing a movement with his/her right or left arm. Nonetheless, the mental task does not necessarily have to be congruent with the desired output: an imagination of a movement of the foot can trigger the activation of a switch. Thus, what is needed for a BMI to work flawlessly is to make sure the patterns of EEG activities are distinguishable enough and repeatable over time

b. BMIs control modes

Here we divide the BMIs into two control modes called Synchronous and Asynchronous. When using the Synchronous mode, the subject is asked to do the task thanks to a stimulus, like an image appearing on a screen or an audio track being played. The EEG signal recorded after the appearance of that cue is then used as the input data for the control of the end effector. In that control mode, the task is thus predefined and fixed. We can find a distinction within the Synchronous control for reactive and active BMIs, with some BMIs relying on the use of Evoked Potentials, which are automatic responses of the brain to a stimulus, and others relying on Mental Imagery where the subject has to actively perform the mental task (whether it is motor imagery or some mental calculation).

As explained by Zhang and colleagues in [133], contrary to the synchronous mode the asynchronous control “provides a more natural human-machine interaction mode” in that there are no cues for the subject to indicate them to perform the mental task. The asynchronous control is thus necessarily used with active BMIs; the EEG data is continuously recorded and processed and whenever a brain activity different from the resting-state activity is detected by the system, the output, composed of the features of this activity, is computed and transformed to activate the end effector. Despite offering a more natural interaction, this type of control is also more prone to triggering unwanted control because of the potential misclassification of the EEG activity. This can also explain why Asynchronous BMIs are more often used as “brain-switches”; they detect if the subject is for example performing a specific task compared to a neutral/idle state, and the detection then triggers the control command [134].

Some studies in the literature propose a hybrid control, combining a specific brain-switch with asynchronous BMIs. One example of such application can be seen in a study by Choi and colleagues [135]. In this work, they combined a brain switch based on the detection of triple eye blinks (the three close blinks create an easily distinguishable artefact on the EEG) and two classifiers trained to classify motor imagery between either a resting state or active gait or between active gait and sitting down. Here the brain switch was used to trigger the recording and processing of the EEG activity but also to choose between the classifiers and change the movement that was to be executed on a lower-limb exoskeleton.

While there is always the desire to aim for the most natural control for a user, we can see that it might not be the best solution depending on the application, the use of a hybrid control can thus provide some more robustness when issuing commands, especially when the used brain-switches are not cognitively demanding tasks.

3. Signal Processing & Feature Extraction techniques

Once the EEG signals for a given paradigm have been recorded, the relevant information hidden behind the brain waves (coded by the brain waves) must be decoded. Indeed, because the EEG signals are composed of electrical activities coming from a multitude of sources there is a need to first clean the signal and then extract the right features for the application.

a. Preprocessing

The first step is thus dedicated to removing as much noise as possible without losing important information contained in the data. Nonetheless, just before looking at this task, it is quite common to reduce the size of the EEG recording. As EEG amplifiers offer sampling rates usually going from 125Hz to 10Khz or above it is quite easy to end up with an EEG signal of substantial size which tends to slow down the various processing steps. To overcome this problem one solution is to resample the EEG signal to a lower frequency; however, this constitutes once again a trade-off as one might lose information because the signal can now be significantly reduced in size. De facto, this method is essentially necessary for online/real-time applications where a larger signal can lead to a delay in the chain of command, something that is not critical for offline processing of the data

We have mentioned previously that the brain activity recorded during an EEG session, despite being partly related to the brain, is also composed of noise coming both from the environment but also from the subjects themselves. As we have said, the power line, whose frequency is 50 or 60Hz, causes the main noise that we observe from the environment. To remove this specific artefact on the signal, it is common practice to use a Notch filter (also called Band-stop filter). Its role is to attenuate the signal in every

narrow frequency band, just to target the problematic frequency. The other sources of environmental noises that can be found in the EEG signals can be explained by the presence of running electronic devices in the room where the EEG recordings take place. The frequencies at which they appear are sometimes well above the frequency bands of interest in the EEG that make them not as problematic, nonetheless, one should always be vigilant to make sure that this noise is not contaminating the signal.

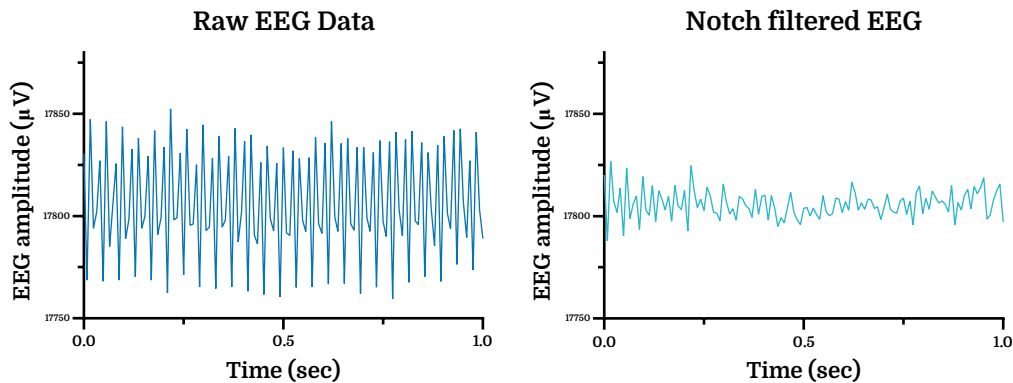


Figure 2.6. Difference between the raw EEG activity (left) and the notch filtered EEG (right) to remove the noise from the electric line.

Regarding artefacts coming from the subjects themselves, we have pointed out earlier the necessity for them to reduce the movements they could do while the data is recorded; this includes artefacts from the muscles of the face or the jaw and artefacts coming from eye movements. It is once again quite a critical issue when dealing with real-time applications. Because, if we are considering a system that is to be used in daily life, the subjects will necessarily have to move around and perform different tasks most of the time simultaneously. This makes the development of this kind of system such a challenge as we always strive to have the best quality of data to the detriment of something robust enough to be used in different conditions. Thereby, as it is probably impossible to avoid the presence of such artefacts on the signal the methods used are aimed at reducing the impact they have.

Eye blinks and movements are artefacts appearing at low frequencies, primarily in the Delta range below 4Hz, the blinks are visible in the EEG signals from electrodes located in the forehead of the subject (see Fig. 2.7) and are fading out in the others while eye movements present a higher propagation through the electrodes. As explained by Lotte and colleagues in [136], the eyes can be compared to “rotating electric dipoles” and as such, they will trouble the electrical field of the brain. There exist some methods to automatically reject eye artefacts during offline processing of the data, but as we have already seen above the eye blinks can be of use in some hybrid BMIs design. Thus, another way to minimize their importance is to simply apply a high-pass filter with a cutoff frequency of around 4Hz. Nonetheless, things are more complicated regarding the artefacts from the muscles in the face. Boudet et al. [137] remind that forehead movement and jaw clenching can be seen in frequencies above 13Hz meaning that those cannot be easily filtered out without potentially letting go

of relevant information. Nonetheless, one usual solution regarding BMI applications using motor imagery or mental tasks is to band-pass filter the EEG data between the alpha and beta bands, as they are the two principal frequency bands of interest.

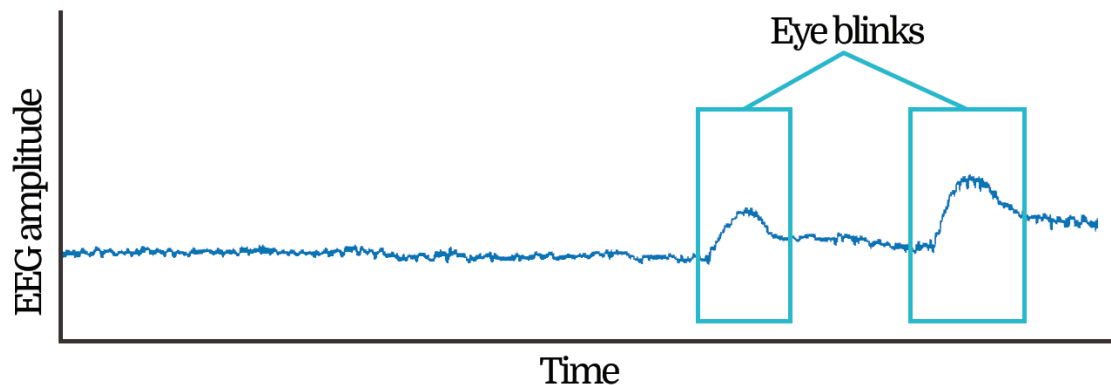


Figure 2.7. Presence of eyeblinks in the EEG activity recorded on a frontal electrode.

Another technique, mainly used in offline analysis but with more and more in online development, is called Independent Component Analysis (ICA). The idea behind the ICA method is to separate independent sources that are mixed linearly in the signal recorded by an electrode. In his videos and on his website Arnaud Delorme [138] explains that as the artefacts are usually independent of the signals from the brain, this technique allows for a separation of the artefacts from the data, it is then possible to reconstruct the original signal by removing the problematic sources. What poses some problems with the implementation of such methods is that on one hand, this algorithm requires enough data during online implementation so that it works properly [139]. And on the other hand, the time needed to clean the data is dependent on the algorithms used in the ICA which can be more or less computationally demanding [140].

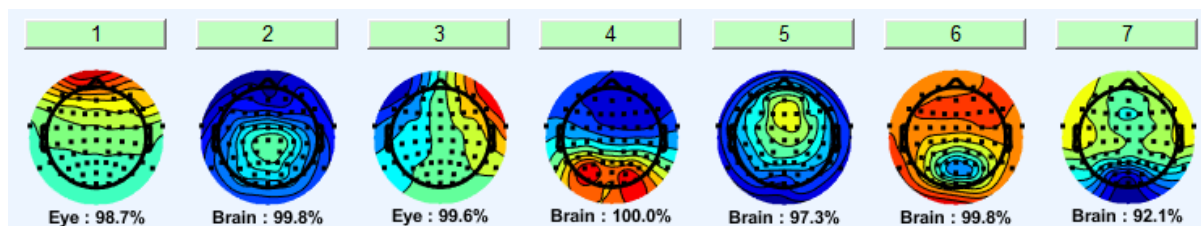


Figure 2.8. Labeling of the EEG activity with Independent Component Analysis on EEGLab.

b. Feature Extraction

As we now have access to a cleaned version of the signal, it is time to deal with the extraction of its representative components (the so-called features of the signal) that will be used to construct the control commands of the end effector. There are different feature extraction techniques depending on the domain we are working on with the EEG signal, whether it is in the Time domain, the Frequency domain or the spatial domain.

The EEG signal that is recorded is a time series, a sequence of data points sampled at a given frequency. As such, and quite naively, it can be interesting to simply look at the changes in the amplitude of the EEG for several electrodes across time. One of the most common paradigms in BCIs is to use Event-Related Potentials (ERPs) which are the changes in the brain activity following the presentation of a sensory, motor or cognitive stimulus to a subject. An example of such use is the P300 speller, which is based on the oddball paradigm for which a repetitive stimulus is presented to a subject with a deviant stimulus being presented from time to time. When the latter is presented, we can observe a spike in the activity approximately 300msec after the onset of the stimulus, hence the name P300 with the “P” meaning a positive activity [141].

In the P300 speller, a matrix containing the letters from the Latin alphabet and numbers from 0 to 9 is displayed to a subject on a screen, the rows and columns are swiftly highlighted while the subject is focusing on a letter or a number. Then, after a few seconds, the computer gives a prediction based on the P300 that can be observed or not for the specific letter/number. To have the prediction, a classifier is trained based on some training trials in which the EEG activity is recorded when the participant is focusing on successive target letters. Once enough trials are recorded, the EEG activity for each letter or number is averaged to increase the signal-to-noise ratio and to have a clearer P300 wave [142].

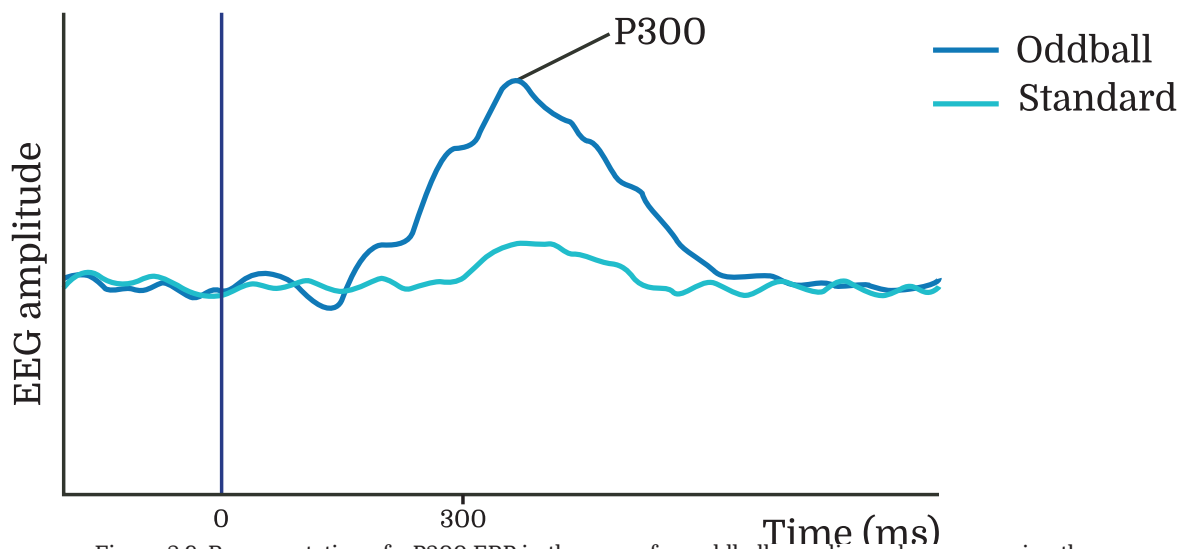


Figure 2.9. Representation of a P300 ERP in the case of an oddball paradigm when comparing the response to the oddball or standard stimuli.

i. Frequency domain techniques

It is also quite intuitive to think of looking at the EEG signal through the prism of the Frequency domain. Indeed, as we have seen previously, some frequency bands have been defined in the literature for EEG studies and we can observe variations of amplitude in some of these bands under different conditions which is what some of the BMIs are exploiting in terms of signal. One of the classic ways of investigating

the frequencies at stake is to compute the frequency components of an EEG signal thanks to the Fourier transform which decomposes the signal into many sinusoids with different amplitudes, frequencies and phases. The Fourier transform of the signal gives us what are the frequencies present in the signal without being able to tell at what time they are appearing in the signal/recording.

To overcome this limitation, one can apply the short-time Fourier transform (STFT) method, which, instead of taking the EEG signal as only one entity, is performing the transform on several time windows from start to finish. It is then possible to compute the spectrogram of the signal; it represents the power of a signal as a function of time and frequency. Yet, a drawback of the STFT is that although it is giving some information about the frequencies in time, some concessions have to be kept in mind. Indeed, as we are working with time windows, the wider the time windows and the less precise we are regarding the frequencies happening at a certain moment in time and inversely.

One method regarding this trade-off issue is to use wavelet transform, which is quite similar to the Fourier one, but instead of representing a signal as a sum of sinusoids, the signal is represented with wavelets. They are functions that are starting at zero, and then briefly oscillate to finally go back to zero. We can play with two parameters of these wavelets: translate it along the time axis or scale it, which is equivalent to stretching or compressing the wavelet. Scaling the wavelet is allowing us to capture either the low or high frequencies of the signal. Similarly to the Fourier transform, the Wavelet method will sort of decompose the EEG signal as multiple wavelets with different scales. As explained by Shawhin Talebi in his article [143], the idea is to slide a wavelet at a given scale along time and multiply it with the signal which is giving a “coefficient for that wavelet scale at that time step”, the process is then repeated with different scales. As the scale can be considered analogous to the frequency but when dealing with wavelets, it is possible to access the frequencies and their localization in time in a signal. One of the figures that can be plotted is appropriately named scalogram and, as the spectrogram, it is plotted as a function of the time and the frequencies.

The process of feature extraction is also often synonymous with dimensionality reduction; we start the process of feature extraction with a certain number of features and end up with a smaller subset of features that contains most of the relevant information. One method for dimensionality reduction is the famous Principal Component Analysis (PCA), which is aimed at offering a response to the problem of Blind Source Separation (BSS) that we can find in EEG. The recorded signal (multiple observations) is a linear mix of multiple independent signals coming from unknown sources and the question is how can we retrieve the signal from the independent sources? Using PCA, the original data recorded in the sensor space (from all the electrodes) is transformed into a linear combination of uncorrelated variables (called Principal Components, PC) that are ranked in terms of how much of the variance of the signal they account for. It is thus possible to get rid of the PCs that do not contain

that much information based on the variance. The inverse process is then done after the removal of the PC and the reduced signal should only present a minimal loss of information while being represented with a lower number of features.

ii. Spatial domain techniques

At the beginning of the chapter we presented how brain areas are dedicated to specific functions such as vision or movements. As such, a part of the techniques used in brain-machine interfaces research aim at taking advantages of the different activations in the brain in that spatial domain. One of the most used method is called Common Spatial Patterns (CSP), and has been popularized by Ramöser et al. in [144], this method is mainly applied for binary classification in which two classes have to be compared. It consists in finding a set of spatial filters which are solutions to an optimization problem where for the first part of the filters the variance of one class is maximized while that of the other class is minimized and vice versa for the second part of the filters. As explained in [145] only a certain number of filter pairs are kept at the end of the optimization process, the pairs correspond to the m first and last columns of the w matrix (see Fig 2.10 for an application).

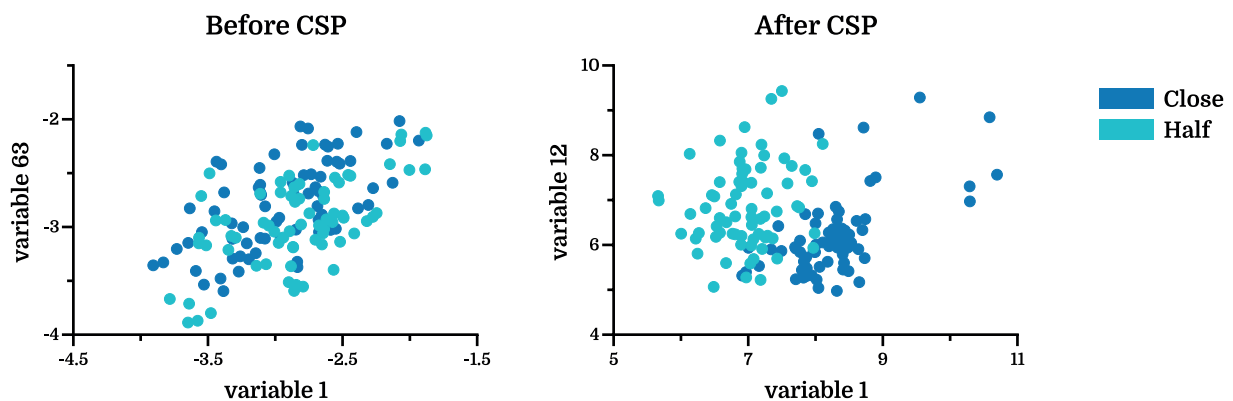


Figure 2.10. Differences between the separation of two recorded movements Close and Half (respectively a movement of full or half closure of the hand) based on the application of the Common Spatial Patterns technique. While offering a better separation of the two groups of features, the CSP technique allows for a reduction of the dimensionality of the signal.

Nonetheless, and despite its large utilization in articles and BCI competitions, the original CSP method is still sensitive to outliers and subject to overfitting on small training datasets as presented by Reuderink and Poel in [145], this led to several proposals to adjust the CSP algorithm. One proposition is to use a regularized version of CSP that can add prior information at different levels of the algorithm: directly on the covariance matrices that are estimated or in the objective function that is to be solved [146]. Some other techniques are tackling the loss of information resulting from the selection of only a small portion of the CSP features at the end of the process, and thus propose a weighting of the features [147]. We also find an adaptation of the CSP method like the Filter Bank CSP, which proposes to compute CSP features for different frequency bands in a range of interest, filtering the EEG data in frequency

windows before applying the CSP technique [148]. Finally, some research has also been dedicated to finding efficient adaptations of the CSP algorithm for multiclass classification, offering perspectives to increase the number of commands for a BMI [149].

The basis behind the use of the CSP technique is the assumption that covariance matrices can be used as “descriptors of the EEG signal” for a given mental task, and that they follow a normal distribution meaning that the same task will lead to slightly different covariance matrices [150]. In 2010, Barachant and colleagues proposed to take advantage of this and explored the use of Riemannian geometry as an alternative to the CSP algorithm [151]. Particularly, they explain that the covariance matrices used in CSP can be represented in the Riemannian space of symmetric positive-definite (SPD) matrices, also referred to as a manifold. The curve giving the minimal length between two points (two covariant matrices in our case) in the manifold is called the geodesic whose length can be defined by the Riemannian distance:

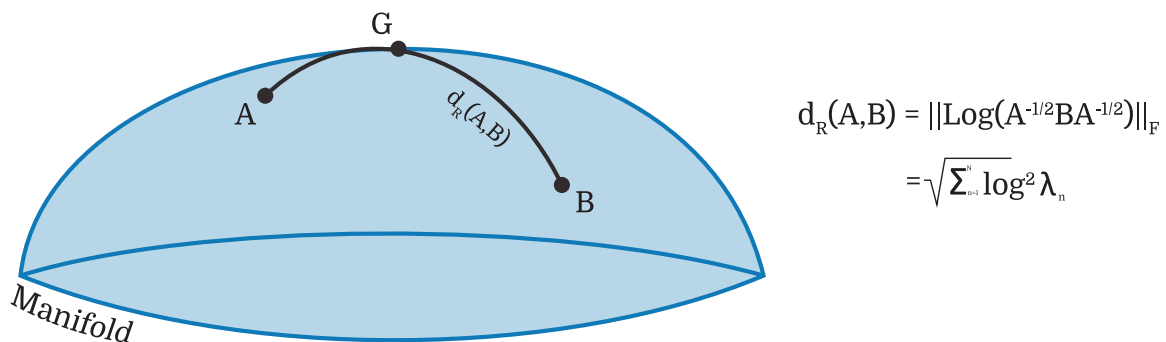


Figure 2.11. Representation of a Riemannian manifold and computation of the Riemannian distance. Here, A and B represent the centroid of covariance matrices for two different classes. G is the geometric mean of the two classes. The distance between the two points A and B on the manifold is called the Geodesic and its length corresponds to the Riemannian distance.

From this, it is possible to use the computation of such a distance to access the Riemannian mean of SPD matrices that can lead to the centroid of all the covariance matrices for a given class. It is then possible to compare the distance between centroids of different classes and use that information for classification, as we will see in the next section. Data can then be mapped from the manifold to a tangent space with Euclidean properties on which the mapped data can be handled as vectors. Thus, using Riemannian geometry, it is possible to compute different features; it can be the geometric mean for each class or the vector projection in the tangent space.

The final step of the feature extraction process is the creation of the input features vectors that will be used just after, in the classification part. As always, we can find different computations of those vectors in the literature. One that is the most found in the BCI field is to compute the logarithm of the variance on the CSP filtered EEG signal. Indeed, the variance of a bandpass filtered signal is equal to its bandpower and, as Alexandre Barachant reminds us in [150], the variances of spatially filtered signals are following a chi-square distribution that can approximate a log-normal

distribution with the use of the logarithm. This approximation is particularly interesting as some of the classification algorithms rest upon the assumption that the inputs are following a normal distribution. There are of course other methods for the creation of the input features; they are dependent on the type of signal that is used as well as the subsequent decoder [152][153].

4. Classification

Far from proposing an exhaustive list of classification algorithms, this section will present the ones that are commonly used in BMI research, which were also the ones used during this thesis (a more detailed and thorough list can be found in [154]). As their name suggests, classification algorithms are algorithms in charge of classifying input data, meaning their outputs will allow the labelling of a class to the input. To achieve their role, classification algorithms can take different forms and present different levels of complexity. We will go through later in the sub-sections how the training is done and how the performance of the algorithm is computed. There are two main approaches regarding the learning part of the algorithms called unsupervised or supervised learning. Most of the time the second approach is used and refers to the use of labelled data to train the algorithms, while the first approach does not use any label and will cluster by itself the data.

a. Artificial Neural Networks

The first category of classifiers that we will present are Artificial Neural Networks (ANN) and, as implied by their name, these classifiers try to replicate what is happening in the human brain with biological neurons. The simplest type of artificial neuron is called a perceptron; it is composed of a single processing element that receives information from one or more inputs, each of them is then multiplied with an associated weight and a bias term is added up, at the end of this perceptron a value is given indicating the class of the data.

Increasing the complexity of the perceptron with more complex layers leads to the appropriately named multi-layer perceptron presenting a succession of layers, each of them with one or more neurons that are connected to all of the neurons from the preceding and succeeding layers [155]. The first layer is the input layer that receives the data from the feature vector, and then we find one or several layers called Hidden Layers and finally the Output layer. The Hidden and Output layers also present an activation function whose role is to add non-linearity to the network, allowing for a more complex mapping between inputs and outputs. When training the neural network, a backpropagation phase can be added that will allow the weights of the network to be updated by comparing the predicted output with the label of the input data.

If more and more layers are added to the neural network, we obtain what is called a deep neural network that is used in Deep Learning. In that case, raw data is directly fed

into the network which is in charge of finding itself the important features that are lying inside the data [156][157][158][159].

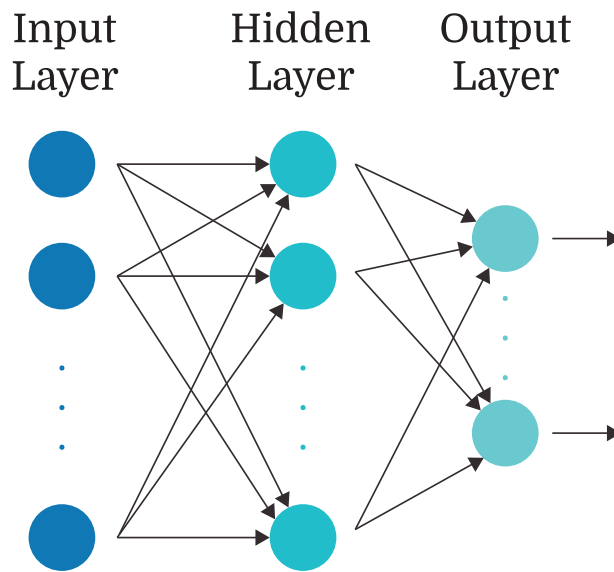


Figure 2.12. Schematic representation of a multi-layer perceptron. It is composed of different layers each made of several «neurons». It is possible to add several hidden layers to increase the complexity of the network

b. Linear classifiers

This second type of classifier revolves around the use of linear functions to separate the different classes. In a binary classification problem, the separation of the two classes comes back to finding a hyperplane (a plane but in a higher dimension, which is the case when dealing with more than 2 features) that divides the feature space into two parts, one being attributed to the first class and the other to the second. The Linear Discriminant Analysis (LDA) algorithm computes a hyperplane that will maximize the distance between the means of the two classes while minimizing the variance around the means of the two classes. This algorithm works under the assumption that the features are following a normal distribution, which can be verified when using CSP and the log-variance for example, and that the two classes have the same covariance matrices, which is rarely a verified assumption. However, the LDA can still be applied even though the assumptions are not entirely respected.

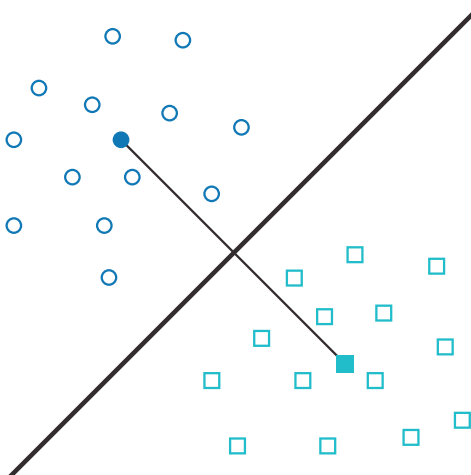


Figure 2.13. Schematic representation of the Linear Discriminant Analysis classifier used for a binary classification problem. The hyperplan is here computed to maximize the distance between the means of the two classes.

Similarly, we find the Support Vector Machine algorithm, which is also computing a hyperplane between the two classes but here the optimal hyperplane that is selected maximize the distance between Support Vectors, which are the features in the two classes that are close to each other. The best hyperplane is the one that will present the largest margin with the features as seen in Fig. 2.14.

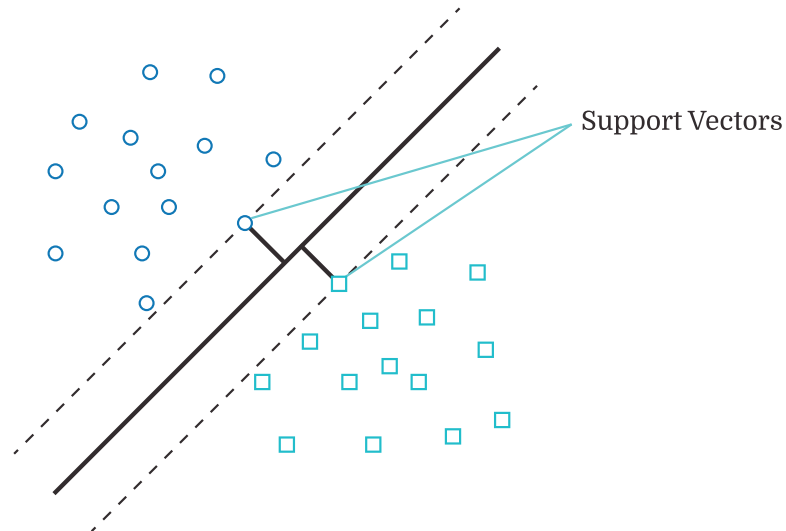


Figure 2.14. Schematic representation of the Support Vector Machine linear classifier used for a binary classification problem. The hyperplan is here computed to maximize the distance between support vectors, which are the points in the two classes that are the closest to each other.

Nonetheless, most of the time the data is not easily linearly separable, which is where kernels are coming into play. The role of the kernels is to project the data from the original space to a higher dimensional space where the data can then be linearly separated. This process is called the “kernel trick” and allows the creation of more complex boundaries between the class, like the examples with polynomial kernels or the radial basis function in Fig 2.15.

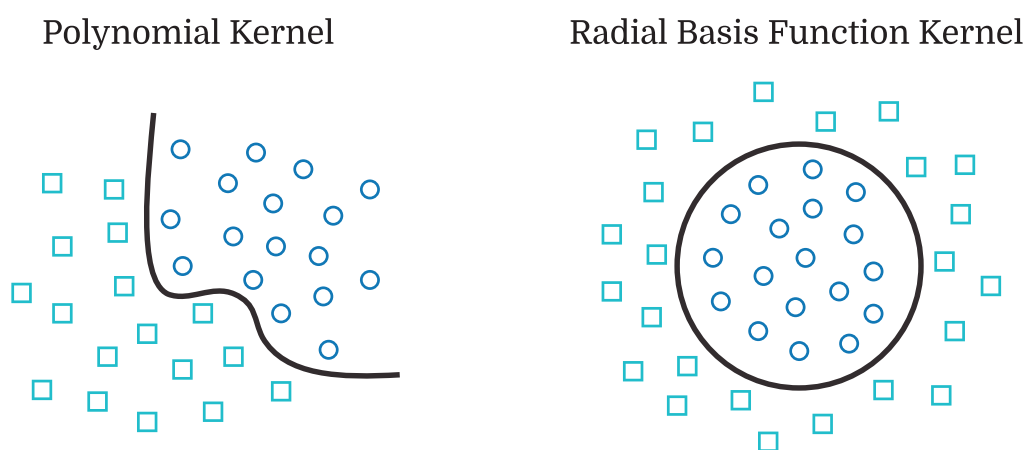


Figure 2.15. Differences in the computation of the boundaries between two classes depending on the kernel used in the Support Vector Machine algorithm.

c. Riemannian classifiers

The third and final type of algorithm that we will present in this part is the continuation of the Riemannian geometry method we introduced in the previous section. We explained that we could indeed use different features if we were to stay in the manifold or map data on the tangent space.

The first approach for classification is named Minimal Distance to Mean (MDM) and is quite straightforward. It consists in using the mean covariance matrices for each class and the covariance matrix for the trial to classify. Then the distance between this matrix and the centroids is computed and the smallest distance indicates which class the trial is affiliated with.

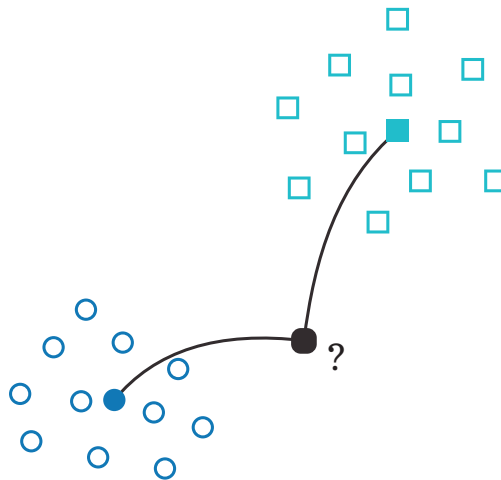


Figure 2.16. Representation of the Minimal Distance to Mean classifier. The two filled shape represent the centroid of two classes and the trial that needs to be labeled. The smallest distance between the trial and one of the centroids is used to label the trial.

The second approach uses the tangent space mapping of the data and the feature vectors created which can be classified with standard classifiers such as the one we presented just before. As explained by Lotte and colleagues in [154], this approach exploits both the strength of the Riemannian geometry and also that of the classifiers which can create complex boundaries. Nonetheless, one drawback to this tangent space approach is that it is leading to such high dimensional space that they are surpassing the number of observations for each class, which can cause overfitting or over-learning of the classifier on the data, reducing its generalization power.

d. Cross-validation and final model

Once the algorithm is chosen it is possible to evaluate its performance on available data but also to try it out on newly recorded data. To properly obtain the performance of the classifier, the usual process is to perform k-fold cross-validation (CV) on the whole dataset.

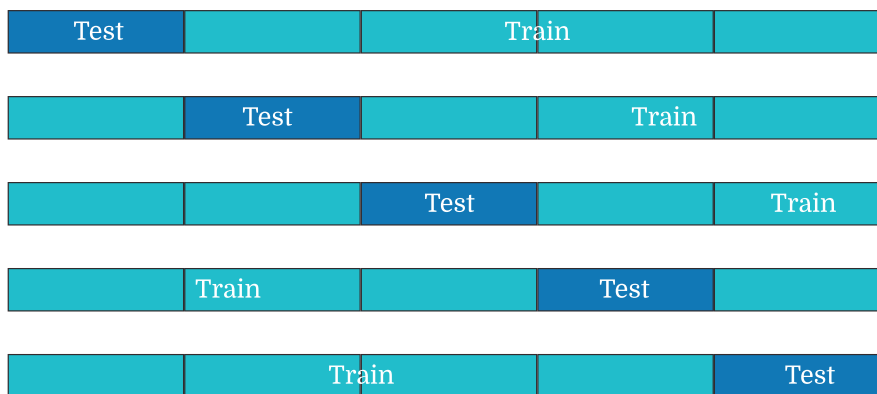


Figure 2.17. Representation of a 5-fold cross validation procedure.

This method consists in splitting the data into k random subsets of equal size then performing the feature extraction (for example computing the CSP filters) and the training of the algorithm on $(k-1)$ subsets (Fig. 2.17). Then, we apply the feature extraction based on the computed parameters on the remaining subset and classify the data thanks to the trained algorithm. The process is iterated k times so that every subset had the opportunity to be used for training and testing. The final performance of the algorithm is obtained as the mean performance from each fold, and it should indicate how both the feature extraction and the algorithm can generalize when faced with unseen data.

What happens when not properly following this process is called “Data Leakage”, which means some data from the test set might make its way into the training set which will cause a bias in the computation of the parameters from the feature extraction or the classifier. This thus advocates for the need to have two sets that are really separated from each other in the processing pipeline. After that we have a good idea of the performance of the model at the end of the cross-validation, the final step will be to train the final model. For this, there is no question of cross-validation as the final model needs to be trained with all the available data, thus the test set will consist of the newly recorded data.

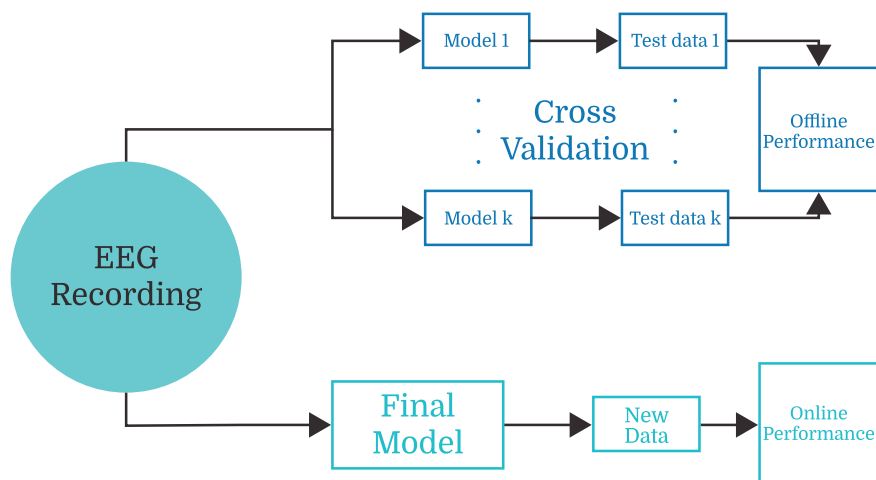


Figure 2.18. Differences between the computation of the offline and online performances for a machine learning model using EEG recordings. The cross validation procedure is used to estimate the generalization skill of the method. To compute the final model, all the data is used and the model is then tested on unseen data, giving the performance measure.

e. Performance evaluation

As the BMI field deals with subjects controlling machines through an interface it is thus straightforward to say that it is possible to evaluate the performance of not only the interface with the machine learning algorithms but also the performance of the subjects, as they are asked to generate commands with their brain activity.

Most of the time evaluating the performance of the machine learning algorithms comes with the computation of a confusion matrix, which is what can be obtained when dealing with classification problems. The confusion matrix represents the results of the classifiers when being fed with test data, as the labels for the test set are known, the confusion matrix shows the difference between the predicted values with the actual ones. Inside this matrix, we thus find the number of correct predictions (called True Negatives, TN, and True Positives, TP, in the case of two-class classification) and the number of incorrect ones (named False Negatives, FN, and False Positives, FP).

	True class	
Predicted class	TP	FN
	FP	TN

Figure 2.19. Representation of the confusion matrix for a binary classification problem. A good accuracy is obtained by maximizing the number of True Positives and True Negatives while minimizing the occurrences of False Positives and Negatives.

Based on that information, the first metric that can be computed is the classification accuracy, which is the ratio of correctly predicted values over all predicted values, as expected the aim is to reach a perfect accuracy of 100% meaning that the algorithm has correctly classified each observation. Yet this metric can be biased when faced with an imbalance in the number of observations for the two classes. For example, if the dataset is composed of 90 observations for one class and 10 for another, then being able to correctly classify all those 90 but none of the 10 would still give a classification accuracy of 90% while not being able to catch any of the other classes.

This point also leads to the computation of other metrics with the values from the confusion matrix. As its name suggests, the precision tells us how precise the classifier is, it is computed by looking at the ratio of TP over the sum of TP and FP

which indicates how many actual positives were obtained out of the observations predicted as positives. The recall is another metric that is commonly used, obtained through the ratio of TP over the sum of TP and FN, which gives the proportion of actual positives out of the observations labelled as positive. Instead of putting a cost on the False Positives like for the Precision, the Recall is thus putting a cost on the False Negatives. Nonetheless, there is a trade-off between the two metrics as a classifier with good precision could have a low recall due to a high number of False Negatives and vice versa. To overcome this limitation and make sure the classifier is performing well, it is possible to combine Precision and Recall by computing the F1-Score, which is the harmonic mean of the two metrics. Maximizing this metric will give the optimal balance between Precision and Recall, which ultimately gives a better classification model.

However, despite giving an idea of the performance of the BMI, it is difficult to tell in the classification accuracy for example if a high value is due to a well-trained subject or only due to a correctly crafted classifier. In their 2018 article [160], Fabien Lotte and Camille Jeunet compared a BCI user and its interface to a Formula 1 driver and its car, with the classification accuracy being compared to the outcome of a race. The outcome will be poor if the driver is not showing good driving skills or if the car is not going fast enough, and usually, the success of a race can be attributed to both the driver and the car, although the driver should be able to show similar skills with others Formula 1 cars.

There is thus a need to have some metrics that can highlight how skilled a BCI user is regarding the mental tasks he/she is asked to perform, without taking into account any classifier to only focus on the subject/brain part of the interface. Lotte and Jeunet remind us in [160] that a skilled BCI user can elicit brain patterns that are “stable within mental tasks” and distinct between them, as such they defined a couple of performance metrics aimed at quantifying such skills. In particular, they took advantage of Riemannian geometry and its concept of distance as a way to define two metrics: stability and distinctiveness.

$$\text{classStab}(A) = \frac{1}{1 + \sigma_{C^A}} \quad \text{classDis}(A,B) = \frac{\delta_R(\bar{C}^A, \bar{C}^B)}{\frac{1}{2}(\sigma_{C^A} + \sigma_{C^B})}$$

Figure 2.20. Computation of the two performance metrics, class Stability and class Distinctiveness based on the article from Lotte and Jeunet. To compute those two metrics, one must have access to the centroid of covariance matrices for the different classes.

The stability relies first on the computation of the centroid of covariance matrices for a given class, then the mean absolute deviation for the covariance matrices is calculated, finally the stability is defined as inversely proportional to the mean absolute deviation. The stability represents the dispersion of the covariant matrices around their mean thus, the lower the dispersion, the higher the stability. As for the distinctiveness, it is

computed for two-class problems (but a multiclass implementation is proposed by the authors) and is re-using the mean absolute deviation for each class as well as the Riemannian distance between the centroids of two classes, the distinctiveness is then computed as the ratio between this distance and the mean of the mean absolute deviation. The distinctiveness is thus high when both the distance between the centroids is high and the deviation within a class is low, which can be compared to the computation of the Fisher criterion as explained by Lotte and Jeunet. We can see that those two metrics only use the EEG data (which can be filtered and processed) and no classification algorithms are trained to obtain them, thus offering a promising alternative to the traditional classification accuracy that is used in the literature while also re-questioning experimenters regarding the tasks they are asking the subjects to perform.

5. Applications of BMIs

With the same prescience as many science-fiction authors, we can find in Vidal's first article about Brain-Computer Interfacing a glimpse of the things that are finally happening around 50 years later, as he envisioned that such an interface could offer control over a large array of devices, from a prosthesis to a spaceship. Moreover, since its conceptualization in the 70s, it is easy to see that a lot has been done in the development of BMIs as both the research and industry worlds are interested in its applications. Here we will categorize them into medical and non-medical applications, starting from the latter to reach the former, which is where this PhD project falls in.

a. Non-medical applications

The presence of neuroscience in the industry is steadily increasing, with companies realizing that they can take advantage of this field for various purposes. It is particularly clear with brain-machine interfaces, as the idea of recording brain activity to control different machines can lead to various applications.

Indeed, BCIs can apply to entertainment or multimedia applications through the development of video games for example. One example has been developed by the GIPSA-Lab in Grenoble, France, and is a re-creation of the classic game "Space Invaders" but instead of a joystick to control the spaceship, everything is done through the recording and processing of brain activity, using a P300 ERP paradigm [161]. Most of the time the use of BCI with videogames comes in conjunction with virtual or augmented reality (VR/AR), as it offers an immersive environment suitable for BCI learning while also increasing the motivation and engagement of the subject [162]. In an article from Leeb and colleagues [163], a tetraplegic was able to move a wheelchair in a virtual environment and accomplish (from 90% of success to 100% in some runs) a task where the subject was asked to stop in front of fifteen avatars in a virtual environment. As pointed out by the authors, the VR setting offers a safe environment for the subject while still offering realism, close to real-world use. Another

recent project proposes the use of a BMI as way to create electronic music. Led by The Absolute Company Creation and the French start-up Nextmind the project, called Brain Performance Mix, relies on the recording of brain activity from the visual cortex to control various instruments, with the first concerts by French electronic artist “Molécule” supposed to happen in Summer 2022 [164].

Nonetheless, and as pointed out by Grégoire Cattan in [165], there are still limitations that prevent the use of BCIs for the public, not only for video games but also for a large array of applications. Indeed, using an EEG system is not as easy as using a smartphone, even despite advancements in the technology which allowed for the appearance of cheaper and smaller EEG systems, yet those usually come from small companies and are mainly dedicated to research teams. Cattan also explains that there are different expectations between video game developers and researchers, with the latter not focusing enough on graphics and the gameplay of the video games. Finally, the low transfer rate of BCIs, which takes into account its speed of information transmission and accuracy, is also problematic for implementation in video games, as it has not reached yet the performance of other types of inputs (e.g. keyboard or mouse).

Another non-medical application (but bordering closely on medical/clinical) of BMIs is the estimation of cognitive or affective states from a user based on the recorded brain activity. This kind of question arises in the context of neuroergonomic, which is about trying to understand the processes in the brain when performing tasks to optimize performance and reduce errors or unwanted behaviours/answers. As such, those applications are mainly found with passive BCIs and can be used for example to get a grasp on the mental workload or fatigue while a subject is performing a task [166][167][168].

BCIs are also benefitting from the neurofeedback field, which is interested in presenting relevant feedback to subjects when they are using the BCI. In particular, a study by Léa Pillette and collaborators [169] is exploring neurofeedback in BCI through the use of a learning companion, a small device that is aimed at providing “social presence and emotional support” to BCI users. They reported that “non-autonomous” users (which are learning better in a social context) were profiting from this learning companion, in the sense that they were more confident about their use of the BCI.

Finally, another potential yet controversial application is found in the military, for example through the Next-Generation Nonsurgical Neurotechnology (N3) program launched by the Defense Advanced Research Projects Agency (DARPA) of the US government [170]. The N3 program is looking at developing technologies that can be used during military operations; to control drones or other unmanned vehicles for example. Some other projects in the N3 program also include Brain-to-Brain interfacing, the decoding of information from one brain to its encoding in another brain [171]. While they can be exciting projects for researchers, such applications are also raising ethical concerns

that we will explore more thoroughly in the final part of this chapter.

b. Medical applications

Even though Vidal presented his concept with medical and non-medical applications, it is clear that the primary purpose of BCIs is in the development of interface aimed at offering solutions to medical conditions.

When mentioning the feature extraction techniques previously in this manuscript, we presented the use of the P300 wave paradigm for the P300 speller, which allows a user to make sentences while looking at a grid of letters and numbers. Such an application is crucial for patients suffering from Amyotrophic Lateral Sclerosis (ALS) or other neuromuscular disorders that are affecting the communication skills of a person. In a 2018 study from Guy et al. [172] reported that with some more improvements, the P300 speller BCI could act as a competitive alternative to other communication tools for patients with ALS.

What is also found in the literature of clinical passive BCIs concerns sleep analysis and more precisely sleep stage classification. To improve the sleep quality of a person, it is needed to have a clearer of their sleep stages (which can be divided in three categories: awake, non-rapid eye movement and rapid eye movement). The gold standard method is a tedious process called polysomnography that combines EEG with ElectroMyoGraphy (EMG) and ElectroOculoGraphy (EOG), the data has then to be reviewed by an experienced sleep technician that can distinguish between the stages. In addition, as reminded by Arnal et al. [173], the recording conditions make it difficult to “reliably capture a patient’s typical sleep” as the recording takes place in an unfamiliar setting for the subject, potentially leading to disturbed sleep. This thus advocates for changes in sleep analysis, with a part of the research dedicated to the development of new devices that could replace polysomnography and the need for a sleep technician [174]. Other studies are interested in how different processing of the EEG activity could give access to a clearer idea of the stages [175][176].

Neurorehabilitation is another field where BCIs researchers are actively looking at implementing solutions, with a large portion devoted to stroke rehabilitation where the traditional rehabilitation procedures might not apply to every patient. As explained by Yang et al [177], BCIs enable a shift from the bottom-up approaches, using movement therapy, to top-down approaches where the focus is put on allowing “neural circuit reorganization to restore impaired motor function”. Indeed, in a study from Ramos-Murguialday and colleagues [178], stroke patients using a BCI triggering contingent movements on hand and arm orthoses showed improvements in scores from an upper-limb test compared to a control group where movements on the orthoses were random. They argue that having this contingent link between the intention of movement and the movement on the orthoses is inducing plasticity that will improve motor functions. Moreover, they considered this BCI training to be supplemental to traditional

physiotherapy and not to be a replacement. Other projects such as the Grasp'it [179] are combining VR and BCI to develop a serious game where patients/subjects are using kinaesthetic motor imagery and receive both visual and vibrotactile feedback to help them better learn the task. The project also focuses on the gamification of the interface to have a better motivation of the subjects regarding the task.

We mentioned in the non-medical applications that a tetraplegic was able to move their wheelchair in a virtual environment by combining VR and BCIs and indeed, by looking at the literature we can see that a great part of the research has been dedicated to the use of BCIs with assistive devices. Specifically, the research on wheelchair control has continuously progressed since one of the first studies about 20 years ago, which dealt with the control of a wheelchair in the left or right direction through a motor imagery paradigm. Moreover, the research does not only use the MI paradigm as other studies showed promising results using SSVEP [180][181] or P300 paradigms [182][183][184]. Yet, as reviewed by Palumbo and colleagues in their 2021 review [185], the BCI control of wheelchairs is currently far from being optimal as most of the performances are obtained through off-line analysis and not online/real-time tests, with studies mainly containing healthy subjects that are tested in a controlled environment, far from daily life conditions. There is thus a need to standardize research on that topic, to better understand the needs of the patients all the while moving forward with the challenges brought by the use of BCIs.

Assistive devices have recently been taking the shape of exoskeletons that can also help patients with disabilities to regain some mobility. Recent works from the team at Clinattec in Grenoble showed a proof-of-concept for the control of a four-limb exoskeleton using an ECoG BCI [186]. Impressively the BCI could be used for up to 7 weeks without any recalibration, and with the simultaneous control of eight degrees of freedom. They also reported differences between the exoskeleton control and the control of an avatar on a screen, according to them the differences in feedback in the two conditions could explain the better performance with the exoskeleton, with the exoskeleton presenting richer feedback to the user. Another study by Choi and colleagues [135] presented the control of a lower-limb exoskeleton with an asynchronous BCI using EEG. While the results in the article confirm that the use of the BCI is still slower than the control with a manual controller (a smartwatch in this case), the developed system still looks promising as the accuracy in both offline and online tests reached more than 80% accuracy. Nonetheless, the results were obtained in this study with healthy subjects in a controlled environment, and while they still expect their system to improve motor recovery, it may be expected that the accuracy could diminish with those conditions.

The last portion of assistive devices that we will present here in this section is composed of robotic arms and prostheses. We find in the literature a large number of articles that are interested in the control of those devices using different BCIs. Indeed, studies regarding invasive BCIs presented how patients with tetraplegia could control a robotic arm with up to seven degrees of freedom [153] [186], those two studies also pointed

out that this performance could be sustained for a long period with a limited decrease in performance. Another study from the same team [187] also showed impressive results for the control of a five DoF robotic arm while also adding tactile feedback through stimulation in the somatosensory cortex, leading to better task performances by the subject. Wang et al. presented in 2013 [188] an ECoG-based BCI that allowed a tetraplegic to control a cursor and a robotic arm in three dimensions to reach targets. Moreover, a noninvasive study from Edelman and colleagues [189] revealed that the control of a robotic arm in two dimensions could be achieved using EEG recordings, the training paradigm making the control of the arm a seamless experience for the users, although none of them had a disability in the study. However, it is also interesting to note the decrease in degrees of freedom that subjects were able to move when going from invasive recordings to semi-invasive and finally non-invasive.

Nonetheless, while we can see that researchers are tackling the topic of robotic arm control, there are fewer studies about the control of prostheses for amputees, especially for upper-limb amputees. As with the control of a robotic arm, it has been shown that it is possible to control a prosthesis using an EEG-based BCI [190], although the subjects were not amputees in this study. This is one of the largest challenges in this field as only a few studies have access to amputees, the reasons are unclear but it is quite reassuring to notice a shift in recent years with more studies recruiting amputees on top of able-bodied subjects. Indeed, we can find for example an fNIRS-based BCI (fNIRS being an optical imaging technique) study from 2022 [191] interested in the classification of six different arm motions with a performance of 64% on average for amputated subjects, which while being lower than with able-bodied ones (78%) is still a promising result to obtain. Other studies are developing hybrid EMG-EEG BCI for the control of a prosthetic arm, which is an interesting axis of research as both recording techniques could benefit from each other [192]. And finally, to pick up with the discussions from the first chapter, a study from 2020 by Yanagisawa and colleagues that even a brief training (three days) of BCI control seems to help reduce phantom limb pain, and potentially offer new pathways for phantom limb management [193].

6. The Ethical issues behind the use of BMIs

The field of BMIs is not only an exciting topic for researchers but also has a tremendous appeal to the general audience. A reason for such appeal might be because neuroscience can be found in the yearning of the population towards neuroscience, as people tend to put more trust in neuroscience explanation for various phenomena, even when the information is irrelevant, as pointed out by a study from Weisberg and team [194]. The attractiveness of BMIs and neuroscience as a whole is thus a blessing and a curse, as it is bringing funding and interest from researchers while also creating expectations for the public as well as commercial promises for a myriad of companies.

However, despite the interest and money coming from different parts, BMIs are no different from any other research field in the sense that findings in any domain will take a long time before being available to a clinical population and then to the general population. Morris, Wooding and Grant attempted to shed some light on that matter in a review from 2011 dealing with time lags in translational research [195]. What is appearing in the literature is that there is an estimated gap of 17 years between scientific discovery and its application in clinical practice/commercialization. This lag is usually acceptable for the general population, as they know that science is taking time and that this process is transparent to them. Nonetheless, it gets much more complicated when there is a passion or an interest from the public caused by marketing build-ups (dare we say “hype”). A striking example of BMI research is the case of the company Neuralink, founded by entrepreneur Elon Musk, whose primary purpose is to develop an invasive BMI aimed at helping people with disabilities. While Neuralink is praiseworthy regarding its target and the technologies they are creating, recent news and warnings from researchers, especially neuroethicists as visible in a January 2022 news article [196]. Several researchers have concerns regarding Elon Musk’s ambitions with Neuralink, arguing that the primary purpose of Neuralink is applicable in a niche market, which can expand if the recorded brain activities are used for another purpose, with a higher return on the investment. Dr Johnson, a neuroethicist from Upstate Medical University, indeed regrets that patients that need this kind of device might be exploited “in risky research for someone else’s commercial gain”.

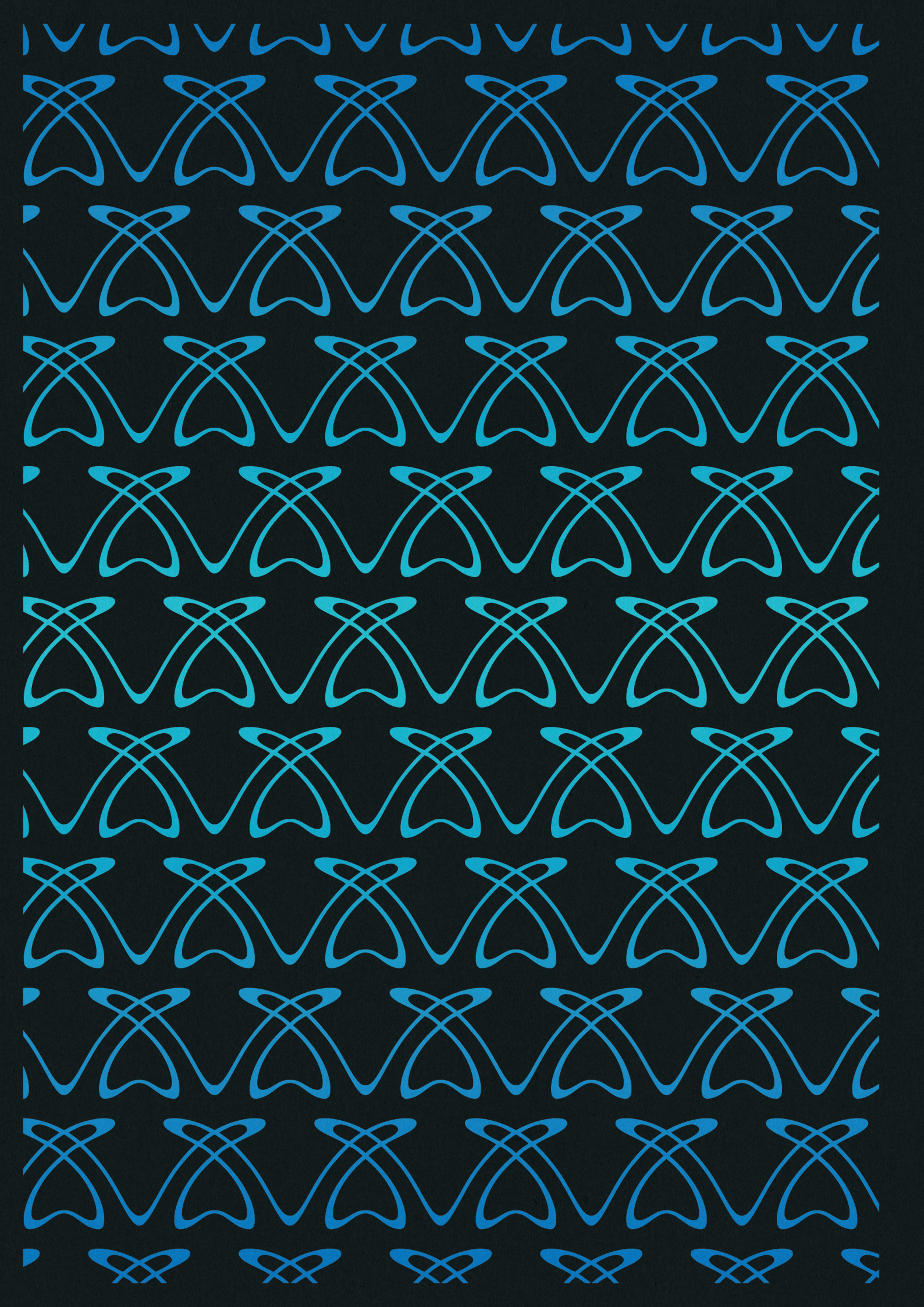
Indeed, during the ethics session that took place at the Cortico conference in March, Stephan Rainey, from TU Delft 2022 [197], reminded us that BMIs are usually prone to three points. First, they are overpromising as they are expected to bring solutions for every problem; this is visible with Neuralink as Elon Musk is pushing new potential applications of his device at each appearance. Dr Johnson also agrees with this point, adding that “they are a long way from being able to do that”, matching with the time lags we presented a few sentences above. Second, BMIs are prone to be underdelivering and it requires time to make sure they are meeting the expectations as the technologies are constantly evolving and improving, along with the science and a better understanding of how the brain is working. Finally, BMIs are prone to bring scandal, which can take many shapes. It can be scandals in the development of the technology, for example, the recent issues raised concerning animal testing [198] or the working conditions at Neuralink [199]. Moreover, and not limited to BMIs, scandals can come from the way science is done, especially when there is a marketing push associated with the development of new technology. Stephan Rainey argued that such development should not come at any cost and should go along with new regulations to ensure that this technology is going in the right direction. Indeed, Selim Eskiizmirliler and Jérôme Goffette discuss in the chapter titled “Brain-Machine Interface (BMI) as a Tool for Understanding Human-Machine Cooperation” from the book “Inquiring into Human Enhancement” [41] that even though BMIs are new ways of achieving aims, they can also undermine the autonomy of users. Indeed, they could influence them on future actions by making decisions without the users realizing it.

In particular, in a Nature article [200], Liam Drew reminds us that the devices used in Deep Brain Stimulation (DBS) can provoke, in certain patients, some personality changes where patients started questioning if they were still themselves after the implantation of the device. According to him, this can be prominent with other BMI applications where the classification algorithms are learning from previous data to make predictions in the future, as the frontier between the user's own choice and the choice of the algorithm becomes blurry. For example, after sending a command with the brain activity, which is supposed to be a conscious and willing command coming from the user, the guidance control is transferred to the BCI. Friedrich et al. add [201] that this transfer raises concerns, as the user might not have any power over the action once the transfer is effective. However, they note, "From the perspective of control, it might allow the person to act in accordance with her own reasons more easily" as the BMI might be able to mute "contrary influencing impulses" that can happen after the "initiating volition".

It is also important to note that the people using this kind of technology, who can be patients or healthy people, are dependent on the company manufacturing the device. Liam Drew also mention a study from Frederic Gilbert, a neuroethicist working at the University of Tasmania, where patients received a device aimed at treating epilepsy by halting seizures. In particular, one patient, who considered that the device "became her" (a "radical symbiosis" in Gilbert's words) had to have that device removed as the company went bankrupt. Drew explains that such technologies can "shape a person's life", to the point where the patients are not viewing the devices as a foreign part of their body, which is similar to what we reviewed in the first chapter when we mentioned prosthesis acceptance and the notions of body schema and body image. Eskiizmirli and Goffette add that this dependency of the person on a company is causing issues with heteronomy, the antonym of autonomy where an individual receives influence from an outside authority.

This call for a proper code of ethics to be followed as brain signals are some of the most private types of personal information that can be obtained. Again from Cortico 2022, Laure Tabouy [202] who is currently undergoing a second PhD in ethics questioned current rights and their ability to protect individuals from the potential intrusions of neurotechnologies on brain activity. She thus advocated for a need for transparency, trying to assess the responsibility of inventors, coders, researchers and users. Quoting Marcello Lenca and Philipp Kellmeyer, two neuroethicists, Liam Drew highlights that there is enough knowledge on that matter to start taking decisions now as the traditional ethics fall short on several parts, and thus could benefit from ethics of human-machine interaction.

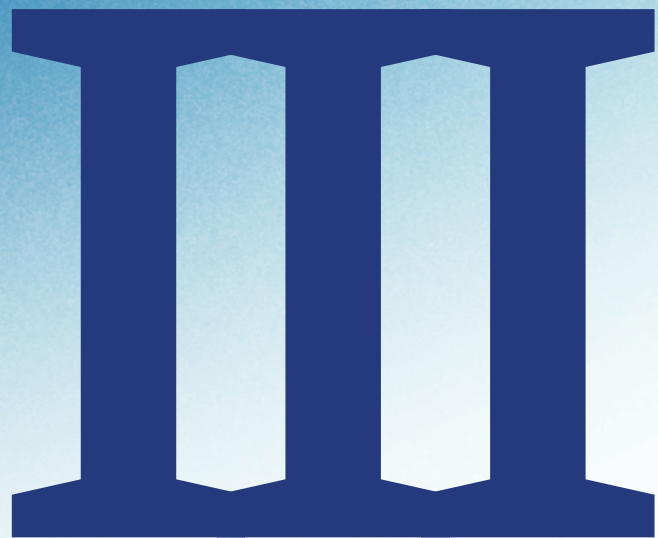
This is also in accordance with the review by Coin et al. in 2020 [203] where they outline eight different themes related to BCI technology, among which are Humanity and Parenthood, Autonomy, Privacy and Security and Research Ethics and Informed Consent. Coin and colleagues explain that even though those themes start to appear more and more in the literature, there is still room for improvement, in particular, they highlight that there is a need for more proposals in ethics literature for BCI policy. We can thus see that BCI ethics is a delicate subject as it is combining all the actors in the field. Its importance cannot be denied or overlooked; we are in a stage where while they present many advantages, the future of BCIs is still containing negative paths that need to be cleared.



Part II

Development of a
non-invasive BMI
for the control of
hand prostheses





**Description of the proposed
system : design criteria and
experimental protocol**

The second part of the manuscript is dedicated to the experimental and development work which has been realized during this thesis. It will first present the experiments that were conducted with amputees and able-bodied subjects and the obtained results. It will also present the software and hardware development and particularly how the principal prosthesis hand, Myobock (Ottobock), used in this work was modified for this specific non-invasive BMI application.

1. Introduction

As briefly explained in the introduction, this project intervenes within the scope of a collaboration between the Vision Team of the INCC laboratory and the prosthesis manufacturer Ottobock. The origin of the thesis stems from different questions and assessments regarding prostheses and BCIs. The first one is that all of the devices available on the market regarding prostheses concern surface electrodes and the recording of muscular activity. Moreover, as we have seen in the first chapter of the manuscript when dealing with the factors behind prosthesis abandonment, a source of dissatisfaction comes from the weight and the sweat generated by using the device, which can degrade the performance of the prosthesis.

On the other hand, from the work done in the laboratory as well as the literature on the subject, it was known that BCIs could be used to control robotic arms, especially with invasive and semi-invasive recording techniques. Nonetheless, around the beginning of the thesis work, there were only limited resources available regarding the control of prostheses for amputees using non-invasive brain activity recordings, which made us think that was an idea worth exploring both for the potential development of devices from an industrial point of view and for the opportunity to tackle such a scientific challenge. Moreover, after meeting our first amputee subject, we realized how important it was to add the topic of sensory feedback to this project as it was one of the most important features that was missing from the prosthesis so far.

The idea was thus to develop a BMI that is offering a level of control superior to traditional myoelectric prostheses while also adding a sensory feedback capacity that could add more information back to the user.

2. Functional specifications and axes of the work

From the context of the project and its aim, we can establish the functional specifications of the system, which gather the principal functions and the constraint functions. We can identify two principal functions, which would justify the development of the system: the first one is to allow amputees to control their prosthesis with their brain and the second one is to bring sensory feedback to the user. The criteria for the first function would be the performance and reliability of the system; we want the

system to be more efficient than myoelectric prostheses which could translate into a high accuracy in terms of classification (with for example more than 90% accuracy). The system also needs to have good reliability as what is dreaded are potential errors in the classification which can lead to unwanted movements. Two levels are thus present, it is first possible to limit the false positives and false negatives (as we have seen with the confusion matrix in the previous chapter) but it is also possible to implement a brain switch in the system which would be needed to both start the system but also stop it in case of unwanted movement. The criteria regarding the second principal function, the sensory feedback, is to have feedback that should be both coherent and informative for the user and a way to assess that they are met is to see if the control performance of the system with the sensory feedback is better than without this later, meaning that it would be integrated by the user in the control loop.

On the other hand, constraint functions are the functions that are restricting or constraining the development of a system; they represent the features that have to be satisfied in the system to make sure it can be used. We thus have established a list of constraint functions related to the BCI we are developing. One of the first constraints that is needed on the system is that it has to fit onto the original material, the prosthesis in our case. Consequently, this function puts constraints on the size and the energy supply of the device. Ideally, the system would have to be powered by the battery pack of the prosthesis and this would have to be located in the socket between the stump and the artificial hand. One solution for the sensory feedback would be to integrate it partly into the prosthesis and another part would be easily removable on the upper arm of the user, or potentially on other regions of interest .

Things are trickier concerning the recording of the brain activity as it first needs to be easy to use; putting an EEG cap on a subject can indeed be a lengthy process involving one or more people. The criterion for such a function is thus to simplify the setup of the system so that the users could do it by themselves, it is possible to act on various levels with the first one being to possibly use landmarks on the EEG cap. Another level of action is to find a solution to easily obtain a clean signal on the electrodes, it can be changing the type of electrodes used or finding a solution to apply the electrolytic gel on the scalp. Moreover, another constraint function for the recording part of the system concern the number of electrodes that should be used for the application. It seems almost impossible to use, daily, a 64 electrodes EEG system, and the aim is thus to reduce this as much as possible this number while still answering the demand regarding the performance of the whole system. Ideally, the number of electrodes would be less than 16 electrodes but the focus is to find a trade-off with the performance and accuracy of the BMI .

So far we have looked at what can be implemented for both the machine and for the brain (recording) parts of the BMI; but what about the interface? It is supposed to connect the two parts, by processing the brain activity and sending the command to the prosthesis. What is usually used for the interface is a bulky and powerful computer to which everything is connected, but it can be agreed that this perspective doesn't match with a marketable product. As a constraint, such a system should be usable wirelessly with a smartphone whose processing power is lower but with a friendlier form factor. Using Bluetooth for example, the system would thus have to assure that the connection is stable with each part. Another crucial constraint is that the system can be used by anyone without feeling that it is a burden, it could be thus recommended to have a playful aspect to the system (in France it is often referred to as "gamification") by integrating it onto video game mechanisms. This aspect could help users to be more confident about their use of the system all the while potentially being rewarded for their efforts and training. It is thus possible to think of different levels of difficulty or different minigames which would drive the motivation of the user and could add more functions to the system.

All of the constraint functions so far center around some technical aspects of the system but it is possible to broaden them by taking into account more general constraints. For example, the aesthetic aspect can be considered as a legitimate constraint for the BMI system, as it is crucially linked to how it will be accepted by the users. The color, shape, and size of the system are criteria to respect, but they also need to be adjusted to the desires of the user. In particular, one of the most critical items that needs to be taken into consideration is how to make the EEG system not look like a regular EEG system and how to hide it into more classic apparel like hats or caps. The prosthesis already benefits from this type of personalization and the sensory feedback part could also be turned into something aesthetic while still keeping its main function. Another constraint associated with the system is to be resistant to collisions and the environment in general, for this the choice of materials will be important especially for the EEG system and the sensory feedback as they will need to be sturdy and watertight so that they can function in various environments. Finally, what also needs to be imposed on the system is that it must not be too expensive. This constraint of the cost can be associated to make sure that the system and the care linked to it will be a part of the devices and services reimbursed by social security.

Function	Criteria	Level
FP1 Allow amputees to control the prosthesis with their brain	-Performance (>90%) -Reliability	-Low number of false positives and false negatives -Brain switch
FP2 Bring sensory feedback to the user	-Coherence -Informative	- Performance with feedback > Performance without
FC1 Must partly fit in the original material	-Size -Energy supply	-Powered by battery pack of prosthesis -Electronic parts located in the socket between the hand and the stump -Integration in the prosthesis
FC2 EEG recording system easy to use	-Design of the EEG cap	-Use landmark on the EEG caps -Good signal with specific EEG electrodes or by applying gel
FC3 Limit the number of electrodes on the EEG cap	-Number of electrodes	-Less than 16 electrodes
FC4 Must be used wirelessly with a smartphone	-Bluetooth connection	-Stable connection between the different parts
FC5 Must not be a burden in the daily life	-Playful	-Minigames to increase confidence and motivation of the user -Rewards with user's progress
FC6 Must be aesthetic	-Color -Shape -Size	-Personnalized with user's preferences -EEG system hidden in cap or hat
FC7 Must resist in most environments	-Materials	-Waterproof -Resistant to collisions -Sturdy
FC8 Must not be expensive	-Price	-System and cares reimbured by social security

Figure 3.1. Bill of specifications regarding the developed BMI system. The functions are either Principal Functions (FP in dark blue in the table) or Constraint Functions (FC in light blue). Several criteria are defined, each with a level that must be respected for the system to be successfully created.

The main goal of our work was to assure that the principal functions of the system were respected as they are the most important ones for prototyping work but also because they correspond to the type of work that could be done in a research laboratory. However, it was also important to keep an eye on the constraint functions because of the potential commercial application of the developed system. The work presented in this second part is thus multivariate, indicating the multi-disciplinarity of the project. Consequently, the work revolved around three main axes of development:

1. Recording of the brain activity: this axis concerned the choice of the suitable EEG system for the application as well as the region of interest for the recording of the brain activity and finally the optimal number of electrodes that are needed to achieve a good performance.
2. Feature extraction and decoding of the brain activity: this axis consists mainly in finding the techniques and classification algorithms that would offer optimal performance.
3. Sensory Feedback: here we were interested in looking at the contribution of the feedback on the performance of the BMI.

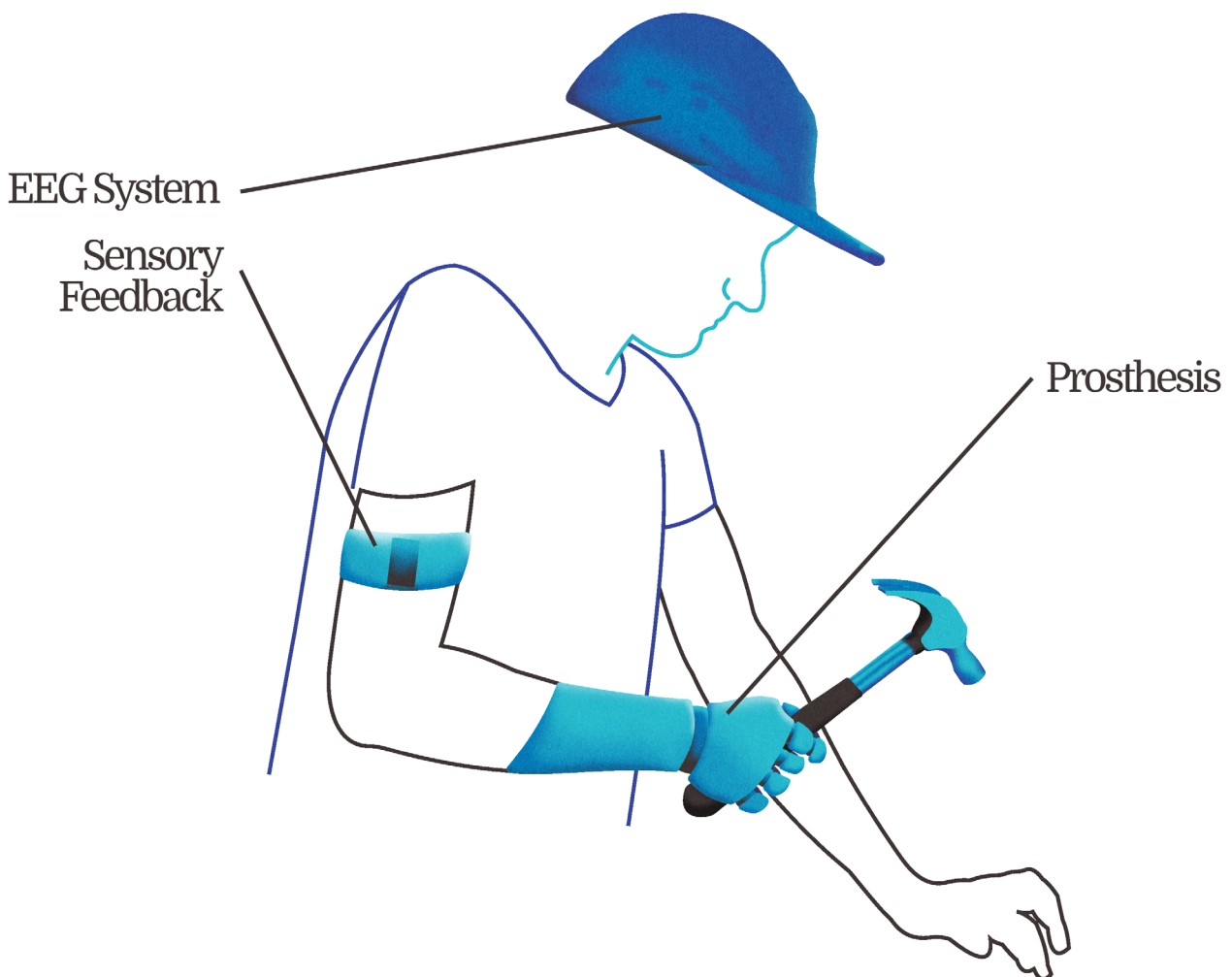


Figure 3.2. Representation of the components of the final system and its intended use, allowing the prosthesis users to easily do all kind of tasks (technical and non technical). The system is composed of an EEG system embedded in a hat, a sensory feedback device located on the upper arm of the user and the upper-limb prosthesis.

3. Inclusion criteria

The different meetings we had with our colleagues at IRMA allowed us to refine the list of criteria for the subjects who would be recruited for the experiments. The subjects would of course have to be upper-limb amputees but we were at the beginning not sure about the degree of amputation which had to be defined. We settled with trans-radial amputation also because of the type of prosthesis we were using at the lab at that time; it was a good starting point for the project without being too complex. We also chose to focus on unilateral amputations without defining them as a main restrictive criterion. What we were interested in is that the potential subjects had to be experienced users of myoelectric prostheses, with no restriction on the model of the prosthesis that they were using, as it was ultimately going to be replaced with our own during the experiments. Our colleagues at the IRMA then determined the patients who would participate in the experiments based on those criteria.

One of the most important things was to make sure that this project was seen as what it was, a research project, and that the experiment was not going to modify in any way the current care they were receiving or the control they have over their prostheses. It was interesting to note that all the subjects with whom we worked during this project were genuinely glad to help us with the development of such a system, giving us advice and raising issues that led us on this path, even though there were and still are years before seeing this kind of application on the market.

4. Material used

Here we are going to present most of the materials we used for this project which we will divide in three parts: EEG, software and hardware.

a. EEG

From the beginning, we had in mind using a portable EEG system to perform the EEG recordings for this project. Indeed, for the first experiments and tests that we did before starting the Ph.D. project, we were using a quite simple EEG helmet called the EPOC from the company Emotiv (Fig. 3.3). The main reasons behind the choice of this helmet were the low number of electrodes, the Bluetooth connection to a computer, and how easy it was to set it up on a subject. The electrodes required to use of some foam pads dipped into a saline solution which would make the bridge with the scalp of the subject. Nonetheless, despite having an undeniable set of advantages, and especially for our application, the signals that we were able to record were not on par with the gold standard systems that are traditionally used in BCI research .



Figure 3.3. Emotiv EPOC EEG helmet.

The researchers from the Vision team in the laboratory have a long experience in EEG research with medical-grade systems which they are using for most of their experiments, allowing them to have signals with a great temporal resolution from electrodes all over the cortex. The quality of the signal, as well as the number of electrodes, are two main advantages of this project and the questions we had. The system we have at the University is an actiChamp from the company Brain Products (Fig. 3.4).

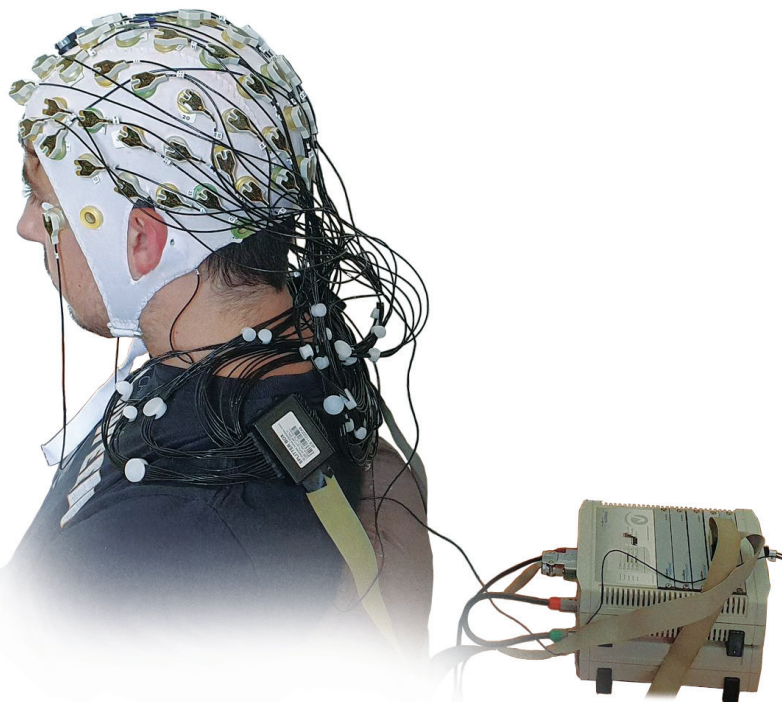


Figure 3.4. ActiChamp EEG system with 64 ActiCap electrodes.

We used 64 electrodes on the cap which used electrolytic gel to improve the quality of the signal. Having such a system has proven to be tremendously beneficial for the research we were conducting yet it was clear that it cannot be used in the event of daily-life activities because of its bulkiness and all the parts that were required. Particularly, medical grade systems are meant to be used by experienced staff who are aware of

their frailty and know how to put the gel on the subjects. They are usually not meant to be moved around except for a laboratory environment. As a matter of fact, and because we could not conduct the experiments with the amputees at the University we decided to use the 64 electrodes system only with the control subjects and focus a part of the work with them, as it was easier to have access to able-bodied subjects for the experiments.

This forced us to find a candidate which could offer some of the advantages of the actiCHamp system all the while being easier to carry around. OpenBCI aims to propose open-source tools for neuroscience. They developed biosensing solutions and in particular EEG systems going from low-cost solutions to medical grade, working with either dry electrodes or gel-based and for a portion of the cost of gold standard systems. Of course, this also means that some concessions had to be made; the number of electrodes had to be limited to 16 with a sampling frequency of a maximum 125Hz, way lower than the 100kHz offered by the actiCHamp. Nonetheless, the OpenBCI system was also using gel-based electrodes, with the same nomenclature as the actiCHamp for the location of the electrodes, yet it offered also a wireless connection which is something we are aiming for in the final BMI system (Fig. 3.5).



Figure 3.5. 16 electrodes OpenBCI EEG cap.

We can aggregate the differences between the ActiCHamp and OpenBCI systems in the table (Fig. 3.6) below which covers some characteristics of interest regarding the development of the system.

	ActiCHamp	OpenBCI
Number of electrodes	Up to 128	Up to 16
Sampling Rate	200Hz-100kHz	125 or 250Hz
Setup time	45min - 1hr	< 30min
Autonomy	6hrs	26hrs
Dry/wet electrodes	Wet (gel-based)	Wet (gel-based) and dry
Portability		✓
Price	~30k€	~2.8k€

Figure 3.6. Comparison between the two EEG systems: BrainProducts ActiCHamp and OpenBCI.

b. Software

Most of the coding has been done on the Matlab programming platform. In particular, Matlab was used to process the recorded EEG data and train the classification algorithms, it was also used for both displaying the experimental protocol employed during experiments by the subjects at the University but also for marking the EEG data with triggers while the recording was done with a software proposed by Brain Products, a python-based recording software called PyCorder which is an equivalent of their software BrainVision Recorder.

For the real-time tests done during the Ph.D. work with control subjects everything happened inside Matlab while PyCorder was running in the background, Matlab was in charge of connecting the EEG system and retrieving the data to be processed in real-time.

We had to do things differently for the amputee subjects at the IRMA as we were not using the same system. First, the recording and the real-time software were both coded in C++ with the use of the Brainflow library which allowed the connection to the OpenBCI board. The reasons for using C++ were multiple: the first piece of software developed in the laboratory with the previous BMI project was coded in C++ and contained a few modules that were useful for the current project, although the EEG system was at the

time the Emotiv EPOC and the machine was a robotic arm. Because of this previous experience, it felt natural to choose this programming language and, it allowed us to tackle some other questions related to the development of the BMI such as creating an open system without paid libraries or software (like Matlab for example), and with few functions so that the interface part can ultimately be run on a smartphone.

Both Matlab and C++ recording codes share more or less the same functions, with the exception that the C++ code also handles the recording of the brain activity so there is a need to connect to the EEG system. Other than that, we retrieve the subject identifier, the number of trials to record, the object used, condition, side, and the number of the current session. Compared to the recording using the PyCorder software where we obtain a single EEG file per object and per condition with all the trials, the C++ software was coded in a way that we are recording each trial in a separate file. The software and codes to test the system are also similar, but we will be able to look more into the specifics in a dedicated chapter.

To push further on our quest of relying as less as possible on proprietary software for the development of the system we also chose to replicate the EEG processing and training Matlab scripts on the Python programming. We tried to find similar functions between Matlab and Python and coded the missing functions that we needed for the latter.

Most of the statistical analysis has been conducted with the scripts for the tests which were all coded under R with Rstudio. Additional statistical tests were done using GraphPad Prism.

Finally, and mostly related to the development around the control of the prosthesis and the sensory feedback, we were using Arduino microcontrollers and the Arduino language which presented the advantage of offering relatively cheap ways of prototyping what we envisioned. It is also quite easy to integrate Arduino inside both the Matlab and C++ environments.

c. Hardware

Here we will just introduce briefly the two main pieces of hardware that were used during the project as both of these will have their dedicated chapters in this part of the manuscript.

The first hardware part of the developed system is the prosthesis, a Myobock SensorSpeed hand from Ottobock (Fig. 3.7) which is one of the most common models of myoelectric prosthesis and usually what amputees are using before transitioning to more developed polydigital hands. The Myobock prosthesis has originally the ability to close and open at various degrees with different speeds, depending on the level of

EMG activity measured by the surface EMG electrodes. It is possible to add a rotating wrist unit between the hand and the socket on the arm of the user to provide pronosupination movements, but we did not use this option for the development of our system.



Figure 3.7. Myobock SensorSpeed prosthetic hand.

The second piece of hardware used for the project is the sensory feedback system, which is composed of two different parts communicating with each other. The first part is close to the prosthesis with force sensors (FSR) located on its fingertips while the other part is located on the upper arm of the subject with a bracelet containing small vibrating electrical motors (Fig 3.8).

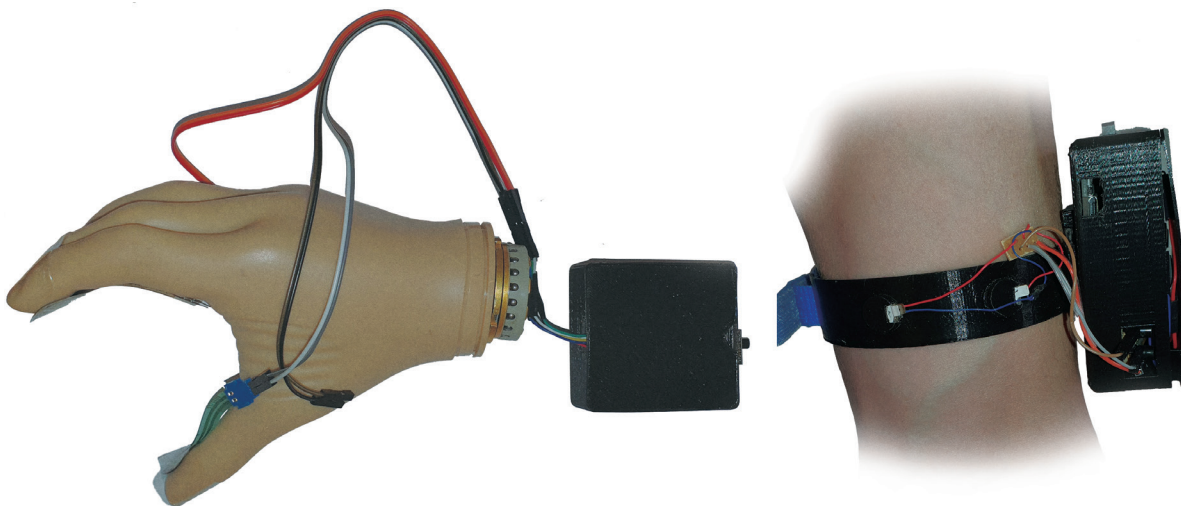


Figure 3.8. Sensory Feedback system used in the experiment. Left : Force resistive sensors connected to an Arduino microcontroller. Right : Vibrating bracelet on the upper arm of the subject, contains vibrating haptic motors connected to an Arduino board. The two parts are communicating with each other through bluetooth.

5. Experimental protocol

The main idea behind the experimental protocol we used during this project was to study and demonstrate if the use of a BMI system for the control of the prosthesis would offer a better control performance over the device.

Our very first test on the project took place on October 2019. At that time, we modified one version of the C++ software we used during previous studies so that it could be used with the Emotiv Epoc and the prosthesis. We were only doing quick recording sessions using a Labview script and we were mainly interested in recording the opening and closing of the hand. On the software the subject could choose between two levels of control “Offline” or “Online”, the first being the use of previously recorded cortical signals while the other refers to signals that are recorded after clicking on a button and letting the subject think about the movement for a few seconds. This work was only done with one or two able-bodied subjects at the University to give the prosthesis a try.

The second attempt to create an experimental protocol was done at the beginning of 2020. We were still working with the Emotiv Epoc but we also did our first recording session with the 64-electrodes ActiCHamp. Instead of only focusing on the opening and closing of the hand, we defined two intermediate positions with one corresponding to a whole-hand grip while the other was similar to a precision grip. The recording was done under two conditions: Motor Execution, during which the subject is actively performing the movement, and Motor Imagery, during which the subject is thinking about the movement. The session consisted of 50 trials with each of the four positions with the dominant hand and 20 trials for the other hand and the two conditions. A trial consisted of three successive steps with two seconds of rest (absence of movement) before 3 seconds for the subject to perform or imagine the movement followed by 1 second of rest. At that moment we had no idea of the maximum number of trials we could ask a subject, able-bodied or amputee, to perform as we were mostly doing some recordings among the members of our team.

The Covid-19 pandemic halted the work on the experimental protocol with subjects, with a shift in favor of the signal processing and classification parts. Yet, thanks to the meeting we had at the IRMA with Ottobock, we were starting to have a clearer idea of the experiments we were going to run there or at the University. First, we wanted to compare the performance of our proposed system either with the conventional system used by the subject or with the performance of able-bodied subjects. Secondly, we were interested in if the testing of the additional sensory feedback system compared with the “no feedback” condition would clear up the grey areas regarding the benefit of sensory feedback in the control of a prosthesis. Finally, we also wanted to see the differences between the Motor Execution and Motor Imagery conditions. We knew that the experiments would thus be divided into several sessions, to track a possible improvement over time for the subjects.

As we were only able to do some tests at the University during 2020, we continued the work with Gabriela with the Emotiv EPOC but added two more movements to the four already presented, but this time four of the six movements were using objects to be closer to activities of daily living. Experiments were run with five able-bodied subjects at the University during Summer 2020 with 600 trials for the dominant hand (50 trials per hand position per condition) and 240 trials for the non-dominant (20 trials per hand position per condition). The results of this preliminary work were presented during the Cortico Conference in October 2020.

After the Cortico conference and the second thesis committee, we listened to the advice from the members of the committee and decided to refocus on a simpler yet solid use of the BMI system for prosthesis control. This change of method is going to reduce the number of movements that will be useful for our application, by going back to the basics of the Myobock prosthesis that we are currently using. This new approach aims to demonstrate the proof of concept for the control of a prosthesis using BMIs. We thus decided to limit the number of movements, going from six movements to three with the addition of a rest/baseline movement. The three movements are the full closure of the hand, the full opening of the hand, and the half closing of the hand. The reasons behind choosing those three movements also come from the fact that we wanted to do some tests with the amputees before the recording sessions and at the end to track some progress. The three tests that we ultimately chose were dedicated to evaluating the dexterity of the amputees regarding prosthesis control. Moreover, as we wanted to see the differences in performance between the control with the original myoelectric prosthesis, the control with our modified brain-machine interface, and its use with the sensory feedback, we established that we needed at least a three-sessions experiment to investigate those differences.

We will thus first introduce the protocol we used for the amputated subjects and its adaptation for the able-bodied group.

This first session is composed of two phases. In the first phase, the subjects were asked to do three tests with their prosthesis to evaluate their dexterity before the use of the Myobock controlled by our BMI system (Fig. 3.9). The first test is called the Box and Blocks Test (BB) and is widely used in rehabilitation to evaluate the object manipulation performance of the subject [204]. The setup is composed of an opened wooden box, divided in the middle with a board. One side of the box contains cubic wooden blocks (2.5 x 2.5 x 2.5cm) and the subject is asked to move as many blocks as he can to the other side of the box in 1 minute. It is reminded that the subject has to move blocks one at a time and that if the subject moves two or more blocks at the same time, only one will be counted for the final result. The total number of blocks moved is used as the outcome score for the test. The second test is derived from [105] and is called the Cup Relocation Test (CUP), it consists of 11 plastic cups stacked on each other and placed

bottom-up on a plank. The subject is asked to move 10 plastic cups (one cup at a time) from a position located 30 cm towards the contralateral side, as fast as possible. The time needed to move the 10 plastic cups is used as the performance score. The final task is called the Clothespin Relocation Test (CS) and is inspired by the work in [79]. The subject is asked to relocate four plastic clothespins from a horizontal position to a vertical position, the plastic clothespins could vary in the force needed to open them. The time needed to relocate the four pins is used as the performance score for the test. Each of the three tests was repeated five times to have a more accurate measure.

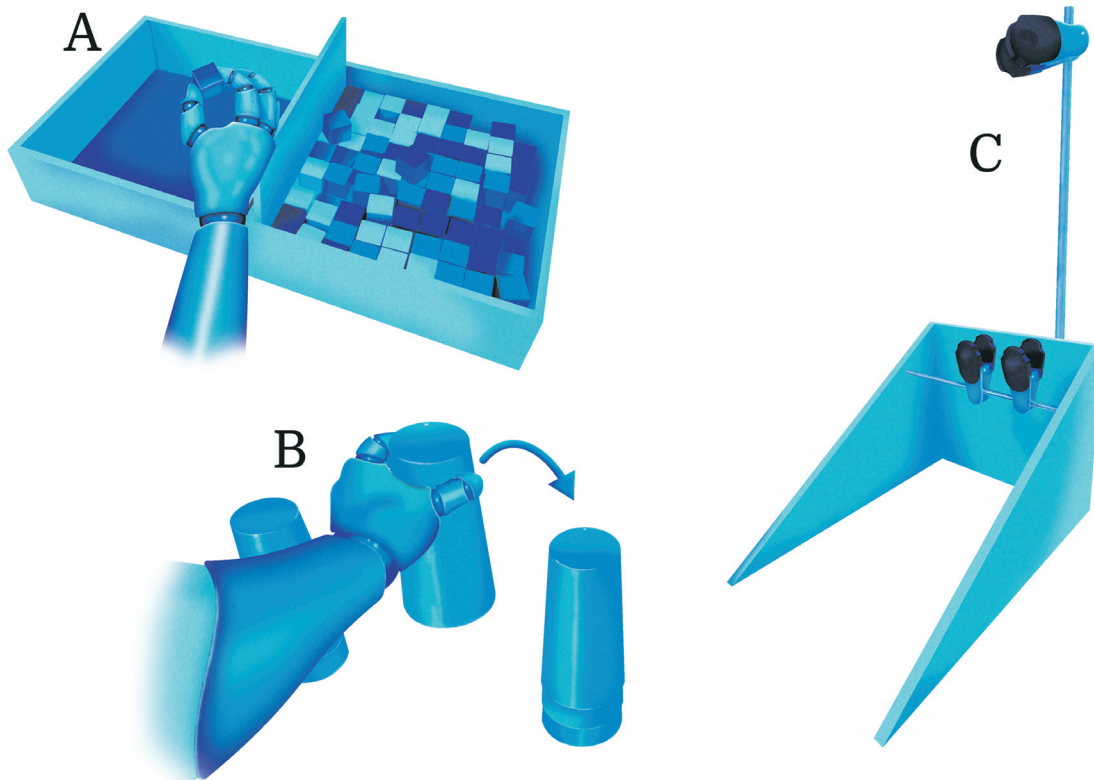


Figure 3.9. Dexterity test to assess the control performance of the prosthesis during the first session. A. Box and Blocks test. B. Cup relocation test. C. Clothespin relocation test.

In the second phase of this first session, we asked the subject wearing the EEG cap (OpenBCI) seating comfortably on a chair and looking at a computer screen to perform a sequence of movements using the same objects used in the first phase but following the visual and audio instructions sent by the computer according to the sequence seen in Fig. 3.10 and in Motor Execution and Motor Imagery. The sequence is composed of 6 successive steps, the 1st and 6th steps are fixation crosses lasting 1 second each where the subject has no action to perform/imagine. The 2nd step (Go) instructs the subject to go to the object represented on the screen, a random time window (1 to 2 seconds following this spacing: 1s, 1.25s, 1.5s, 1.75s, 2s) is used to alleviate the habituation effect coming from the repetition of the sequence. The 3rd step (Grip) asks the subject to grasp the object with his prosthesis and lasts 3 seconds. The 4th step (Move) asks the subject to move the object to his right or his left (depending on the previous motion done). Similarly to the Go step, the Move step contains a random time window of 2 to 3 seconds. The 5th step (Release) asks the subject to release the object and to go back to his/her initial position. This step lasts for 2 seconds..

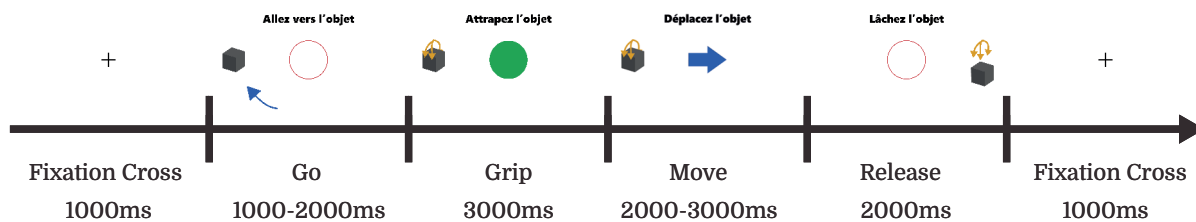


Figure 3.10. Sequence and timing of the phases for the Motor Execution condition. The Go and Move phases have a time window of random length.

Based on the feedback of the first amputated subject we modified the experimental protocol for the MI condition by removing the random time windows (1 second for the Go step, and 2 seconds for Move) and by reducing the time in the Grip step (2 seconds instead of 3). The experiment consisted of 30 trials with each object and for the two conditions, on which was added the recording of 10 trials of neutral/baseline activity where the subject was asked to simply look at the screen without performing or thinking of any movement. Finally, the subject was instructed to reduce as much as possible the eye blinks during the movement.

The second session consists of experiments with EEG recording identical to the ones presented in the first session but with an important difference in the ME condition; instead of using his original prosthesis the subject uses a modified Myobock prosthesis that is connected to the computer. The PC is controlling the opening and closing of the hand in the Grip (Closing) and Release (Opening) steps during the experiment. This ME, which we call MEP (for Motor Execution with Prosthesis), recording is thus changing into a hybrid (or intermediate) condition between the classic ME condition and the MI condition as the subject is now seeing his prosthesis being opened or closed without the motor command coming from the EMG electrodes. At the end of the recording session, the sensory feedback is tested for a few minutes on the subject to give her/him an idea of the content of the third recording session. The third recording session is identical to the second (MEP and MI) except for the addition of the sensory feedback system in the MEP condition (that we are calling MEPS), which adds sensory information to the user during the Grip, Move and Release steps of the sequence.

	Content of the session
Session 1	Box & Blocks, Cup Relocation and Clothespin Relocation tests Motor Imagery + Motor Execution with original prosthesis
Session 2	Motor Imagery + Motor Execution with modified myobock prosthesis
Session 3	Motor Imagery + Motor Execution with modified myobock prosthesis + Sensory feedback

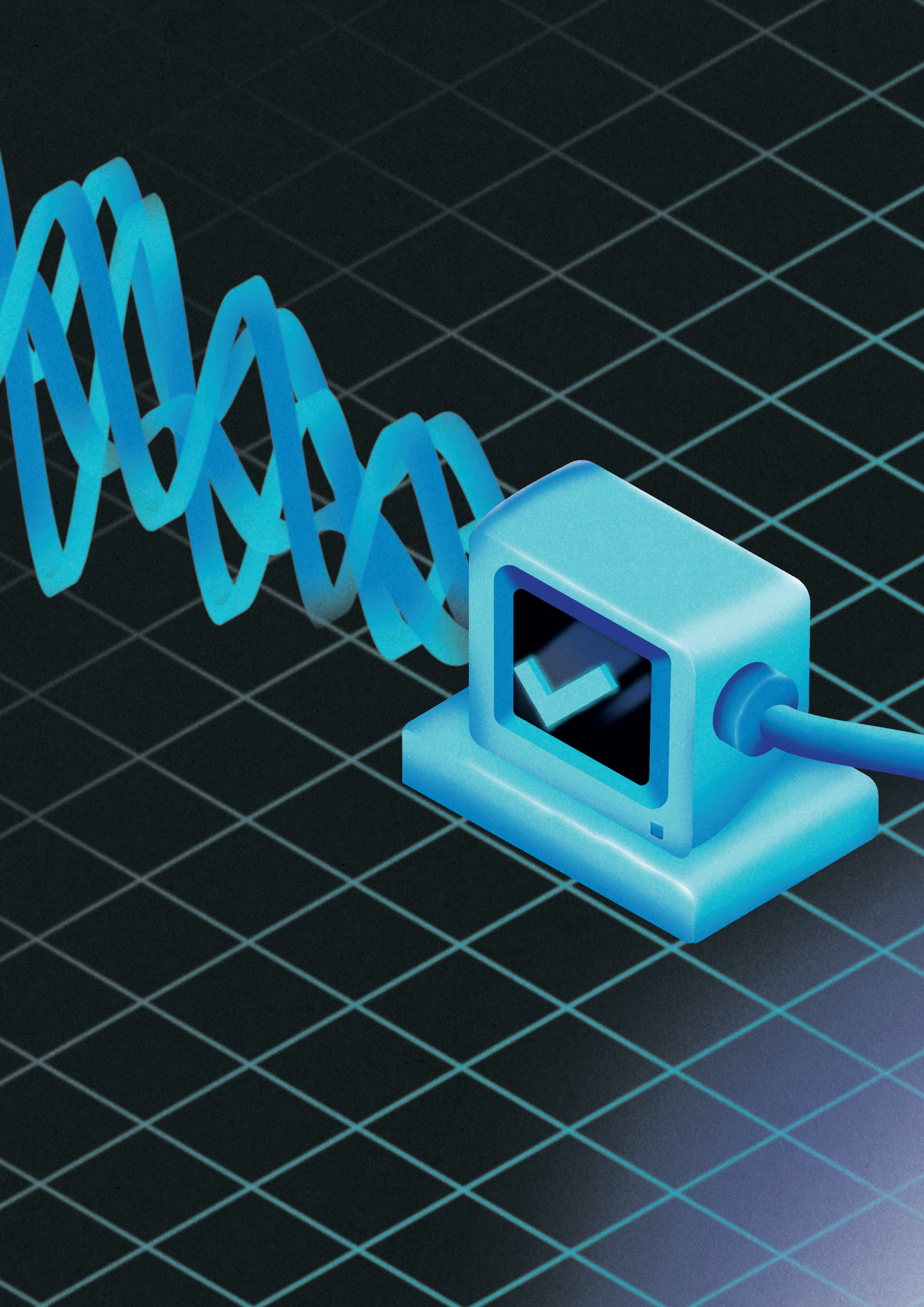
Figure 3.11. Description of the session with the amputee subjects at the IRMA. The two blue colored texts represent the EEG recordings in the two conditions : Motor Imagery and Motor Execution

The sequence of movements and number of trials for control (able-bodied) subjects (Fig 3.11) are identical to the ones defined in the first session of the experimental protocol for amputated subjects (Fig. 3.12) in ME and MI conditions. For the first article published regarding this project, the control subjects did not perform the experiments of the second and third sessions using the apparatus allowing them to control a prosthesis with their EEG signals and with or without a sensory bracelet. The results of the second and third sessions are presented in the following articles.

	Content of the session
Session 1	Motor Imagery + Motor Execution with dominant hand
Session 2	Motor Imagery + Motor Execution with modified myobock prosthesis
Session 3	Motor Imagery + Motor Execution with modified myobock prosthesis + Sensory feedback

Figure 3.12. Description of the session with the able-bodied subjects at Université Paris Cité.

Now that we have presented the expectations behind the project as well as the protocol and materials used for it, we can tackle in the next chapter the work on the recorded data that we did and the results obtained .



IV

Work on the feature
extraction and decoding
methods

This chapter will present the experiment and results that have been published during this thesis. In particular, the first published article is interested in the selection of a feature extraction method as well as the decoding algorithms usable with the system.

1. Material and Methods

The following details and results have been presented during the 10th International Winter Conference on Brain-Machine Interface in February 2022 and published in the proceedings of the conference [205] under the reference:

C. Piozin et al., «Motion prediction for the sensorimotor control of hand prostheses with a brain-machine interface using EEG,» 2022 10th International Winter Conference on Brain-Computer Interface (BCI), 2022, pp. 1-8, DOI: 10.1109/BCI53720.2022.9734823.

a. Participants

Seven healthy participants (3 females and 4 males, 5 Right-handed, 2 Left-Handed, 29.8 ± 13.3 years old,) composed the control group and four amputated subjects (4 males, 2 transradial amputations of the left hand and 2 of the right hands, 58.25 ± 3.86 years old) participated in this first phase of experiments. All participants were given information in oral and written forms before giving written informed consent to participate in the study. The protocol was performed in accordance with the Declaration of Helsinki. The criteria of inclusion for the amputated subject were the following: a person above 18 years old with a transradial amputation and a user of a myoelectric prosthesis. All amputees except for Amputee #2 declared using their myoelectric prostheses - a polydigital hand (Michelangelo©, Ottobock) daily; the second amputee is using his prosthesis (Myobock SensorSpeed©, Ottobock) occasionally.

b. Experimental setups

Two experimental setups (see Fig. 4.1. A & B) were developed to perform experiments and recordings respectively with able-bodied and amputee subjects using two EEG caps with a different number of electrodes and different sampling rates but placed following the 10 - 20 position system and referenced to the CPz electrode for each system.



Figure 4.1. Experimental setups used during the experiments. A. Experimental setup with able-bodied subjects at Université Paris Cité. B. Experimental setup with amputee subjects at IRMA. C. Prosthesis and sensory feedback devices used during the second and third session with the amputees.

Experimental Setup for able-bodied subjects (Fig. 4.1.A): Continuous EEG data were collected from 64actiCAP EEG electrodes (BrainProducts GmbH) mounted on an elastic cap using the PyCorder system on the recording computer and actiCHamp amplifiers (BrainProducts GmbH, Gilching, Germany) with a sampling rate of 2000 Hz. The second computer was running the experiment on a custom script written with MATLAB 2016b (Mathworks, Navick, MA) using the Psychophysics Toolbox [206].

Experimental setup for amputee subjects (Fig. 4.1.B): Continuous EEG data were collected from 16 sintered EEG electrodes (OpenBCI, United States) mounted on an elastic cap using the BrainFlow library on the recording laptop and the Cyton+Daisy boards with a sampling rate of 125Hz. The recording laptop was also used to run the experiment via a custom C++ program written and compiled on the QT IDE (QT Creator 4.13.3).

A modified Myobock hand prosthesis, allowing the control of the prosthesis via a computer or via the EEG signals of the user, and a sensory feedback system (Fig. 4.1.C), composed of force sensing resistors (FSR) and vibration motors communicating via Bluno microcontrollers, were used during sessions with amputees.

c. Modification of the Myobock prosthesis

As presented in Chapter III, the Myobock prosthesis we used during this Ph.D. project is probably one of the most commonly used prosthesis for upper-limb amputees and allow them to perform opening and closing movements at various degrees of aperture but also with different speeds of execution. Originally the Myobock prosthesis can be used with two surface EMG electrodes located over two antagonistic muscle groups, for example, the wrist flexors and extensors of the forearm in the case of upper-limb amputations. Each of those two opposing muscle groups is thus controlling either the opening or closing of the hand. As we aimed to replace only the EMG signals with the EEG ones without changing any other electrical or mechanical component of the prosthesis, we started by investigating first the part of the prosthesis that processed the EMG signals.

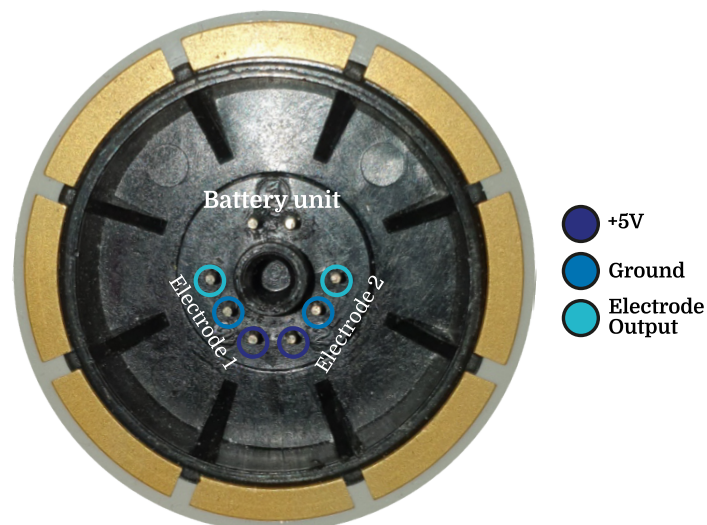


Figure 4.2. Coaxial plug of the Myobock prosthesis.

On the bottom part of the prosthesis, there is a series of pins that are used to connect both the EMG electrodes as well as the battery unit. For the EMG we have three pins for each of the two with one pin providing a +5V voltage from the battery, a second one acting as the Ground, and the third one being the output of the electrode. We then investigated with a voltage generator the range of values that were necessary to make the prosthesis open or close. We noted a minimum of 0.6V to see the prosthesis move and a maximum of 1.6V for which there is no difference in the opening/closing speed beyond that limit. Similar results have been obtained by Nakamura and colleagues [207] where they noted a minimum input voltage of 0.56V and a maximum of 1.5V. It is worth noting that we were able to test with several different Myobock prostheses over the project, with left-handed or right-handed models and we found some small differences in the required voltages.

From the beginning of the project, we were set on using Arduino microcontrollers as the principal element of the new controller of the prosthesis. The form factor of the boards, the easy connection to the computer, the possibility to have them in different

sizes with a different number of input/output ports as well as the low price were some of the main reasons behind that choice. During our first test, we used an Arduino UNO controller that could be either connected to a computer via a USB cable or through the use of a Bluetooth module. With the second option, the input voltage to the Arduino board was provided by the battery pack of the prosthesis. Nonetheless, the Bluetooth connection led to latency issues when communicating with the computers which we thought could be solved using two Arduinos connected via Bluetooth with one also connected to the computer, but to no avail because of unresolved connection issues between the two boards. The first test we did at that time was to connect the “electrode” cables directly to the digital pins of the Arduino, a simple script then sent the commands to the prosthesis by changing the state of one of the pins from LOW to HIGH which was delivering a 5V voltage to either fully open or close the prosthesis. Nonetheless, we could only realize that using those output pins would only prevent us from accessing the positions in between the endpoints of the prosthesis. Moreover, testing the PWM outputs of the Arduino showed to be inconclusive for the control of the prosthesis, probably because it does not create an analog DC output that is required for the motor on the hand.

The solution we found to overcome this issue has been to use two Digital-to-Analog Converters modules that can generate DC output voltages. Given that the two DACs are the same model, they originally shared the same I2C address. The I2C (Inter-Integrated Circuit) is a communication protocol created to standardize the transfer of information between two devices, with a master/slave pattern. The I2C communication use two cables, one for data transfer named SDA (Serial Data) et the other named SCL (Serial Clock) acting as a clock to set the transfer frequency. The I2C protocol is commonly used with Arduino as a large variety of peripheral devices use this type of communication. To be recognized by the Arduino, the device must have a unique I2C address This is a problem when you want to work simultaneously on multiple peripheral devices that share the same I2C address.

There are a few solutions to solve this problem; the first one would be to use an I2C multiplexer that is intended to connect and use up to eight I2C devices with the same address. Luckily, the DAC reference that we bought had an easy way of changing the I2C address with a simple soldered joint on the address selection pins of the board. This simple modification enables the two DACs to be recognized independently by the Arduino controller and they are thus able to deliver voltage to control separate actions on the prosthesis.

We then ran a quick test to verify the voltage output coming from one of the DAC using a potentiometer, we noticed a range of 0,001V – 4,88V which was more than enough for the prosthesis. Thanks to those modules we not only set the voltage to several values within that interval but also we could define for how long we were delivering this voltage. In other words, both the amplitude and the time are parameters when setting a voltage on the DAC, very much like what we observe with EMG electrodes where

subjects are controlling the intensity of the contraction and its duration. The next step was thus to implement, in the code of the microcontroller, a lookup table that for a given movement was defining the value (in mV) and the duration (in ms) of the voltage, when a specific movement had to be triggered, the parameters were retrieved from this lookup table and sent to the corresponding DAC. For this purpose, we did several tests to adjust the two parameters and be sure that the movements were replicated effectively; in particular, when holding the cup, we had to guarantee that the grasp was not too tight or too loose.

What can be considered the final step for this part was to ensure that the connections were secured and without risk of breaking during the experiments. A 3D-printed enclosure has therefore been designed and it is used to fit both DAC modules but also the Arduino board. (Fig. 4.3)

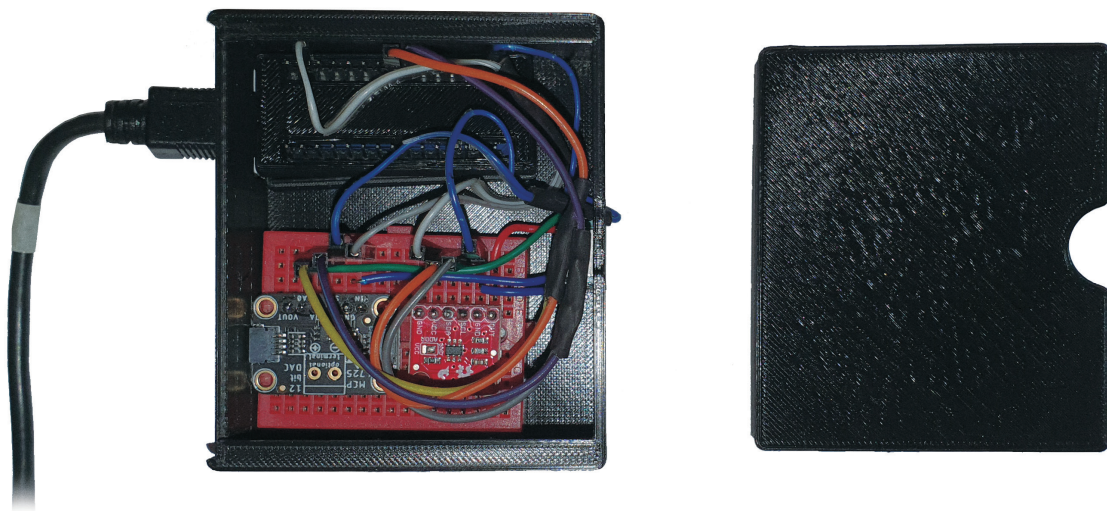


Figure 4.3. 3D-printed enclosure that fits the two DACs (bottom left) and the Arduino Nano microcontroller (top left).

As for all prototyping work aiming at easily and quickly testing different alternative solutions to different problems to propose an optimal design, the current version of the system still uses a cable connection to the computer. However, the final goal of the project is to develop a fully wireless system by relying on other smaller microcontrollers and using the battery of the prosthesis to power the different elements of the system, all the while being fitted inside the socket of the prosthesis that would remain unchanged.

We faced several problems when trying to use the modified prosthesis with the amputees, particularly due to the incompatibilities between the various sockets on the prostheses of the amputees and our modified prosthesis. To make the modified prosthesis easily usable with the amputees we first used a small apparatus that we obtained from the IRMA which contains a Myobock plug encapsulated in resin (Fig 4.4). Then we used some tape to attach the prosthesis to the socket of the amputee.



Figure 4.4. Myobock socket used at the IRMA to quickly test the prosthesis on the patients.

Nonetheless, this apparatus did not allow us to secure perfectly the prosthesis because it was both not wide enough and too short to fit on the sockets. After taking a few measurements on the socket of one subject, we designed our intermediate socket using the Computer-Assisted Design (CAD) software Solidworks (Fig 4.5). The aim was to be able to replicate the apparatus from the IRMA by adding the coaxial plug of the prosthesis while offering more adjustable length and circumference. This first version of the design has then been 3D-printed at the University and then later successfully tested on subjects at the IRMA.

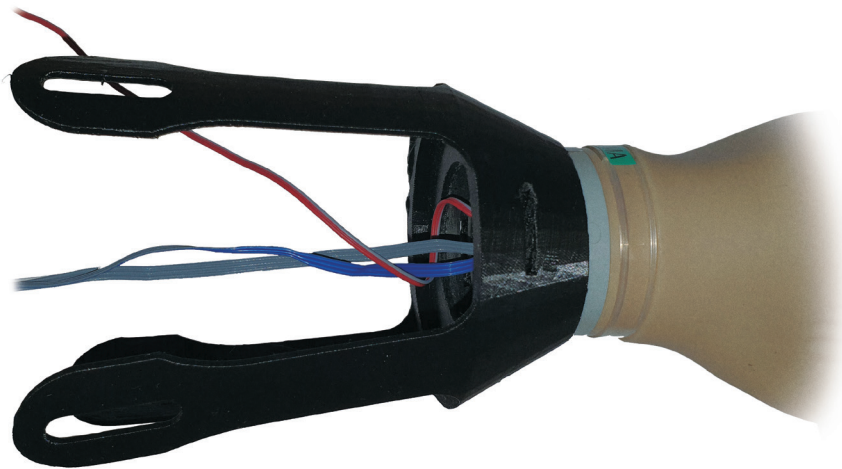


Figure 4.5. 3D-printed custom socket for the experiment with amputees at the IRMA.

d. EEG signal processing

i. Preprocessing

EEGLAB functions were used to segment the trials and retrieve the data from the Grip and Release steps from the EEG files recorded with the ActiChamp system [208]. To speed up the computation time, each trial was downsampled from 2000Hz to 250Hz. Similarly, the OpenBCI data were segmented but the sampling rate was kept

at 125Hz (internal limitation of the system). We considered the movement Close (full closure of the hand) as the motion type of the Grip step of both the BB and CS objects while the movement Half (half closure of the hand) was considered as the motion type only of the Grip step of the CUP object. The Open movement (full opening of the hand) is a state in common for the Release steps of BB, CS and CUP. Moreover, the neutral/baseline condition is considered to be Rest.

We only kept the first second of each trial after the stimulus onset on which an infinite impulse response notch filter set at 50Hz and a 4th order Chebyshev type II bandpass filter between 8 and 30Hz was applied, to minimize noises and artefacts on the trials. but also because we are dealing with movements most of the activity should be contained in the alpha and beta bands as presented in Chapter II. In particular if we look at the Fourier transform over the second of data for different movements we can see that most of the amplitude is located between 0 and 30Hz with high amplitudes in the alpha and beta bands (Fig. 4.6).

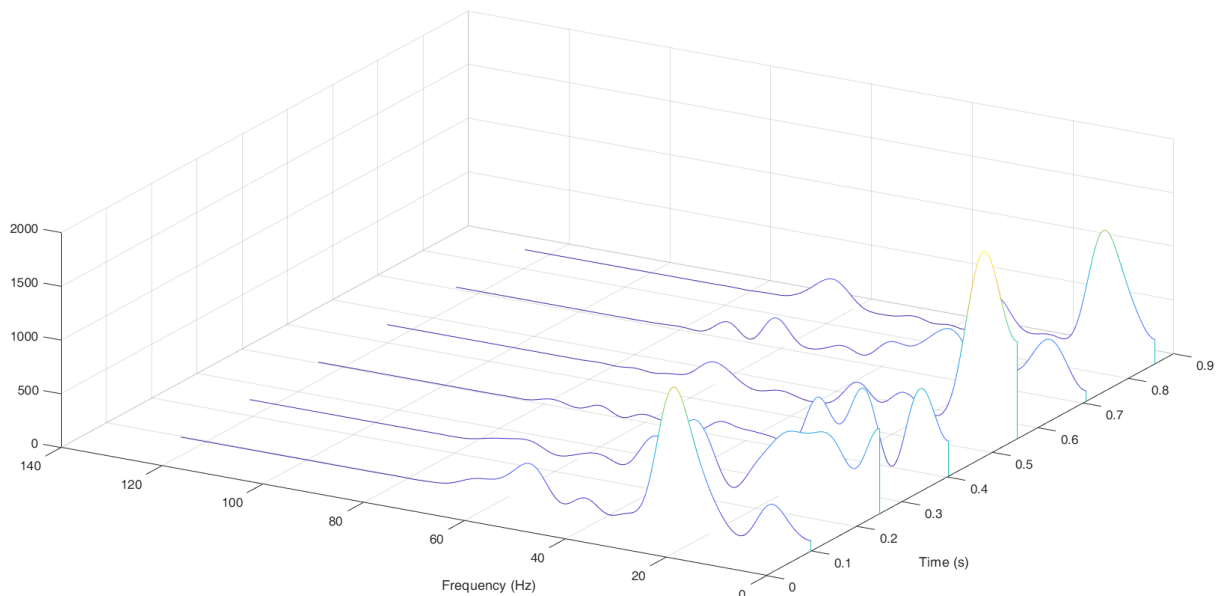


Figure 4.6. Waterfall plot of the spectrogram obtained after applying Short-Time Fourier Transform on EEG data (filtered between 1 and 100Hz with a notch filter set at 50Hz) for the Grip phase of the BB/Cube object (corresponding to the Close movement). The time period corresponds to 1 second after stimulus onset.

In order to increase the size of the dataset and minimize the effect of imbalanced classification, the analogy method from [209] was used so that each class now contains 90 trials. The method consists in computing a ratio between two trials of the same class (using its principal components) and applying this ratio to a third trial of the class to create a new and artificial trial. As the Open motion is common for the three objects and because we have 30 trials for each of them, we already have 90 trials for this type. Close being common to BB and CS only means that there were 60 trials in total for this type, leading to the use of the dataset augmentation technique to create 30 trials, 15 from the data based on BB and 15 for the data based on CS. Because Half only originated from the Grip data of the CUP object, 60 trials were artificially created

to reach 90. Similarly, as only 10 trials of the Rest condition were recorded during a session, 80 trials were created.

Then the z-score of each trial was computed and used as the starting point for the feature extraction pipeline, this in order to minimize within-session non-stationarities in the EEG signal.

ii. Feature Extraction

In the following, we first present the feature extraction techniques we used in constructing the input vector contents for the classification algorithms. We then study the effect of the use of different combinations of those techniques in the classification performance of the two decoding algorithms used in the current version of the proposed system.

In the first step in the feature extraction process, we applied the Common Spatial patterns technique, which is probably the most commonly used spatial filtering technique in BMIs [144][210][211]. This method is applied mainly to binary classification and commonly used to differentiate patterns from the left hand right hands for example, yet almost no or few works were interested in looking at the application of the technique for movements of the same limb. the CSP technique consists in computing a transformation matrix W that is maximizing the variance of the signal for one class while minimizing it for the other [212]. Finding the optimal transformation matrix W requires solving:

$$w_c = \max_w w^T \Sigma^{(c)} w \quad \text{with } c = 1,2 \quad (\text{IV.1})$$

$$w^T (\Sigma^{(1)} + \Sigma^{(2)}) w = 1 \quad (\text{IV.2})$$

$\Sigma^{(c)}$ is an estimate of the spatial covariance matrix of class c . Using the Generalized Eigen Value Decomposition (GEVD), the solution to this optimization problem is the transformation matrix composed of the eigenvectors corresponding to the maximal and minimal eigenvalues obtained from $\Sigma^{(1)}$ and $\Sigma^{(2)}$. This technique is applied here to four movements using a One-vs-One approach, leading to the computation of six different transformation matrices W ($(n*(n-1))/2 = 6$, with $n = 4$, the number of movements to classify). Following recommendations from Blankertz et al. [212] on the number of components to keep after the computation of the matrices, 6 pairs of CSP filters were kept using the setup with healthy subjects while 8 pairs were kept in the setup with amputees subjects, thus giving a matrix size of $(m, n, 90)$ for each of the projection (with $m = 248, 124$ and $n = 12, 16$ for the ActiCHamp and OpenBCI EEG systems respectively).

The EEG signal is known to be non-stationary meaning that its properties are changing with time, by applying traditional techniques such as the *Fast Fourier Transform* (FFT) it is possible that one can miss relevant information regarding the movements. Applying the Wavelet Decomposition method allows the retrieval Time-Frequency

information on the original signal [213]. For this operation, a function called the Mother Wavelet – which starts at zero, briefly oscillates, and comes back to zero – is scaled and translated to create a set of wavelets on which the signal is convoluted. Here a Daubechies 4 mother wavelet has been used. Two filters are used to convolute the signal: a low-pass filter (LPF) and a high-pass filter (HPF). Following the convolution, downsampling is done on the two filtered signals and the approximation coefficients a and details coefficient d are obtained. To continue the decomposition to further levels, the approximation coefficients are considered as the base signal for the next decomposition. As the WD technique keeps frequency information of the signal it is possible to choose the decomposition level based on the frequency band of interest of the signal, in our work we chose a 2-level decomposition for the OpenBCI EEG system and a 3-level decomposition for the ActiCHamp EEG system to fall approximately in the 0-32Hz frequency band. We decided to use the approximation and detail coefficients from the last level – sufficient for the reconstruction of the original signal with inverse WD – for the next step of the feature extraction process. After the CSP computation, we obtained 12 signals as each of the 6 transformation matrices is used to project the signals of 2 different classes, we thus applied the WD on those 12 signals which gave us a matrix size of $(m', n, 90)$ (with $m' = 62$ and $n = 12, 16$ for the ActiCHamp and OpenBCI system).

From the features vectors composed of the wavelet coefficients, a basis $q_{(c,f)}$ (with $c = 12$, corresponding to the numbers of comparisons signals and f the number of filters kept after the CSP step) was obtained by orthonormalization following the Gram-Schmidt procedure [214]. For each of the c comparisons and f filters a projection matrix $TT_{(c,f)}$ is computed from the $q_{(c,f)}$ bases and used to project the feature vectors obtained during the previous step. As we are comparing two different classes, we also use the projection matrix $T_{(c,f)}$ of the first class to project the feature vector from the other class. Moreover, and as we are computing orthonormal bases for the 12 signals obtained after wavelet decomposition, the Gram-Schmidt technique is moving up the number of one-vs-one comparisons from 6 to 12 (see Fig. 4.7).

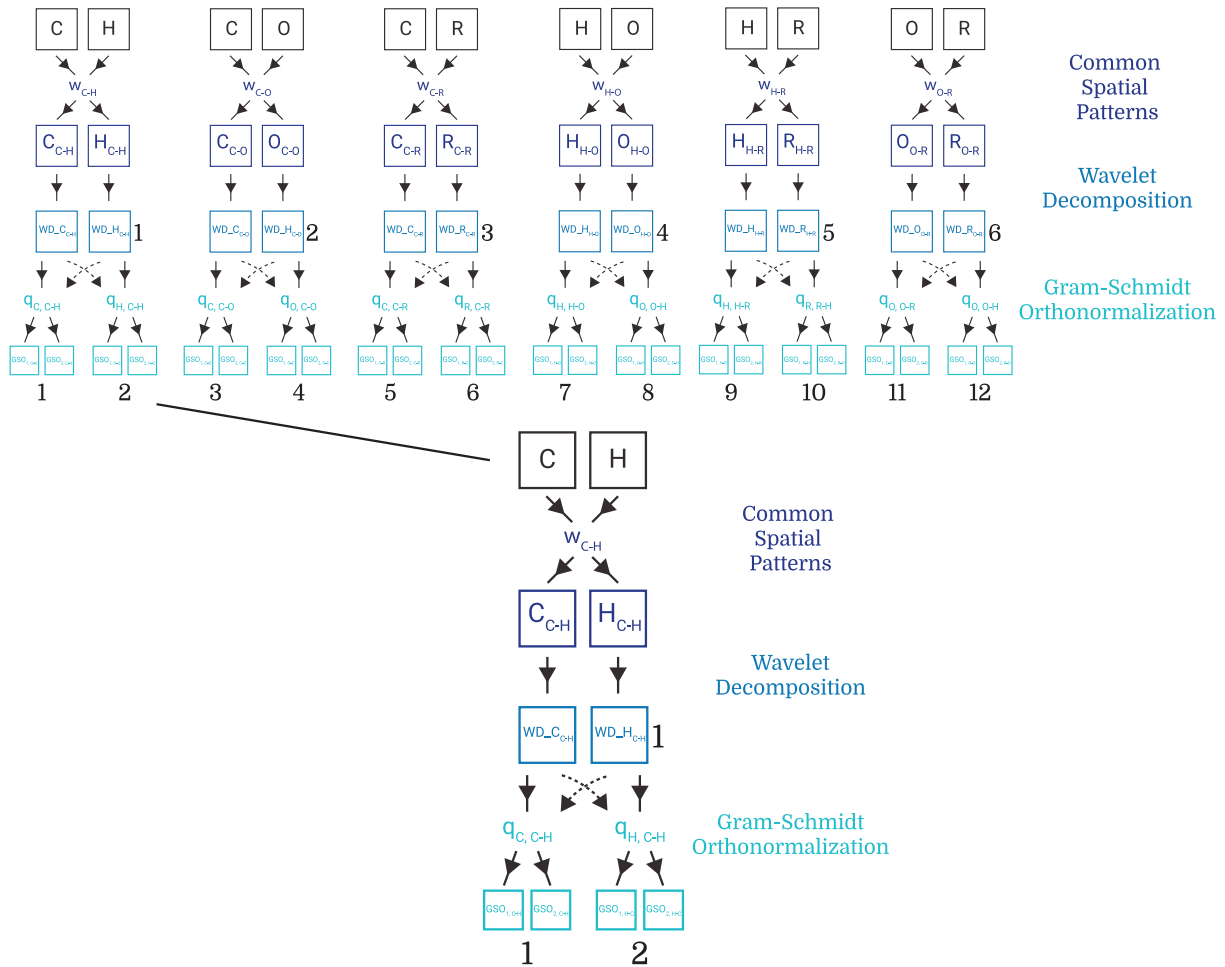


Figure 4.7. Schematic representation of the feature extraction pipeline and zoom on the first pair. 6 pairs of one-vs-one classification models are created from the four movements. During the Common Spatial Patterns step, for each of the 6 pairs the signal from the two classes is projected using the CSP filter matrix w . The projected signals is then used as the input for the Wavelet Decomposition step. The final method is the Gram-Schmidt Orthonormalization where an orthonormal basis is computed for the 2 signals of each pairs and used to project the signals obtained after the decomposition, hence resulting in 12 input vectors.

Finally, for each projection and no matter the combinations of feature extraction techniques the logarithm of the variance is calculated, and the values obtained are used to build the input vectors for the classification algorithms.

iii. Input Vectors

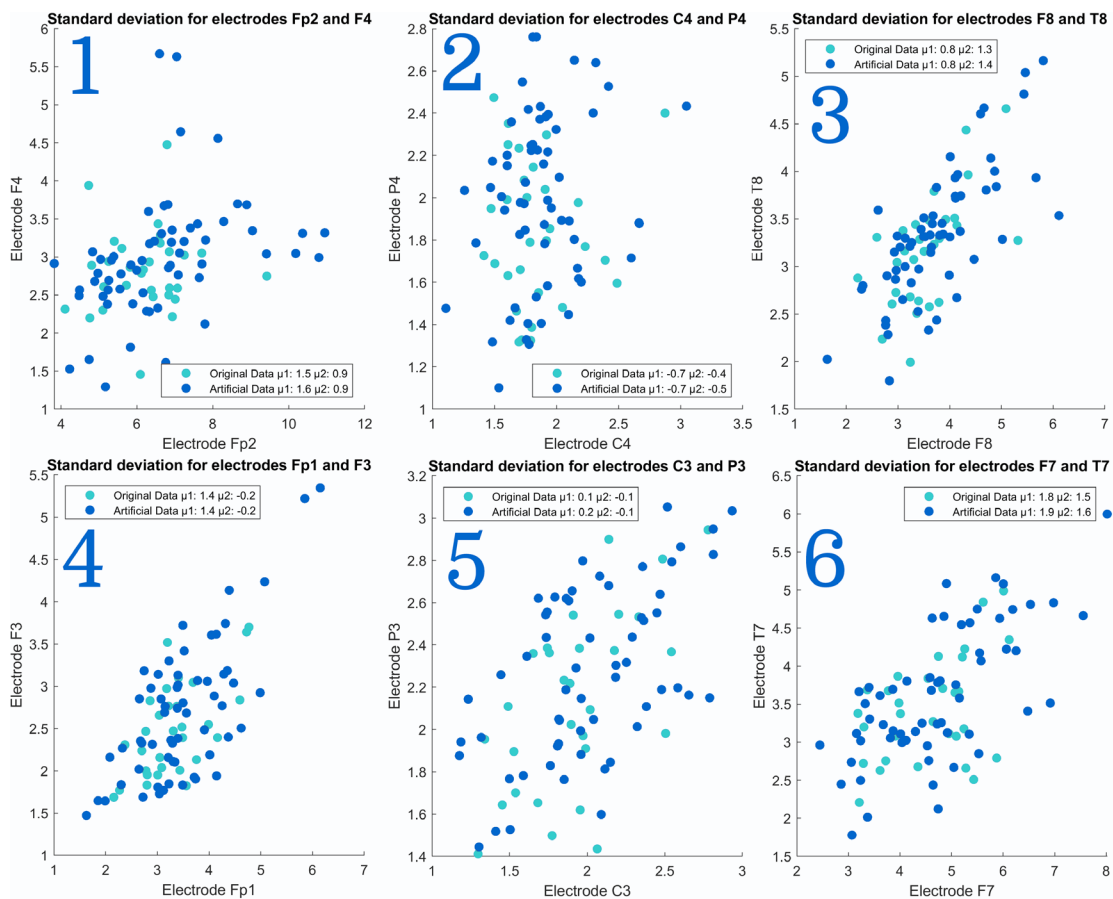
With this experiment, we aim at comparing different feature extraction methods by using a combination of the three processing techniques we described. The first method is CSP+WD, the application of CSP then WD in the FE, leading to 6 binary classification models with inputs sizes of 180×12 or 180×16 , for the ActiChamp or OpenBCI systems respectively (90 trials for the first class and 90 for the second). The second method is CSP+GSO, it gives 12 binary classification models with once again inputs sizes of 180×12 or 180×16 for the two systems. The third method is WD+GSO, for this one we obtain 12 models and the input size is either 180×63 or 180×16 as we decided to keep all the electrodes during the FE. Finally, the last method is CSP+WD+GSO, the application of the three techniques leads to 12 binary models with inputs sizes of 180×12 or 180×16 , similar to the CSP+GSO method.

iv. Classification

The training performance has been obtained offline on Matlab 2021a using three different classification algorithms: An Artificial Neural Network (ANN) with a Training/Validation/Test split of 70%-15%-15%, and two Support Vector Machines (SVM) with a Training/Test split of 80%-20% using a Linear and a Radial Basis Function (RBF) kernels. The ANN is composed of three layers, an input layer with 12 or 16 inputs depending on the EEG system, a hidden layer with 15 neurons, and finally an output layer with two outputs. The Accuracy, Precision, and F1-score metrics were computed for all the models and the three classification algorithms.

2. Results and discussion

As our BMI control system uses classification algorithms that need to be trained by the user, one of the most important issues concerning the easy use of the final product would be to get the amount of data necessary to train the classification algorithm in a reasonably short time. In machine learning, extending the training dataset by adding to the originally recorded signals an artificial data set is commonly used to increase the amount of data without increasing its collection, especially in image classification [215]. Fig. 4.8 shows the standard deviations of original and artificial data obtained for seven different pairs of electrodes using the data augmentation method described in 1.d.i.



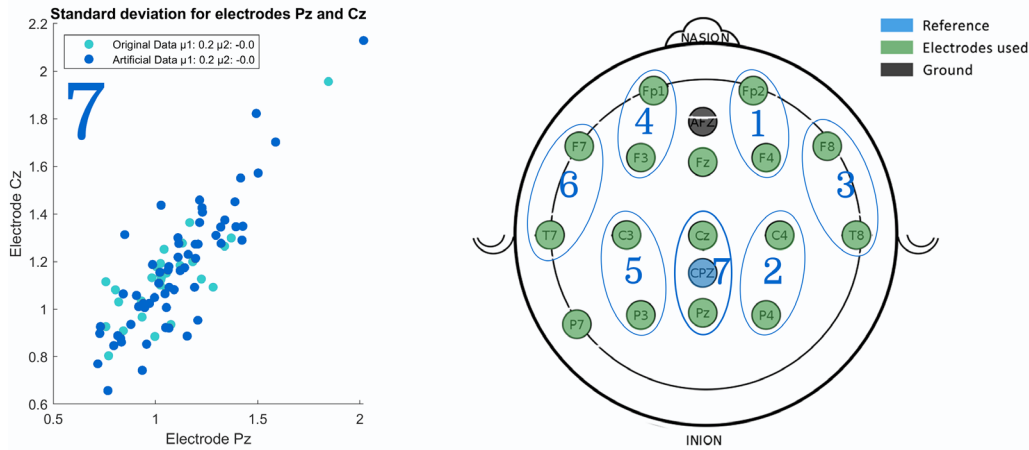


Figure 4.8. Computation of the standard deviation of the original and artificial data for several pairs of electrode on the OpenBCI EEG system. The artificially created trials occupy the same space as the original data.

Following the axes of work evoked in Chapter 3 and particularly the second group, first wanted to explore the training performance of different combinations of the 3 feature extraction techniques (namely CSP, WD, and GSO) described respectively in section 1.d.ii. Four different combinations, namely CSP+WD+GSO, CSP+WD, CSP+GSO and WD+GSO, have been studied. Fig. 4.9 shows the distribution of the log variances corresponding to the first and last variables of the input vector (1st and 12th for CSP+WD+GSO, CSP+WD & CSP+GSO, and 1st and 63rd for WD+GSO for two extreme types of hand movements (Close and Rest), which can be controlled on the Myobock. As it can easily be seen in Fig. 4.7, results obtained by using CSP+WD are the most promising ones as it is the technique that most efficiently separate the two classes.

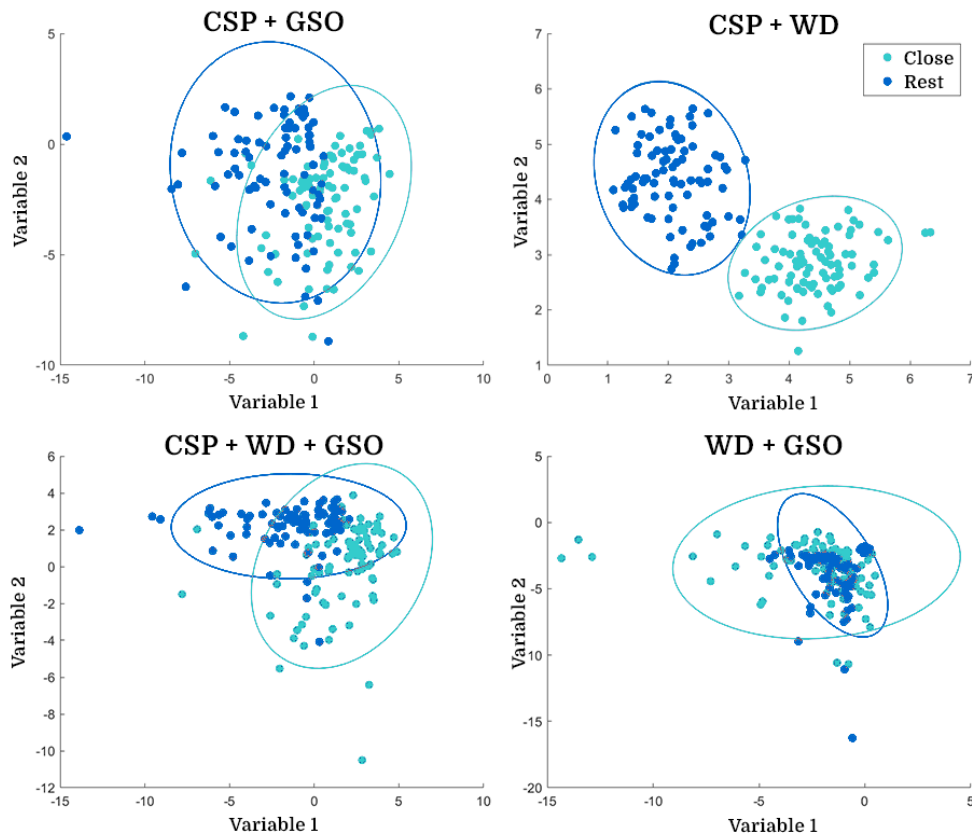


Figure 4.9. Distribution of the log variances for each of the trials of the Close and Rest movements for different combinations of feature extraction techniques. For CSP+GSO, CSP+WD and CSP+WD+GSO variable 1 and 2 represent the most discriminant features obtained after CSP. For WD+GSO, variable 1 and 2 represent two electrodes.

We then studied the accuracies of the classification performance of four different types of desired hand positions obtained by different classification algorithms. Table A, Table B and Table C from Fig. 4.10 represent respectively the accuracies of the ANN and SVMs classification results for several combinations of the Feature Extraction techniques described in 1.d.2. obtained from the first session in Motor Imagery with the control and amputee groups.

A

Groups	Close /Half	Close /Open	Close /Rest	Half /Close	Half /Open	Half /Rest	Open /Close	Open /Half	Open /Rest	Rest /Close	Rest /Half	Rest /Open	
CSP+ WD+ GSO	Control	0,776	0,635	0,883	0,710	0,699	0,901	0,631	0,660	0,876	0,873	0,918	0,855
	Amputees	0,656	0,586	0,948	0,634	0,697	0,946	0,557	0,573	0,926	0,944	0,947	0,943
CSP+ GSO	Control	0,767	0,676	0,904	0,749	0,731	0,899	0,663	0,717	0,894	0,907	0,911	0,889
	Amputees	0,658	0,589	0,944	0,627	0,694	0,941	0,571	0,583	0,921	0,937	0,950	0,949
WD+ GSO	Control	0,638	0,514	0,839	0,641	0,632	0,884	0,529	0,601	0,828	0,862	0,901	0,844
	Amputees	0,612	0,553	0,776	0,651	0,603	0,862	0,534	0,577	0,824	0,853	0,868	0,854
CSP+ WD	Control	0,987	0,954	1		0,974	1		1				
	Amputees	0,902	0,752	0,993		0,839	0,997		0,994				

B

Groups	Close /Half	Close /Open	Close /Rest	Half /Close	Half /Open	Half /Rest	Open /Close	Open /Half	Open /Rest	Rest /Close	Rest /Half	Rest /Open	
CSP+ WD+ GSO	Control	0,793	0,662	0,906	0,725	0,731	0,922	0,666	0,689	0,903	0,869	0,927	0,872
	Amputee	0,693	0,617	0,946	0,680	0,730	0,950	0,592	0,614	0,932	0,911	0,908	0,917
CSP+ GSO	Control	0,764	0,644	0,875	0,701	0,716	0,901	0,660	0,689	0,887	0,863	0,914	0,861
	Amputee	0,690	0,614	0,943	0,665	0,726	0,954	0,591	0,607	0,933	0,906	0,912	0,916
WD+ GSO	Control	0,676	0,549	0,852	0,688	0,655	0,886	0,570	0,672	0,842	0,862	0,897	0,848
	Amputee	0,693	0,617	0,946	0,680	0,730	0,950	0,592	0,614	0,932	0,911	0,908	0,917
CSP+ WD	Control	0,989	0,964	1		0,978	1		0,999				
	Amputee	0,908	0,781	0,998		0,842	0,997		0,996				

C	Groups	Close	Close	Close	Half	Half	Half	Open	Open	Open	Rest	Rest	Rest
		/Half	/Open	/Rest	/Close	/Open	/Rest	/Close	/Half	/Rest	/Close	/Half	/Open
CSP+ WD+ GSO	Control	0,839	0,683	0,947	0,793	0,760	0,955	0,675	0,728	0,932	0,947	0,970	0,938
	Amputee	0,800	0,655	0,957	0,800	0,793	0,954	0,582	0,688	0,940	0,954	0,949	0,957
CSP+ GSO	Control	0,825	0,672	0,934	0,787	0,769	0,949	0,675	0,716	0,917	0,947	0,962	0,922
	Amputee	0,787	0,647	0,954	0,802	0,788	0,953	0,600	0,690	0,948	0,953	0,946	0,959
WD+ GSO	Control	0,810	0,596	0,959	0,799	0,763	0,974	0,609	0,760	0,949	0,965	0,980	0,958
	Amputee	0,781	0,608	0,906	0,794	0,762	0,937	0,588	0,713	0,922	0,944	0,952	0,944
CSP+ WD	Control	0,989	0,958	1		0,978	1		1				
	Amputee	0,935	0,774	0,995		0,873	0,998		0,997				

Figure 4.10. Mean accuracies across participants for the two groups of subjects with four feature extraction combination of techniques. A. Result for the artificial neural network. B. Results for the support vector machine with linear kernel. C. Results for the support vector machine with the radial basis function kernel.

The use of a fast and efficient Feature Extraction method in constructing the inputs to the classification/prediction algorithm is also critical for such applications with real-time processing needs. For the first part, we showed in Fig 4.10 that the combination of CSP & WD gives the most promising results both for the two groups of subjects (above 90% of accuracy for the Control group, and above 70% for the amputees). While the Feature Extraction could probably have given similar results if it stopped after the application of the CSP technique, the addition of WD allows a reduction of the size of the signal, as only the coefficients from the last level of the decomposition were kept. This is of course not so important for a research work (offline study) aiming at searching for the best feature extraction method but it will reveal of extreme importance when we will tackle real-time control of the prosthesis, as we need to continuously process data and thus need that processing to be done as fast as possible. Even though the addition of the GSO was found to be interesting we selected the CSP+WD as the feature extraction method to be used for the remaining part of the study by taking into account those aspects. Fig. 4.9 also confirms those results by representing how the partitioning of the features space by the two classes is more clear/distinct for the combination of CSP+WD comparing to the other possible combinations.

Finally, the three different classifiers we used in this work to decode the desired motions provided very close prediction performances without any statistically significant difference, confirming the results we reported in our previously published [216] and submitted work. Moreover, among these three classifiers, the two SVMs were the fastest to train while the ANN presented a longer training time. This allowed us to designate the SVM with a linear kernel as the potential decoding algorithm in future

work, being the fastest classifier to train and the simplest one to use in a real-time application.

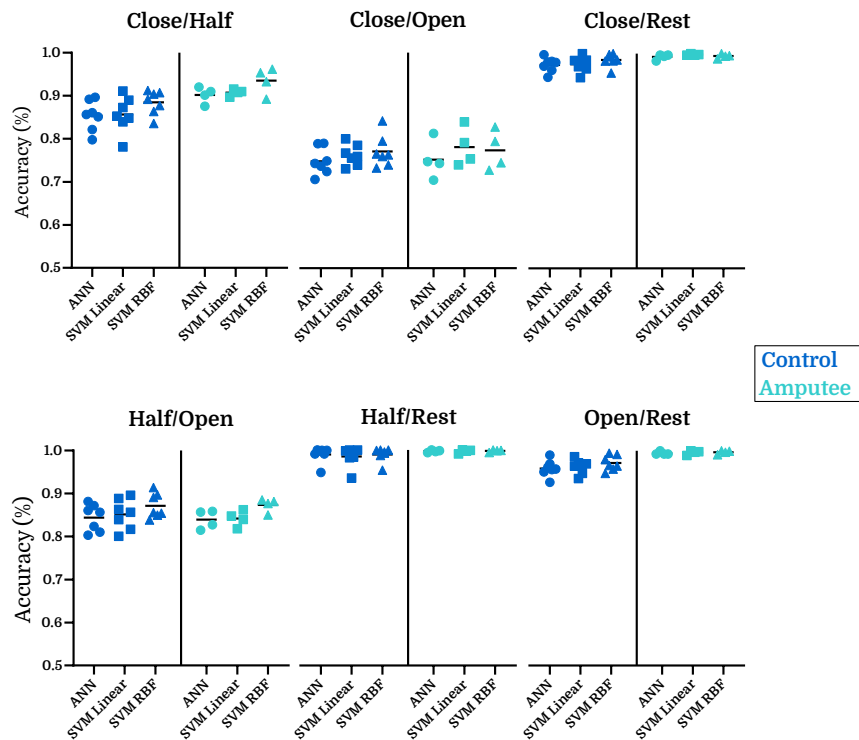


Figure 4.11. Comparisons of the performance between the Control group (in dark blue) and the Amputees (in light blue) using three different classification algorithms (ANN, SVM Linear & SVM RBF, respectively the circle, square and triangle symbols) after feature extraction with CSP+WD, using the same locations of electrodes for the two EEG systems. More data is needed for statistical analysis.

From the results summarized above, we can say that the use of a wireless EEG system, with fewer electrodes rather than a research-grade system, can give satisfying results when looking at the classification performances of the four movements, which are movements that can be performed by this type of prosthesis. Indeed, the results reported on Fig. 4.11 shows how, when the locations of the electrodes used for the feature extraction are identical between the two recording systems, the classification performance in the Control and Amputee groups evolves in the same range for the different binary classification models, a range that is much higher than the chance level in the case of binary classification (50%).

3. Conclusion

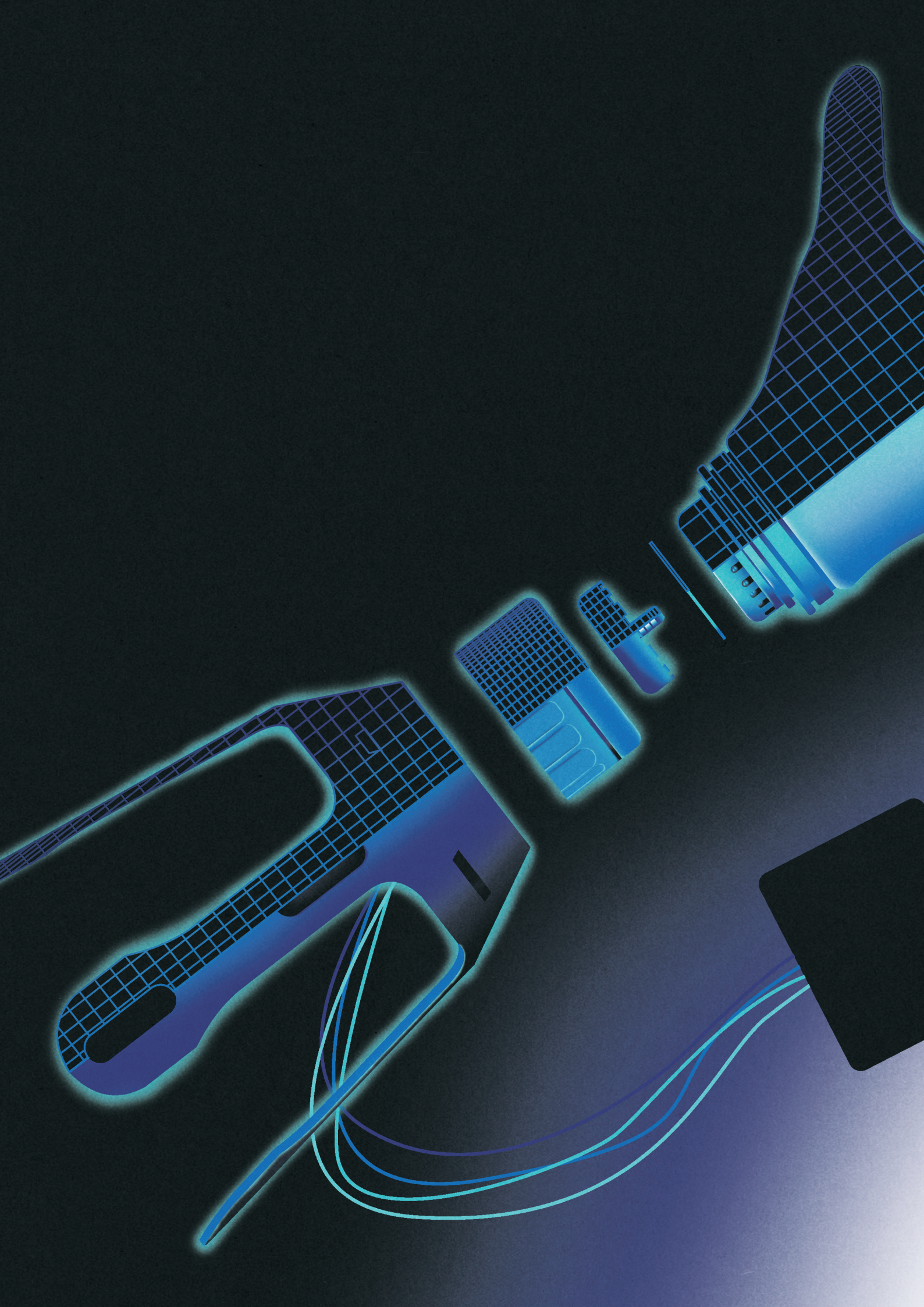
This study investigated the use of a Brain-Machine Interface to control a commercially-available myoelectric prosthesis (Myobock®, Ottobock). Even though the current research project is being conducted on the three groups of problems evoked in II, due to difficulties concerning the recruitment of both able-bodied and amputee subjects for the experiments with the Covid-19 pandemic conditions, the results reported in this article are the ones obtained by processing the EEG signals recorded during the first session of the experimental protocol for both groups.

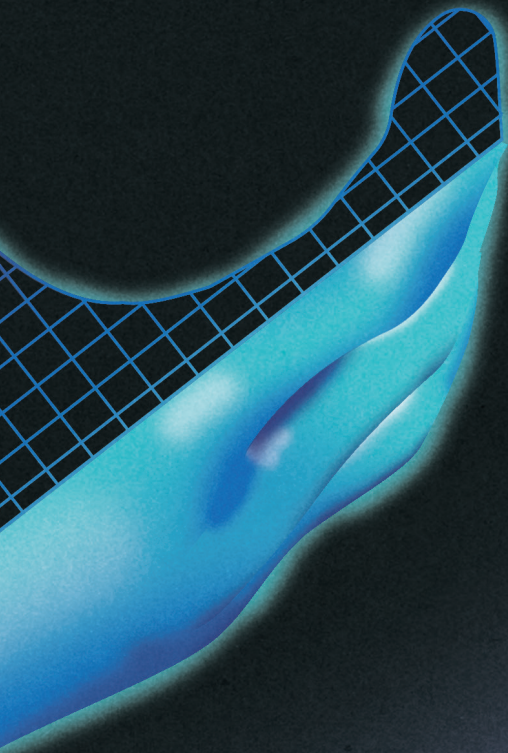
One of the first aims of this work was to propose to the potential users of the BMI system a reduced calibration time, comprising both the recording of the EEG signals and their processing. The data augmentation technique we used [209], is a promising solution to answer such needs. The results presented in Fig. 4.4 confirm that the original and artificial data sets occupy the same feature space, which supports the use of this technique. Therefore, we always used the augmented dataset in the remaining steps of this study.

The final evaluation step of the project will be the comparison of the scores obtained during the three tests (BB, CUP, CS, described in the first session of the experimental protocol for the amputee subjects) with the scores of these subjects obtained while they use the modified prosthesis. Only one amputee among four could finish the three sessions and realized a first trial of using the modified prosthesis together with the vibrating bracelet to perform a CUP test. Therefore, the following development and research phases of our project focused particularly on performing the experiments with more amputee subjects for all three sessions. Secondly, we aimed to be able to perform the experiments of the three sessions also with the control subjects, by allowing them to use a copy of the modified prosthesis and control it with their EEG signals and use the vibrating bracelet.

Nonetheless, we were well aware that the results presented here were only preliminary ones and that we required more subjects in both the control and amputee groups to bring answers to the various issues we raised in this article. In particular, there was a need to analyze the potential changes in the control performances that would occur with the amputees all along the three sessions: would the training of the task give higher performance? or does it stay the same over time for the two groups? Can we see distinct activation patterns on the EEG recordings? Does the addition of the sensory feedback change anything on the decoding and control performances?

We obtained more clear and more concrete answers to those questions as the experiments went by, but the presented results show a promising proof of concept for the efficiency of the use of BMIs for the control of myoelectric prostheses for amputees.





V

Work on the offline
performance analysis of the
proposed system



1. Material and Methods

The experiments and results presented are the continuation of the results from the first study. Here the able-bodied subjects were able to use the modified Myobock prosthesis during the recordings of the second and third sessions.

a. Participants

Twenty healthy participants (9 females and 11 males, 17 Right-handed, 3 Left-Handed, 30.05 ± 9.28 years old,) composed the control group and four amputated subjects (4 males, 2 transradial amputations of the left hand and 2 of the right hands, 60.25 ± 3.20 years old) participated in this first phase of experiments. All participants were given information in oral and written forms before giving written informed consent to participate in the study. The protocol was performed in accordance with the Declaration of Helsinki. The criteria of inclusion for the amputated subject were the same as for the first study. All amputees but Amputee #2 declared using their myoelectric prostheses - a polydigital hand (Michelangelo©, Ottobock) daily, and the second amputee is using his prosthesis (Myobock SensorSpeed©, Ottobock) occasionally.

b. Adapting the prosthesis for the able-bodied

As we wanted to test the system also with able-bodied subjects we needed to come up with a special device that would allow them to use the prosthesis easily. With the first design we envisioned, which only consisted of a handle that the subjects would have to grasp, the main concern was that the prosthesis would be too heavy to be carried around during the experiments (the prosthesis weighs around 500g) and would come at the risk of breaking the 3D-printed parts. The second design still kept the idea of the handle but also integrated a sort of board that would be following the forearm and on which several bracelets can be put to be adjusted on the forearms of the subjects. This next iteration allowed for a repartition of the weight of the prosthesis from the hand to the forearm which made the system bearable for long time use. Every part is 3D-printed, except for the prosthesis and the socket, which makes the device easily replaceable (see Fig 5.1).

This design proved to be really effective during the experiments and successfully used for more than 40 sessions without showing any signs of damage. For future iteration of the design we will be implementing dedicated areas to put the battery for example or to pass the cables from the prosthesis to the computer.

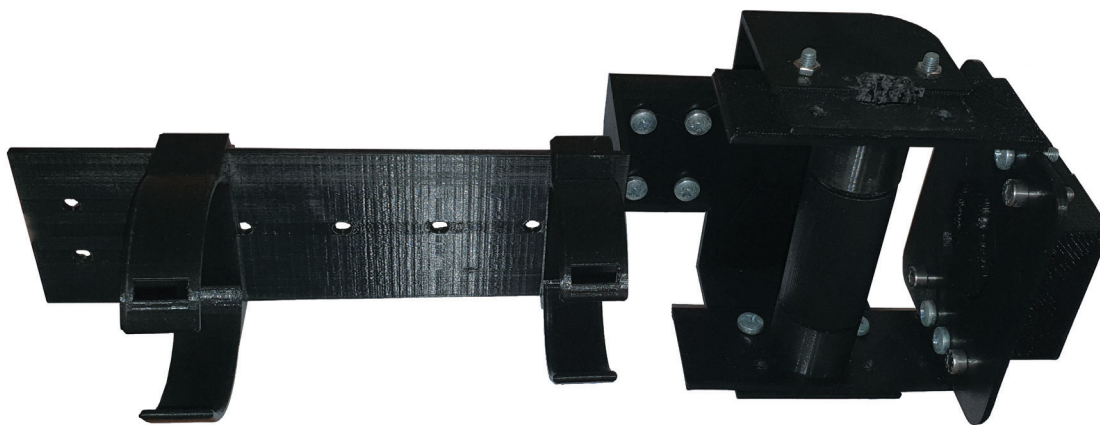


Figure 5.1. 3D-printed apparatus used to test the prosthesis with able-bodied subject at Université Paris Cité. The subject slide their dominant arm in the left part, grab the handle and can move the prosthesis around.

c. Experimental setups

The experimental setups were identical to the ones used in the first experiment with the only exception that the able-bodied were able to use the modified prosthesis using a 3D printed apparatus that they could hold with their dominant hand, as seen in Fig 3.11 from Chapter 3.

d. EEG signal processing

i. Preprocessing

We have almost no difference in the preprocessing compared to the first study, the EEG signal is retrieved from the first second of the Grip and Release phases. It is then filtered and the data augmentation technique is used to have 90 trials for each class. Compared to the previous article, the data is z-scored using the 50th percentile as the centering value and the difference between the values of the 95th and 5th percentiles as the scaling value. Those scaling parameters are computed after combining the EEG data from the four movements.

ii. Feature Extraction

5-fold cross-validation has been used to obtain train and test datasets from the pre-processed data, the performance obtained at the end will thus be the mean of the performances from the 5-fold.

Following the first article, one of the feature extraction pipelines we used here is the combination of the Common Spatial Patterns technique with the Wavelet Decomposition. The WD part is identical, only retrieving the coefficients from the last level of the decomposition, which is set at 2 or 3 for the OpenBCI or ActiChamp systems respectively.

Regarding the CSP technique, here we applied a shrinkage regularization for the estimation of the covariance matrices. As explained by Lotte in [209], one of the issue with CSP is that the covariance matrices are estimated with too little training data, which make them not representative of the classes. In particular, he adds that the “largest and smallest eigenvalues will be respectively over and underestimated”. To act on this issue, he proposed one approach which uses auto-covariance matrix shrinking, adapting a proposition from Ledoit & Wolf in [217] for the computation of a shrinkage estimator, and implemented it in the CSP computation.

As previously the log variances of the Wavelet Decomposition feature vectors were used as the inputs for the classification algorithms.

We decided to try using Riemannian Geometry on our data as an alternative method to perform feature extraction as the results are extremely promising regarding BMI applications. The Riemannian Geometry framework present the advance of being both computationnally and algorithmically simple while also being applicable to all BCI paradigms. Starting from the same preprocessed data as with the first pipeline, the first step is to extract the covariance matrices for all the trials of the four classes. Similar to the CSP we mentioned previously, the covariance matrices were estimated using the same shrinkage method. The next step is the computation of the mean covariance matrices from each class, this is done using a toolbox from Alexandre Barachant [218] which allows for the computation of the centroids using different techniques. Here, after a few trials with different methods (among which the Riemannian mean, arithmetic mean, or harmonic mean), we chose the Log Euclid technique. The final step we need with the Riemannian geometry pipeline is the projection of the covariance matrices on the tangent space of the two classes. The rationale behind this projection is simple, with a detailed explanation found in [219]. In short, the tangent space to the Riemannian space is Euclidean which means that it is possible to use classic machine learning algorithms, the feature vectors being composed of the vectorized projected covariance matrices.

iii. Movement type estimation

For this experiment we used two different feature extraction pipelines, broadening the range of algorithms we could try for our system. In particular, with our first pipeline combining Common Spatial Pattern + Wavelet Decomposition we still decided to compare the performance of our Artificial Neural Network and two Support Vector Machines with a Linear or a Radial Basis Function kernels. And we also added a Linear Discriminant Analysis classifier to the list.

The two other classifiers were used with the inputs obtained following the Riemannian geometry feature extraction pipeline. The first one is the Minimal Distance to Mean (MDM) classifier which uses as inputs the mean covariance matrices of the two classes and then computes the distance between those means and a trial which has to be labeled. Here the distance used is the log-euclidean distance between the mean

covariance matrices and the covariance matrix of the trial.

$$d_i = \|\log X - \log C_i\|_F^2 \quad \text{for } i = 1,2 \quad (\text{V.1})$$

The F stands here for the Frobenius norm. Whichever distance is the smallest indicates the affiliation of the trial to the class.

The other classifier is the Tangent Space SVM (TSSVM) with an RBF kernel, it uses as inputs the feature vectors obtained after projection on the tangent space. Other than the inputs, it is similar to the classifier used in the other pipeline.

For each of those classifiers, we computed the mean Accuracy, F1-Score, and Precision over the 5-fold of the cross-validation process.

2. Results and discussion

a. Comparison between the algorithms

The first comparison was to check the differences between the algorithms using a Kruskal-Wallis ANOVA on each one-vs-one model and for all the conditions. If we observed significance in the performances, a Dunn's posthoc test was run to determine which were the algorithms significantly different between them.

	ANN			SMV L			SVM RBF			LDA			MDM			TS-SVM		
Session	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
ANN				ns	ns	ns	ns	ns	ns	ns	ns	ns	*	*	*	ns	*	*
SVM L							ns	ns	ns	ns	ns	ns	*	*	*	ns	ns	ns
SVM RBF										ns	ns	ns	*	*	*	ns	ns	ns
LDA													*	*	*	ns	*	*
MDM																*	*	*
TS-SVM																		

Figure 5.2. Results of the Kruskal-Wallis Anova for the able-bodied group in the Motor Execution condition. The * indicates a significant difference between two classification algorithms (with $p < 0.05$). "ns" means non significant. The red colored * means lower performance and green colored * means better performance for the algorithm on top of the column.

From Fig. 5.1. we can see that the prediction performances of the four algorithms used with our first feature extraction pipeline, ANN, SVM Linear, SVM RBF, and LDA, are not different from each other, and this, for all the binary models and the two conditions (ME/MI). When looking at the results from the second and third sessions which used the modified prosthesis, the MDM and TS-SVM algorithms, based on Riemannian geometry, are offering significantly different performances from the ANN and LDA algorithms. In particular, the posthoc tests revealed that the performances of the MDM were lower than that of the ANN and LDA (and by extension of the three others, SVM Linear/RBF and TS-SVM) while the performances of the TS-SVM were higher.

These comparisons show that the performances obtained with the two methods of feature extraction are similar when looking at the SVM models with the TS-SVM being a little above the others, these results also confirm what was noted from the previous article concerning the algorithms used with the first feature extraction pipeline, in that they are not different from each other. We once again observe that it is easier to discriminate between a movement and the absence of movement, with performance close to 100% accuracy for the models Close/Rest, Half/Rest, and Open/Rest.

b. Comparison between the binary classification models

Following that last sentence, we were interested in finding which binary classification models were significantly different from each other, once again with a Kruskal-Wallis and posthoc Dunn test.

	Close/ Half		Close/ Open		Close/ Rest		Half/ Open		Half/ Rest		Open/ Rest	
	ME	MI	ME	MI	ME	MI	ME	MI	ME	MI	ME	MI
Close/ Half			*	*	*	*	ns	ns	*	*	*	*
Close/ Open					*	*	*	*	*	*	*	*
Close/ Rest							*	*	ns	ns	ns	ns
Half/ Open									*	*	*	*
Half/ Rest											ns	ns
Open/ Rest												

Figure 5.3. Results from the Kruskal-Wallis ANOVA and post-hoc Dunn test to compare the one-vs-one binary classification models between each other. "ns" means non significant.

For all groups, all sessions, and all conditions we find first that there are no differences between Close/Rest, Half/Rest, and Open/Rest with each other and we can also note

that there is no difference between Close/Half and Half/Open.

c. Comparison between able-bodied and amputees

Next, the third comparison we did was to compare the performance of the two groups of subjects. When comparing them we select the electrodes on the ActiCHamp which match the locations of the 16 electrodes found on the OpenBCI system. The comparisons have been done in each session for the two conditions and the 6 classification models.

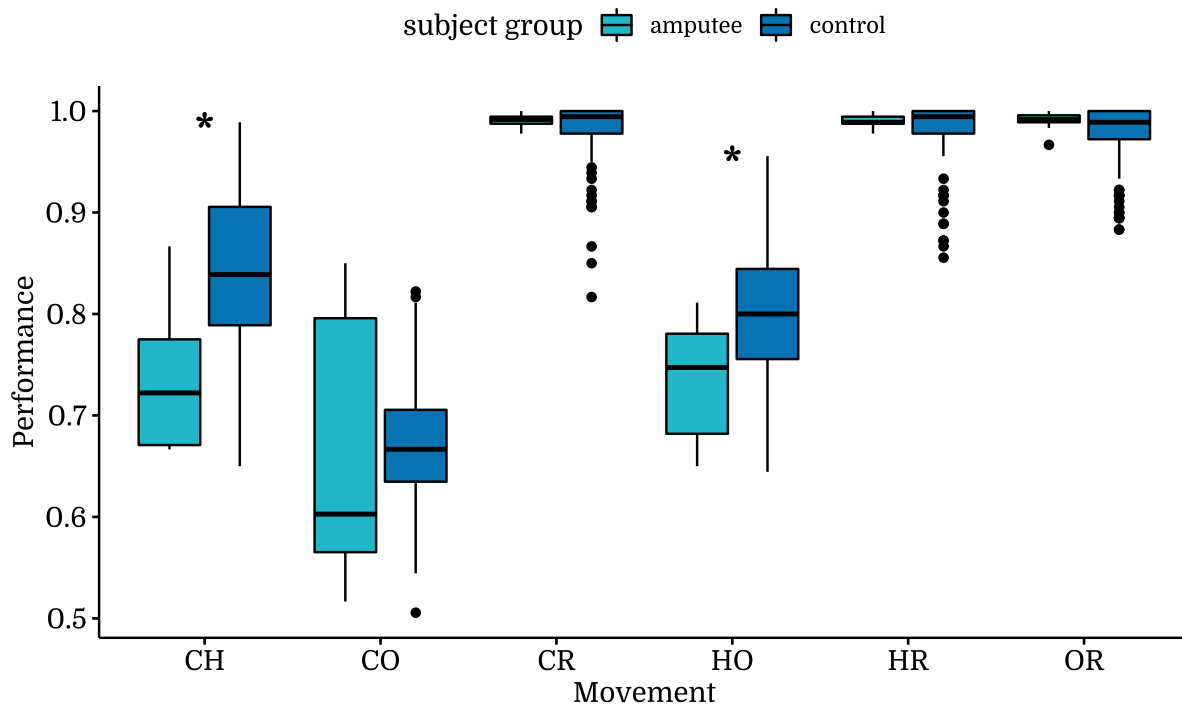


Figure 5.4. Accuracies for the Artificial Neural Network for each of the binary one-vs-one models for the two groups of subjects in Motor Execution of session 2. The * indicates a significant difference between the two groups for the one-vs-one model.

What we can observe is that there are significant differences with some of the classification models, but those differences change over the sessions and from one condition to another. For example, for Fig. 5.4 in the Motor Execution condition for session 2, we note a significant difference in the motion estimation performances between the two groups for the comparisons Close/Half and Half/Open.

More generally we can highlight that in Motor Execution when there were significant differences the performances of the amputees were lower than that of the able-bodied ones. On the contrary, in Motor Imagery with the models with significant differences the performances of the amputees were higher than the able-bodied. Nonetheless, these results can be nuanced by the low number of subjects in the amputee group, to act on this issue we applied a bootstrap procedure with 1000 repetitions of the Wilcoxon test by selecting randomly four able-bodied subjects among the 20 and comparing them with the four amputees. After the bootstrap, we obtained identical significant differences for the performances on the same one-vs-one models as when

the Wilcoxon tests were done with the full number of able-bodied subjects. Multiple reasons could explain the differences between the two groups: first the differences can be due to the different EEG systems that are used for this experiment, the actiCHamp being more precise than the OpenBCI. We also have different recording environments between the two groups, which could potentially affect the recorded data, although those effects should be minimized during the pre-processing part. Yet this does not fully explain why sometimes the performances in Motor Imagery are higher for the amputees. One hypothesis that we can draw is that Able-bodied subjects are better at Motor Execution as they should be more skilled in that condition compared to amputees. Moreover, and quite interestingly, the performances when the able-bodied used the prosthesis, with the 3d-printed apparatus, are also better than the amputees. The fact that amputees are better at Motor Imagery than the able-bodied is difficult to explain but potentially the absence of a limb could lead the patients to rely more on Motor Imagery than the able-bodied for which the skill is not as useful daily.

d. Difference between the ME and MI conditions

We investigated whether, in the two groups of subjects, there were any differences between the ME and MI conditions during the three sessions. For this, we did on each classification model a Wilcoxon test between the performances of the two conditions.

	Close/ Half			Close/ Open			Close/ Rest			Half/ Open			Half/ Rest			Open/ Rest		
Session	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Able bodied	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	*	*	ns	ns	ns	ns	*
Amputees	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	*	ns	ns	ns	ns	ns	ns	ns

Figure 5.5. Comparison for each of the binary models between the Motor Execution and Motor Imagery conditions, for the three sessions and each group of subjects. “ns” means non significant.

In Fig 5.5, we observe that there are some differences between the execution and the imagination of the movements for some of the binary models without observing a repeating pattern over the three sessions. Moreover, we can highlight that there are fewer differences for the amputees indicating that there would be fewer differences between their imagination and their execution for them, nonetheless, that could be explained by the lower number of subjects in that group.

e. Evolution of the performance

We then studied if the performances got better during the three sessions. As we have more subjects in the control group, we decided to focus on this group for the comparisons as well as looking at the accuracies obtained with the RBF SVM.

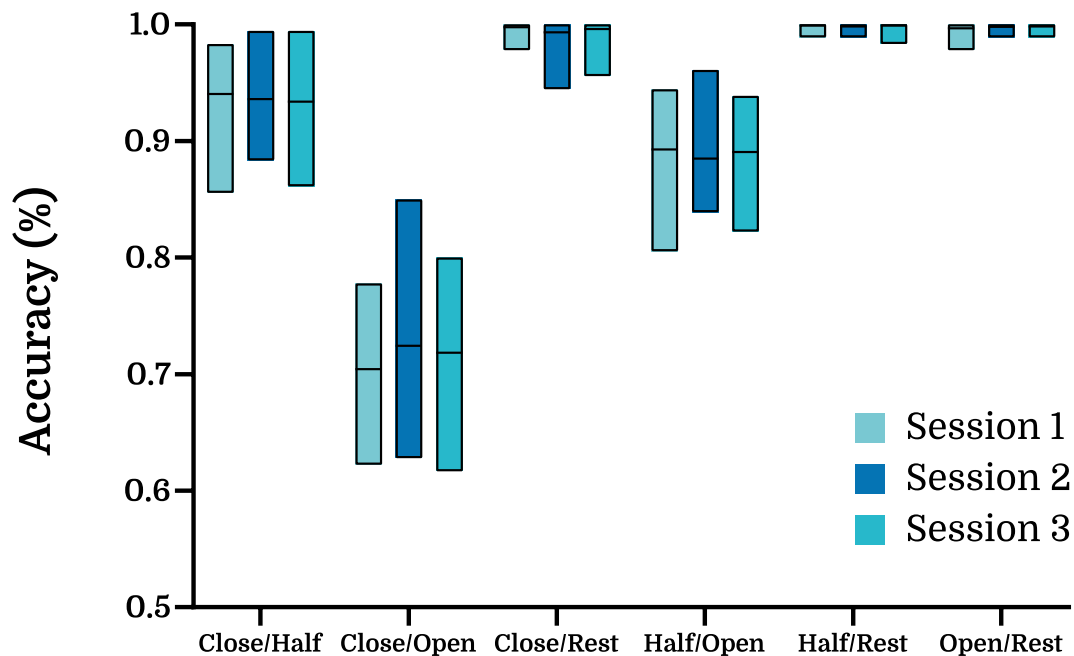


Figure 5.6. Accuracies of the RBF SVM for the 6 binary models along the three sessions with the Able-bodied.

From Fig 5.6 we can see that the performance of each of the 1-vs-1 models is stable along the sessions; this has been confirmed with Wilcoxon tests between the sessions which revealed non-significant for the six models and the two conditions. However, we can add that when doing some linear fitting on the data, the slope of the fit is slightly negative but the loss of performance is negligible.

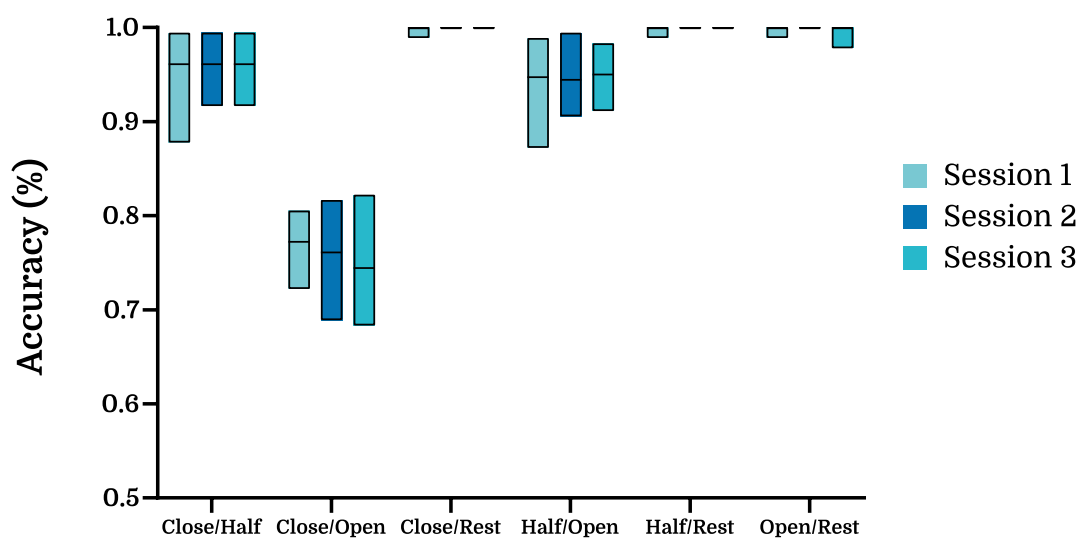


Figure 5.7. Accuracies of the Tangent Space SVM for the 6 binary models along the three sessions with the able-bodied.

We obtain similar results when looking at the performances obtained with the TS SVM algorithm (Fig. 5.7) except in Motor Imagery for the comparison Half/Open where the performances are significantly better in the first session than in the third ($p = 0.0355$). The fact that we don't observe significant differences between the performances is, on one hand, expected for the Motor Imagery condition as the subjects are doing the same recording in the three sessions. On the other hand, in the Motor Execution condition, it is quite interesting to note that the introduction of the new device with the modified prosthesis and then the sensory feedback device is not inducing brutal changes in the performance of the BCI system.

f. Evolution of the class distinctiveness

We computed the class distinctiveness, a metric we presented in the second chapter of the manuscript, which represents how two classes are separated from each other by looking at the distance between the means of each class and their dispersion around their means. Here we looked at the evolution of this metric over the three sessions for the two groups of subjects for each condition. The ideal result would be that the distinctiveness gets better with time as the subjects should be more trained for the task.

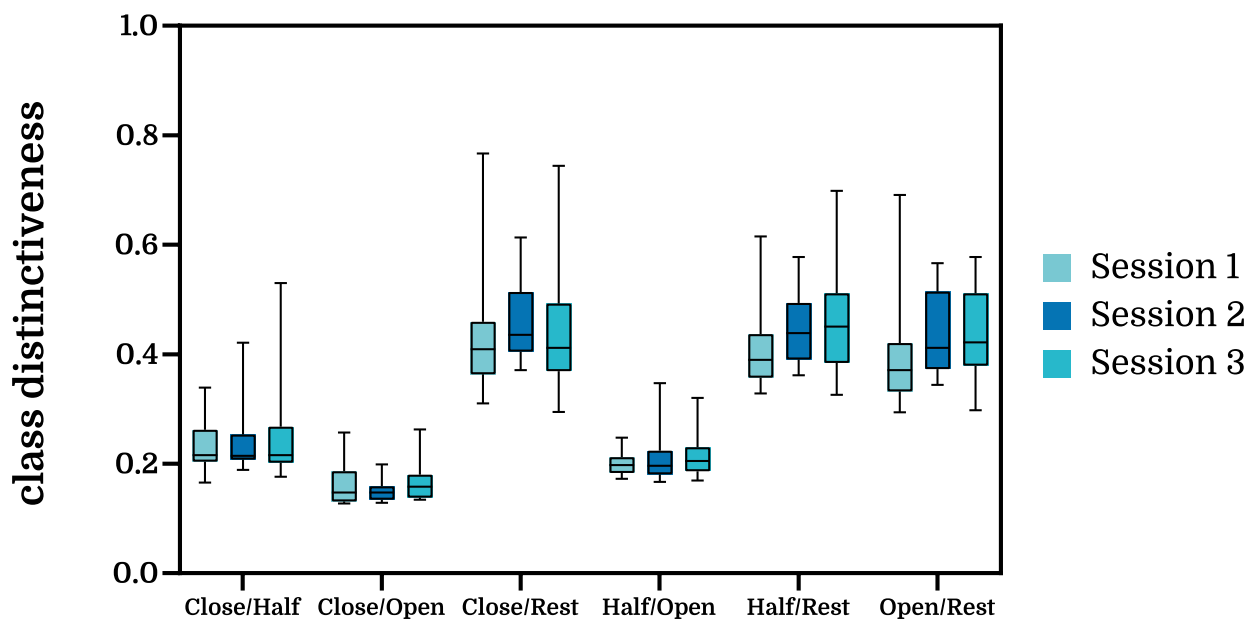


Figure 5.8. Evolution of the class distinctiveness metric along the three sessions in the Motor Execution condition for the able-bodied group.

As seen in Fig. 5.8 for the able-bodied group in Motor Execution we can observe that for some of the one-vs-one models the distinctiveness is improved over time. In particular, if we try to fit a line over each of the models we obtain the results presented in Fig. 5.9.

	R-square	Slope
Close/Half	0.09514	0.01106
Close/Open	0.03179	0.001189
Close/Rest	0.3526	0.01147
Half/Open	0.9473	0.006446
Half/Rest	0.955	0.02207
Open/Rest	0.789	0.02037

Figure 5.9. Linear fit parameters for each of the one-vs-one models.

The distinctiveness of Close/Half, Half/Open, Half/Rest, and Open/Rest is close to following a linear evolution, with a clearer improvement for Half/Rest and Open/Rest over the others. We do not observe the same evolution for Close/Open as the distinctiveness does not seem to improve over time. After running some Wilcoxon tests to compare between sessions, we found non-significant differences except in Motor Execution with an improvement in Close/Rest between the first and third sessions, and in Motor Imagery where the classDis is better in the second session compared to the first for Close/Rest, Half/Rest and Open/Rest.

From these results, we can note that the subjects are getting better at creating distinguishable patterns between a movement and the absence of movement/Rest but that it does not apply when it is a movement versus another movement. Nonetheless, these results are not surprising as the source of the activity for the Close, Half, and Open movements are localized in a very narrow region of the cortex as seen on the somatotopic maps.

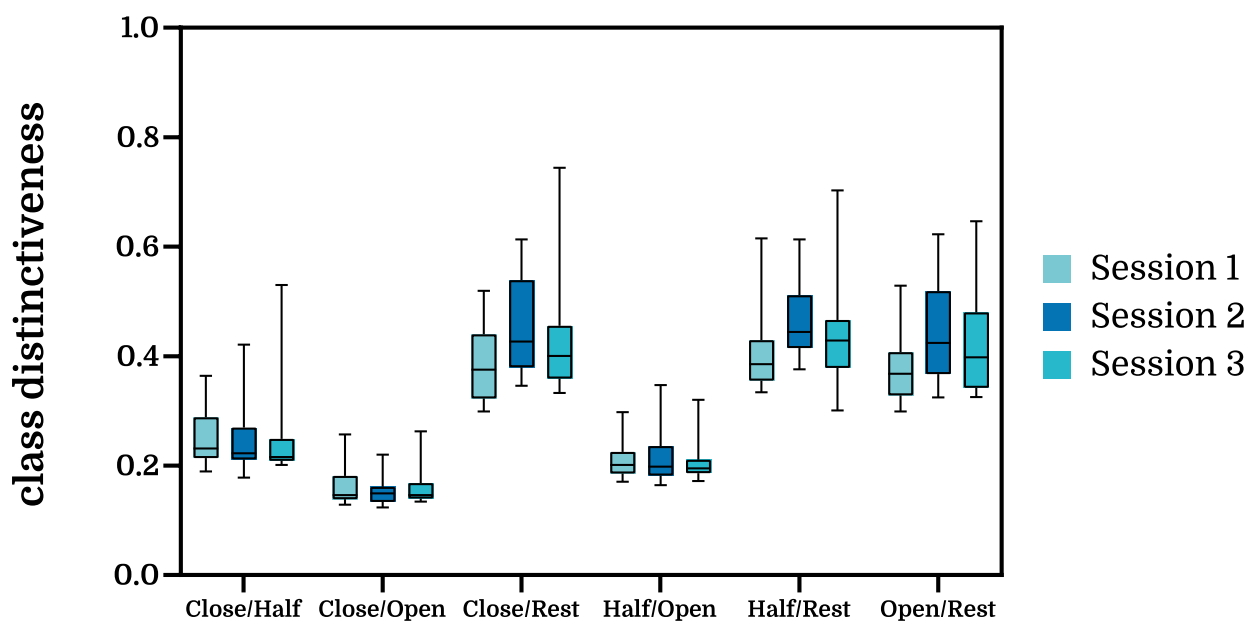


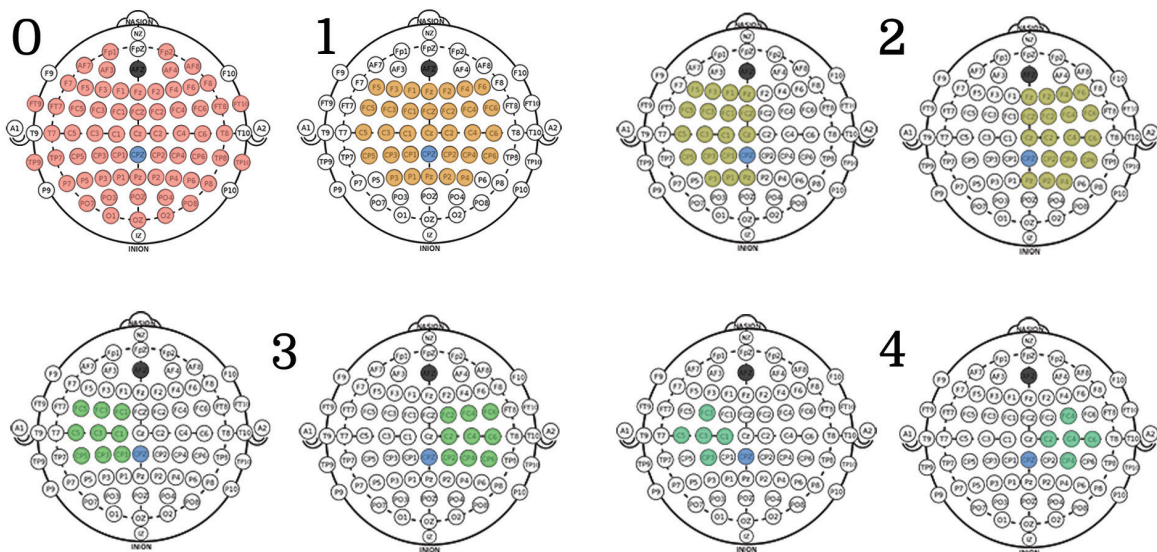
Figure 5.10. Evolution of the class distinctiveness metric along the three session in the Motor Imagery condition for the able-bodied group.

Moreover, while we observe similar results in Fig.5.10 for the Motor Imagery condition in that there is an evolution over time of the distinctiveness, it seems that the distinctiveness in Session 2 is better than in Session 3 especially for the Movements vs. Rest models while keeping similar values for the others. One explanation could be that the subjects are usually tired at this stage of the recording as the Motor Imagery comes after the ME recordings.

g. Electrode Selection

Having access to the data of 20 subjects in the control group with 64-electrodes recordings allowed us to look into the potential reduction of the number of electrodes for the BCI system.

We investigated 9 different combinations of electrodes as presented in figure 5.11 with the set of reference (0) being what was used during the EEG recordings with the able-bodied. Combination 1 is composed of 32 electrodes centered around the motor cortex. Combinations 2, 3, 4, and 5 gradually reduce the number of electrodes around electrode C3 for the right-handed subjects and around electrode C4 for left-handed subjects, corresponding to the contralateral part of the cortex involved in motor functions. Combination 6 takes electrodes localized around the Occipital cortex, which is related to vision. Combinations 7 and 8 are concerning electrodes over the frontal lobe, with combination 8 presenting the same contralateral splitting as the others. Finally, combination 9 corresponds to the locations of the 16 electrodes on the OpenBCI system we used with the amputees.



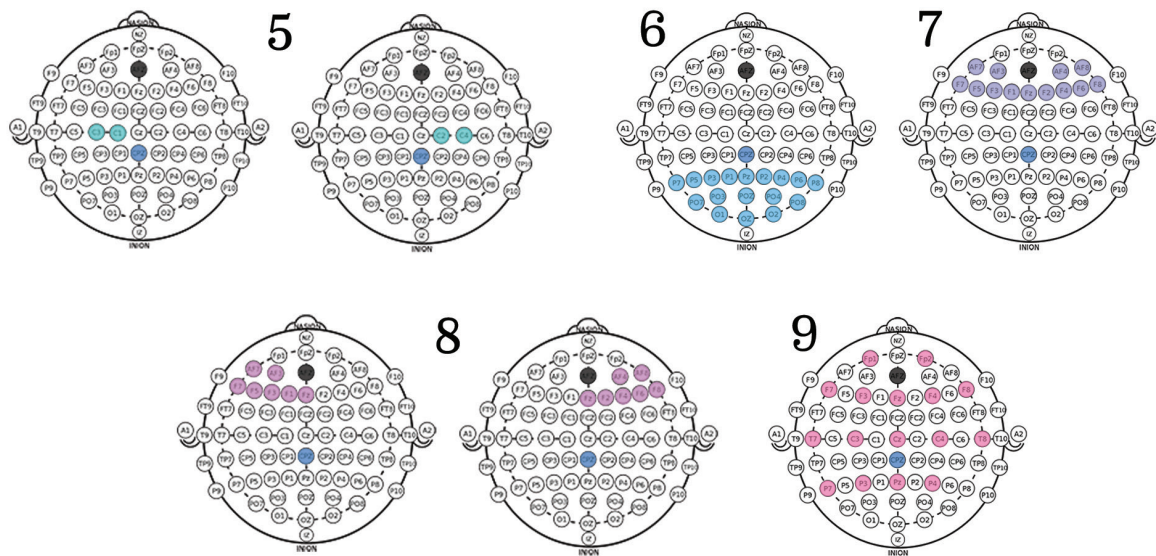
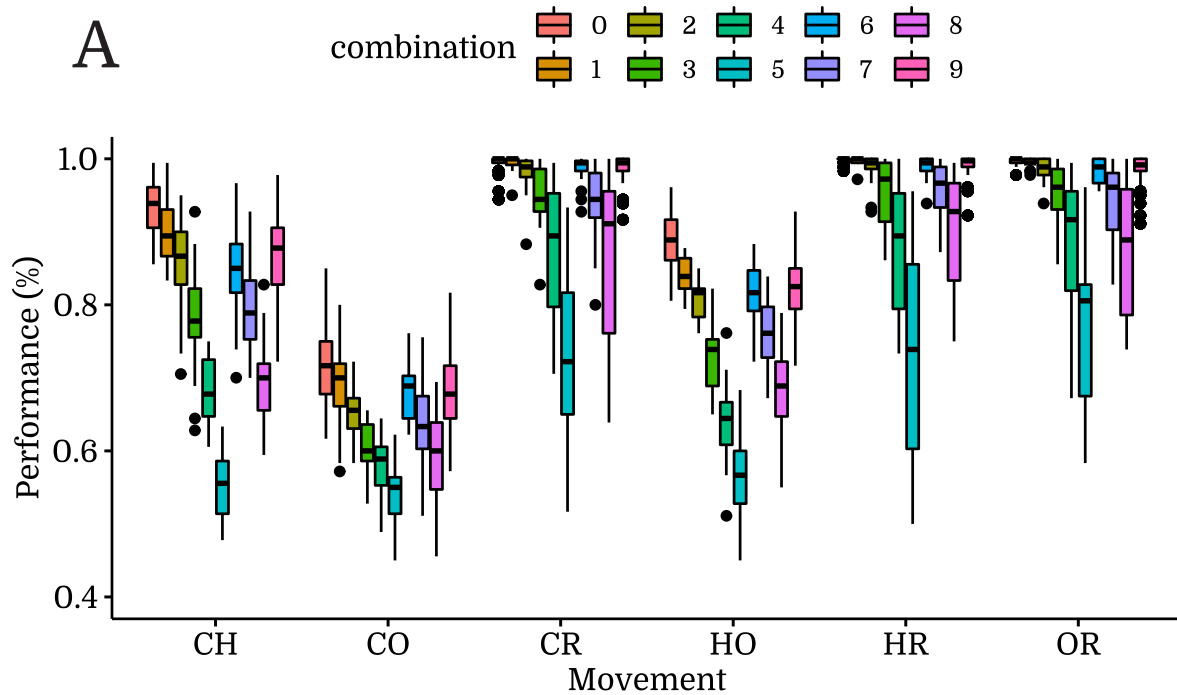


Figure 5.11. The different combinations of electrodes tested. 0 is the original combination with all the electrodes while combinations 1 through 9 present a reduced number of electrode, with combination 9 being the same as the OpenBCI system. Combinations 2, 3, 4, 5 and 8 are doubled to take into account left-handed and right-handed subjects.



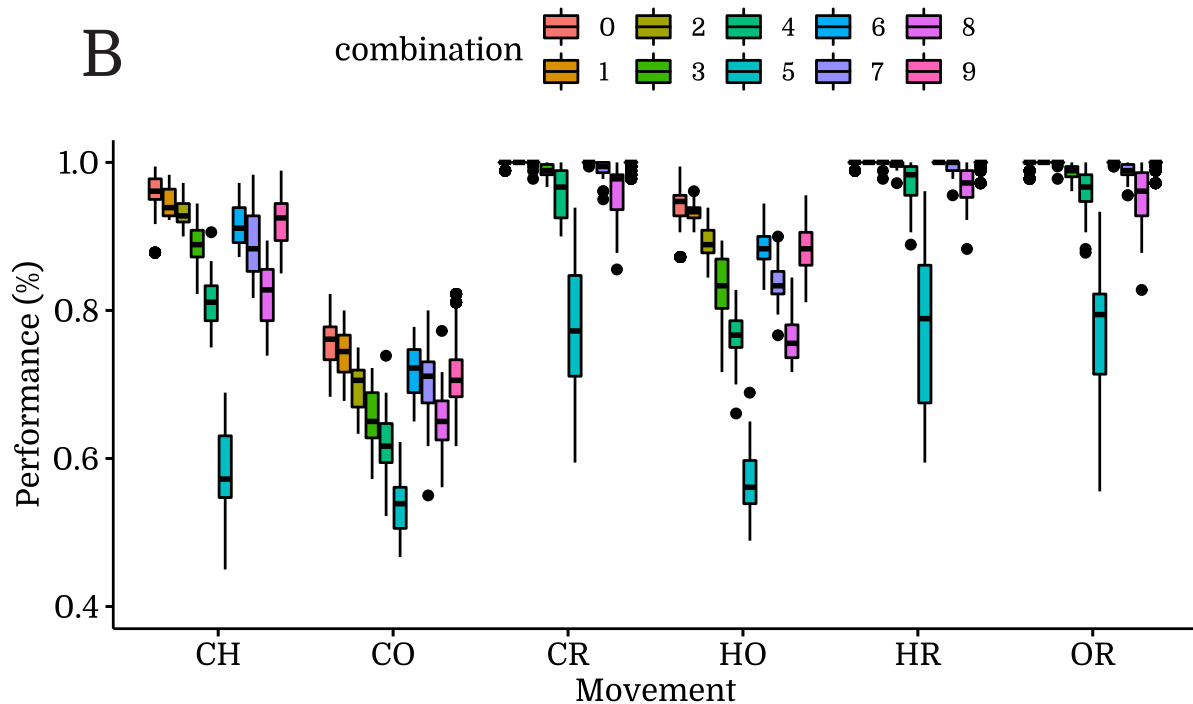


Figure 5.12. Classification performance for the six one-vs-one models for the ten combinations of electrodes for the third session in Motor Execution. A. Performance for the RBF SVM. B. Performance for the TS SVM.

Fig. 5.12 shows the classification performance of the RBF SVM (feature extraction 1, Fig 5.12.A) and the TS-SVM (feature extraction 2, Fig 5.12.B) for the six one-vs-one models for the ten combinations of electrodes during the second session in Motor Execution with the modified prosthesis. We obtained similar results for the first and third sessions. We can note that the performances of the various test combinations are all lower than the performance of the set of reference, especially for the comparisons Close/Half, Close/Open, and Half/Open. Wilcoxon tests between each of the 9 combinations with the original one all gave significant p-values except for Close/Rest and Half/Rest of combination 1 for the three sessions, with the results from those combinations being significantly lower than that of the reference. While most of the performances from the combinations evolve in the same range, we observe the most significant drop for combination 5 which only contains 2 electrodes above the Motor cortex.

It is also possible to look at the changes in the class distinctiveness between the set of reference and the nine other subsets of electrodes. We observe from figure XX that for the comparisons Close/Rest, Half/Rest, and Open/Rest the distinctiveness is improved compared to the three other models where the changes are less visible.

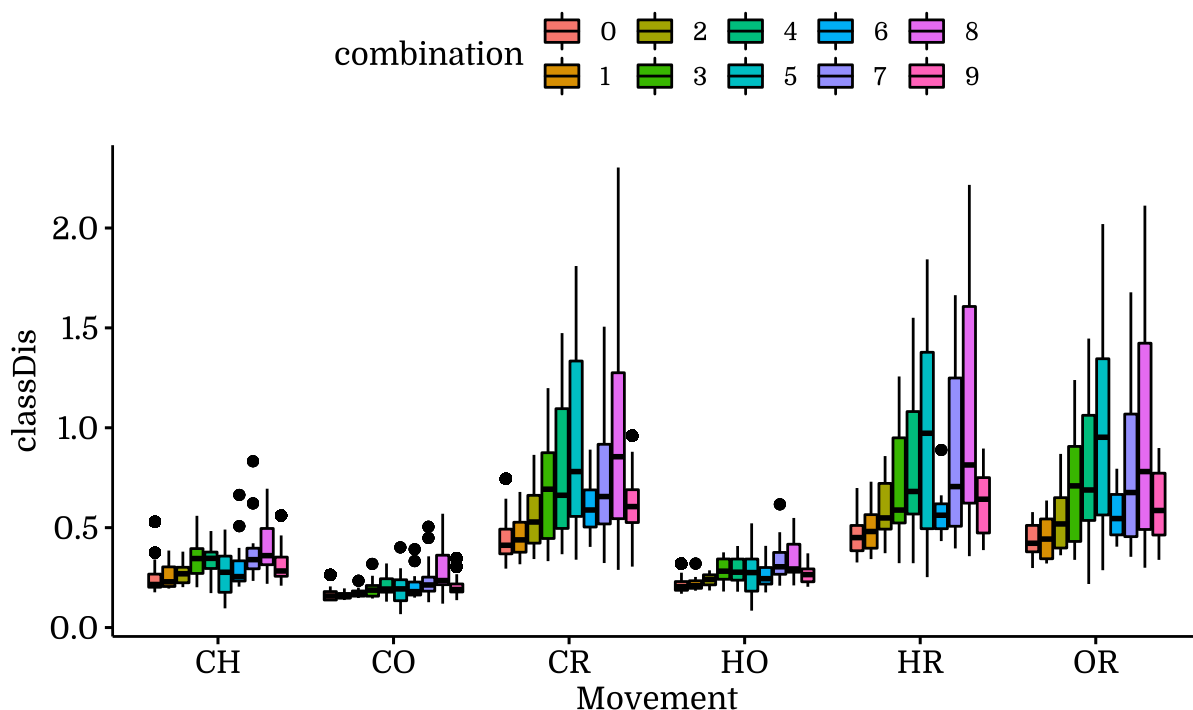


Figure 5.13. Evolution of the class distinctiveness with the ten combinations of electrodes in the third session in Motor Execution for the able-bodied group.

Fig. 5.14 represents the result from the Wilcoxon tests comparing each of the nine combinations to the set of reference for the six models in Motor Execution. From the table, we can note that combination 1 is the closest to the original in terms of class distinctiveness with occasional differences appearing in some of the models. Interestingly combination 5 becomes close to the set of reference in session 3 for Close/Half, Close/Open, and Half/Open.

	Close/ Half			Close/ Open			Close/ Rest			Half/ Open			Half/ Rest			Open/ Rest		
	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
Session	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
Comb. 1	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns
Comb. 2	*	*	ns	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Comb. 3	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Comb. 4	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Comb. 5	*	ns	ns	*	*	ns	*	*	*	*	*	ns	*	*	*	*	*	*
Comb. 6	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Comb. 7	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Comb. 8	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Comb. 9	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*

Figure 5.14. Results from the Wilcoxon tests comparing the performance of the 9 combinations of electrodes to the original set of electrodes for each of the models in the three sessions. “ns” means non significant. The red colored * means lower performance.

In an ideal setting, we would want to improve the accuracy of the system while also improving the distinction between the movements, here we observe that if we select fewer electrodes there is a trade-off in that we need to sacrifice some of the accuracies if we want to have a better distinction. We can thus compute the loss of accuracy obtained when selecting one of the nine combinations which are represented in Fig. 5.15 for the RBF SVM and TS-SVM.

Session	S1	S2	S3
Comb. 1	2,1%	2,7%	2,4%
Comb. 2	4,3%	5,2%	5,2%
Comb. 3	9,9%	10,5%	10,7%
Comb. 4	18,3%	19%	18,3%
Comb. 5	33,2%	33,7%	29,9%
Comb. 6	5,1%	4,2%	4,6%
Comb. 7	9,6%	9,8%	9,4%
Comb. 8	17,1%	18%	17%
Comb. 9	3,5%	3,9%	3,7%

Session	S1	S2	S3
Comb. 1	1,1%	0,8%	0,7%
Comb. 2	2,8%	3%	2,7%
Comb. 3	5,9%	6%	5,8%
Comb. 4	10,5%	10,8%	10,6%
Comb. 5	30,4%	31,4%	29,2%
Comb. 6	3,6%	2,5%	2,7%
Comb. 7	5,8%	5,7%	4,8%
Comb. 8	9,7%	9,6%	10%
Comb. 9	3,5%	2,2%	2,7%

Figure 5.15. Loss of performance for the RBF SVM (left) and TS-SVM (right) in the three sessions when comparing combination 0 with the nine other combinations of electrodes.

There is close to 2% loss of accuracy when using combination 1 compared to the set of reference, with a 1% loss when looking at the performance of the TS-SVM. As hinted with Fig. 5.15, we note a loss of about 30% of accuracy when choosing combination 5 with only two electrodes. Choosing the same location as the OpenBCI system, with combination 9, results in a loss of accuracy of 3 to 4% depending on the algorithm.

What is interesting about those results is that we see that we are losing only 2% of accuracy when splitting the number of electrodes by 2 (from 63 to 32 more precisely, without taking into account the ground and reference electrodes), and when we are splitting this number by 4, like what is happening for combination 2 or 9, the loss of accuracy is close to 3 or 5% of the original accuracy. Moreover, by reducing the number of electrodes, the loss of accuracy comes with a slight improvement of the class distinction as seen in Fig. 5.13. What is potentially happening is that, for the set of reference, we have some overfitting of the classification algorithms which are giving a good accuracy but might suffer from a lower generalization when applied to new data. By centering around electrodes that are probably less subject to noise (removing electrodes in the frontal or temporal regions, prone to muscle or eye artefacts) we could thus obtain a lower accuracy but models that could ultimately handle new data in a better way.

3. Conclusion

In this study we continued the work presented in our previous article, delving deeper into the comparison within and between the two groups of subjects during the three-session experiment. While first evaluating the performances of the classification algorithms we also took the opportunity to compare between two feature extraction methods, the first one being the best method we chose at the end of the preliminary work and the second one being based on Riemannian geometry. We found no differences between the algorithm used with the first feature extraction pipeline while the two algorithms used with Riemannian geometry presented either slightly better or lower results, respectively for the TS-SVM or the MDM. We did not find any improvement of the classification performance over the course of the three sessions in Motor Execution or Motor Imagery. Nonetheless, while we did not observe any improvement of the performance over time, the computation of the class distinctiveness metrics showed that the subjects were able to generate brain activity patterns that were more distinguishable over the sessions. Finally, the EEG recordings with the able-bodied subjects allowed us to work on the question raised by the number of electrodes needed for the BCI system, which goes along, in terms of a potential commercial application, with the acceptance of the system by amputees.

The next step of the project was to record and process the results during a real-time control of the system and compare the performance with the training performance presented so far in the articles. This brought us to look at the different control strategies that were available to ensure the best use over our system. We will also be looking at the possibilities of applying transfer learning either between sessions or between subjects and explore ways of reducing the setup time of the system.





VI

Work on the real-time
performance analysis of the
proposed system

In this chapter we are not only presenting the results obtained during the real-time tests we did but we also were interested in discussing how we can change the control mode of the BMI from synchronous to asynchronous.

1. Using the system during real-time test

The goal of the EEG experiments was not only to record the brain activity during executed or imagined movements but it also was the occasion to test our system with the subjects and see the differences in performances compared to the offline performances we would be getting.

a. Description of the test

The tests were carried out after the EEG recordings of sessions 2 and 3 with the two groups of subjects. Just before proceeding with the test, the raw EEG data recorded during the experiments with the ME and MI conditions is processed and the filters and classification models are computed, all of the files of interest are then copied into the appropriate folders for the tests. They consisted in doing the same movements with the three different objects, with the modified prosthesis and with or without the sensory feedback device. Unlike the experiments where we were recording the EEG data, here during the Grip and Release phases the subject is in control of the prosthesis, to do this, at the beginning of the Grip and Release 1 second of EEG is recorded and processed before triggering a movement on the prosthesis (Fig 6.1). If the wrong movement is decoded from the brain activity, a safeguard is coming into play by triggering the correct movement on the prosthesis, which prevents the subject from being disturbed in the sequence of movements.

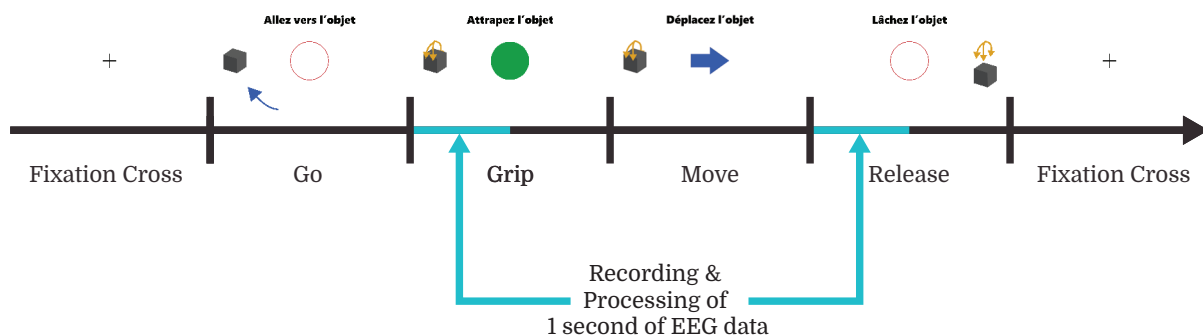


Figure 6.1. Sequence of phases during the online test of the BMI system. In the Grip and Release phases 1 second of data is recorded and processed before triggering a movement on the prosthesis based on the result from the classification algorithm.

b. The architecture of the control software

Similar to the EEG recordings, we used two different control software when working with amputees or able-bodied subjects. But the inner structure of the two software is identical. If we look at the graphical interface made for the OpenBCI system used by the amputees, we see different functions and buttons (Fig 6.2). However, in what follows we will particularly focus on the description of the second and third rows which are more important for the tests.

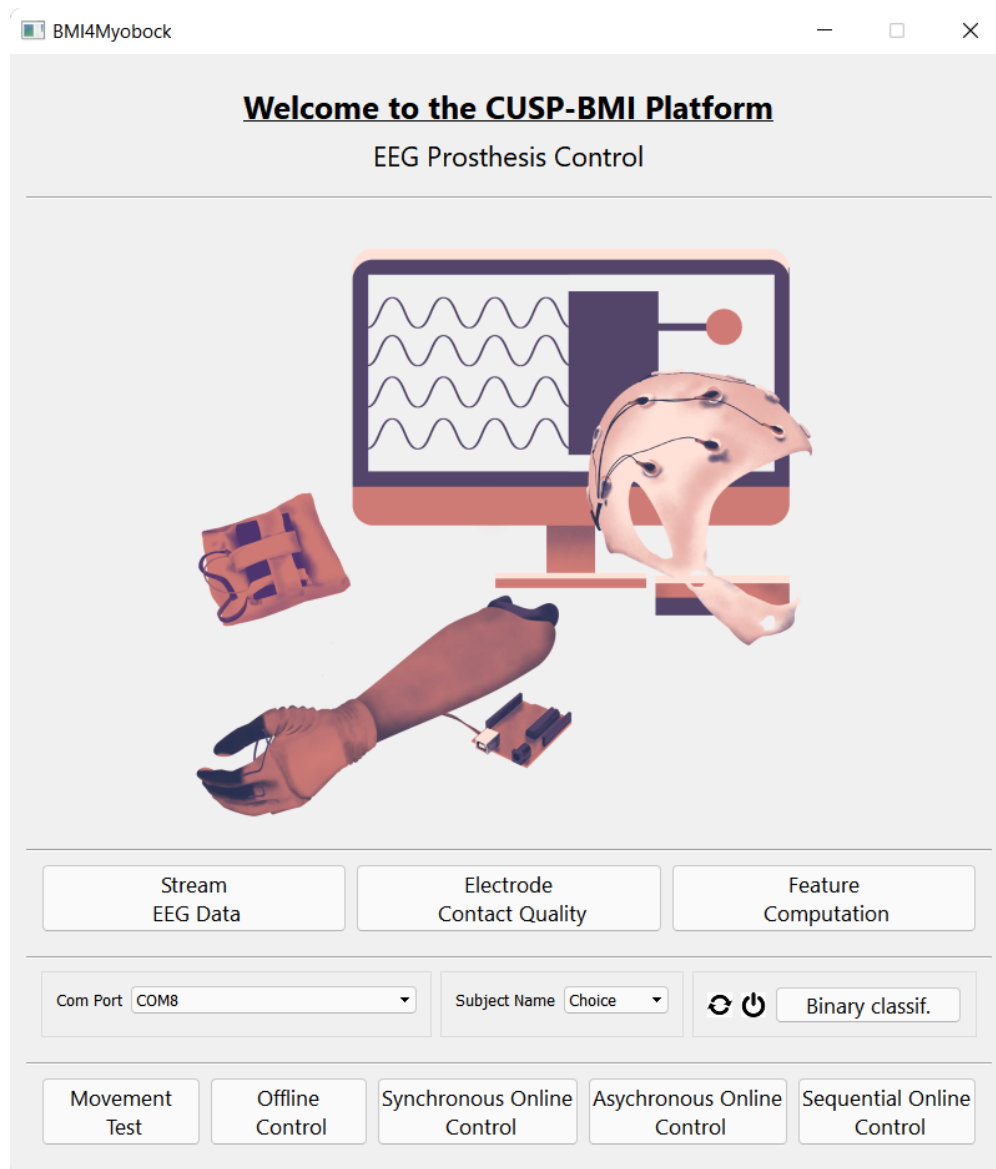


Figure 6.2. Graphical User Interface of the prosthesis control software developed with the QT IDE. The software is used to connect to the EEG system and prosthesis as well as start the online test experiments with the amputees.

The first item is also present on the EEG recording software and allows the experimenter to choose the COM port on which the OpenBCI system is set. Then we find a drop-down menu that is used to select the name of the subject that will do the test. Once selected, the filters, models, and coefficients of the subject are loaded and ready to be used.

The last item of the second row concerns the choice of the classification method, we developed the option but we did not extensively use it during the experiments. By clicking the button, the experimenter can choose between Binary Classification, which is the default choice, and what was used during the experiments, and Multiclass Classification. This will modify the classification algorithms that are used for the tests by going from six one-vs-one classification models to only one classification model with four outputs. To focus on other parts, we did not investigate the results obtained with the multiclass option, but it is something that can be done in an offline manner, similar to the results we presented in Chapter 5.

The third row contains the functions used for the real-time control of the prosthesis. The first button “Movement Test” is only used to display the movements “Close”, “Half” and “Open” that can be performed on the prosthesis. Then the “Offline Control” button allows the user to load and process an already recorded EEG trial on the computer and see the movement which has been decoded by the algorithm.

Next, we have two different types of Online (real-time) Control: “Synchronous Online Control” and “Asynchronous Online Control”. In [220] Zhang et al. are presenting the various EEG-based BCI systems design and especially the control modes. The Synchronous control works with fixed time windows; in our C++ software, we need to click on the button which is launching a 1-second recording of EEG. Then at the end of the subject’s brain activity recording session, the EEG data is directly processed and classified and the movement is executed on the prosthesis.

Unlike the Synchronous control modality, Asynchronous Control does not rely on a cue/stimulus to be used. When clicking on the dedicated button on the C++ software, a 1-second buffer of EEG data is recorded and refreshed twice per second (every 500ms). Each time the EEG data is refreshed the software performs simultaneously the processing and store the result in another buffer/counter; once this counter reaches a specified value (here we arbitrarily choose a value of 10) the movement is executed on the prosthesis. In [135] Choi et al. used a similar approach for the asynchronous control of a lower-limb exoskeleton, each time the prediction is done for a movement the buffer of the corresponding movement is filled (one by one). If the subject was not thinking of any movement then the buffer would empty (3 by 3). The fill/empty ratio was thus 1:3; once the movement buffer reaches 10 the movement is performed on the exoskeleton. This type of approach has been implemented to avoid unwanted movement, making sure that the subject wants to do a specific movement.

We applied this approach here by adding three classification buffers with the same fill/empty ratio of 1:3 and a maximum of 10. We implemented this technique but we did not have the opportunity to test it with subjects yet, we will thus need to do a few tests to select the best maximum value that will not discourage subjects from using the system and is fast enough to be easily used to perform the movements.

Finally, the “Sequential Control” mode is what we described previously in 2)a). In that mode, the experimenter can select between “BB & CS” or “CUP” and the software will open the same window as what the subject sees during the recording of the EEG signals. The same steps will be displayed on the screen but during the GRIP and RELEASE phases, classification is done at the end of the first second after stimulus presentation (i.e. the image asking for the movement to be performed). Two settings can be used in the software: classification of Mvt vs. Rest or classification of Mvt 1 vs. Mvt 2 (Fig 6.3).

In the first setting we only looked at the classification result from the following one-vs-one models:

- Close vs. Rest and Half vs. Rest for the GRIP phase of “BB & CS” and “CUP” respectively
- Open vs. Rest for the RELEASE phase

In the second setting we will compare the classification results of two movements:

- Close vs. Open for the GRIP and RELEASE phases for “BB & CS”
- Half vs. Open for the GRIP and RELEASE phases of “CUP”

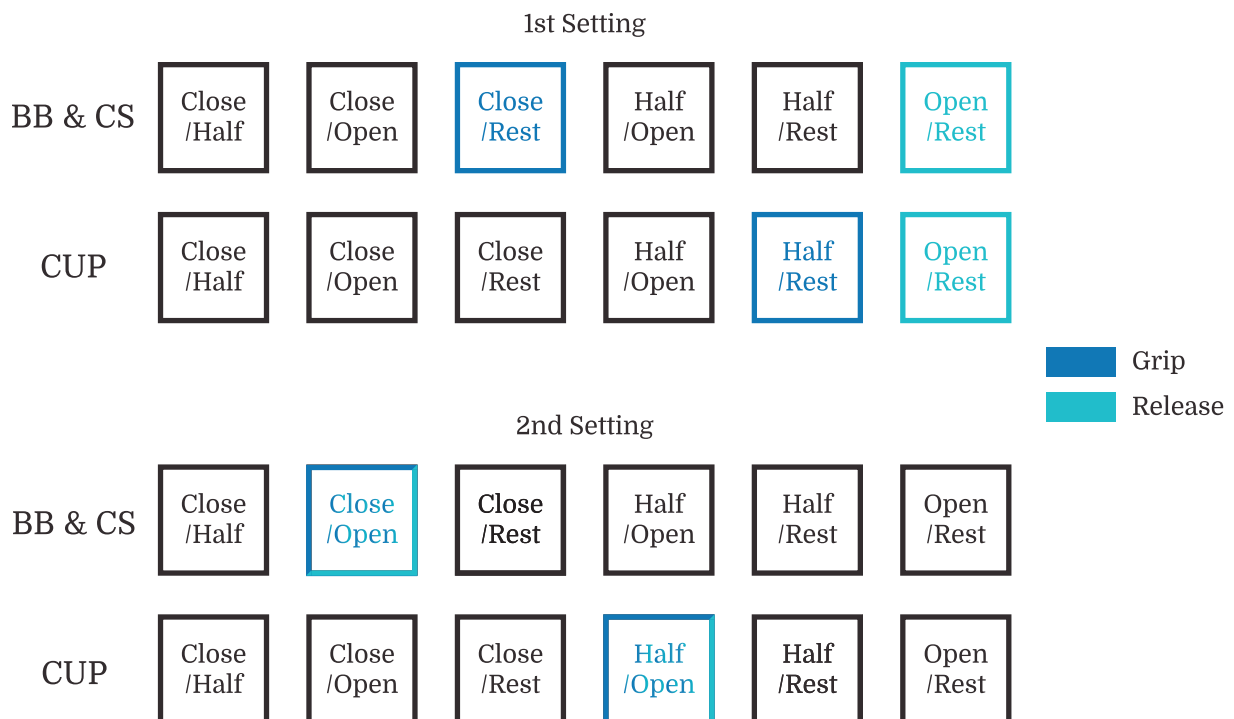


Figure 6.3. Schematic representation of the choice for the classification output to look at depending on the setting and object. The dark blue color indicate the model used for the Grip phase while the light blue color indicate the model used for the Release phase, the classification result indicating the movement to trigger (for example Close or Rest). When the color is both dark and light blue, it indicated that the same model is used for the Grip and Release phases.

In the first setting, we thus try to distinguish between a Motor intent and an absence of movement while in the second setting we try to distinguish between two motor intents. As we showed in Chapter IV with the results of the experiments, it is easier to spot a difference in the EEG activity between a movement of the hand and the absence of movement compared to the imagination of two movements of the same hand. Therefore, those two settings could be considered as different difficulty levels for the classification in real-time, nonetheless, for all the real-time tests we used the second setting as the first one was deemed too easy.

c. Preliminary results

We will now present the results obtained by the subjects when they were controlling the BMI system during the real-time test in the second part of session 2 and session 3. 30 trials were recorded for each of the three objects, with a small break every 10 trials if the subject wanted to rest. The results presented here were obtained by the decoding of the EEG activity using the SVM RBF presented earlier, we are focusing mainly on the results obtained with the able-bodied subjects but we will also display the results we obtained with some of the amputees who were able to do the second and third session. Due to technical problems, the data from subject 7 for the second session is not reported as well as the data for the second and third sessions of subject 6.

If we are to look at the results from the second session (Fig. 6.4), we can note that there is an apparent dichotomy between the results obtained in the Grip phase and those obtained in the Release phase. More precisely if we look at the results for the Cup, they tend to have a low accuracy during the Grip phase if the subjects are good at opening the hand during the Release. It means that the classification algorithm will be biased toward the movement Open with a mean performance of about 88% for the three runs while we observe an accuracy of around 16% for the Grip phase. This trend is particularly apparent in some of the subjects who are reaching an excellent accuracy for either the Grip or the Release phases and have an accuracy close to 0 for the other phase. We also note that the performances are quite homogeneous between runs, there is no clear improvement in the accuracy over the course of the three runs of 10 trials.

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	100	100	80	93,3	20	10	30	20
2	80	50	60	63,3	50	80	30	53,3
3	90	90	60	80	50	50	50	50
4	90	50	50	63,3	30	20	50	33,3
5	50	50	70	56,7	40	40	50	43,3
6								
7	50	60	70	60	50	50	40	46,7
8	90	40	60	63,3	50	50	80	60
9	60	60	80	66,7	50	50	50	50
10	80	70	80	76,7	60	20	70	50
11	50	70	60	60	80	30	50	53,3
12	80	60	100	80	50	80	50	60
13	10	30	60	33,3	100	100	80	93,3
14	80	30	50	53,3	70	90	80	80
15	0	0	10	3,3	100	100	90	96,7
16	30	70	30	43,3	90	80	90	86,7
17	30	20	10	20	90	100	100	96,7
18	50	80	50	60	50	40	40	43,3
19	100	80	100	93,3	0	30	10	13,3
Mean	62,2	56,1	60	59,4	57,2	56,7	57,8	57,2

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	10	50	0	20	100	70	100	90
2	10	10	20	13,3	100	100	90	96,7
3	0	0	0	0	100	100	100	100
4	20	30	20	23,3	90	90	80	86,7
5	10	0	10	6,7	100	90	90	93,3
6								
7	20	0	20	13,3	90	100	80	90
8	10	30	30	23,3	90	60	100	83,3
9	10	30	80	40	60	90	30	60
10	0	30	10	13,3	100	100	90	96,7
11	30	30	10	23,3	60	100	100	86,7
12	20	10	30	20	90	80	100	90
13	0	0	0	0	100	100	100	100
14	20	20	20	20	60	90	100	83,3
15	70	80	40	63,3	100	70	90	86,7
16	10	20	10	13,3	80	80	90	83,3
17	10	10	10	10	70	100	100	90
18	0	0	0	0	100	100	100	100
19	0	20	0	6,7	100	100	100	100
Mean	13,9	20,6	17,2	17,2	88,3	90	91,1	89,8

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	100	50	40	63,3	30	40	70	46,7
2	50	40	60	50	100	50	70	73,3
3	90	70	70	76,7	30	30	40	33,3
4	60	70	50	60	20	50	50	40
5	80	50	30	53,3	50	50	30	43,3
6								
7	70	80	30	60	20	60	50	43,3
8	30	0	10	13,3	80	80	100	86,7
9	60	50	60	56,7	30	50	40	40
10	10	0	0	3,3	100	100	100	100
11	50	30	50	43,3	80	100	80	86,7
12	90	80	100	90	40	40	40	40
13	70	80	20	56,7	80	90	60	76,7
14	40	10	0	16,7	100	70	100	90
15	30	10	0	13,3	100	80	70	83,3
16	30	50	50	43,3	80	80	80	80
17	20	10	0	10	90	100	100	96,7
18	90	60	50	66,7	40	50	30	40
19	100	90	80	90	10	20	20	16,7
Mean	59,4	46,1	38,9	48,1	60	63,3	62,8	62,0

Figure 6.4. Performance of the second session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases. A. for the cube. B. for the cup. C. for the clothespin.

Looking at the table from the third session (Fig 6.5), we observe similar results as what we obtained from the previous test in that there is still a bias with subjects being better at one phase compared to the other. Nonetheless, for the Release phase of BB and CS as well as the Grip phase of CUP we observe an improvement in the decoding performance with a raise of around 10%. What is also interesting is that we can observe that the performance of the previous session cannot give us a hint at the performance of the next session if we look at individual subjects. Indeed, while the performance might hover around the same values for some of the subjects, this is not the case for all of them with the performances being better in different phases compared to the previous session.

A

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	50	60	10	40	80	80	100	86,7
2	60	90	70	73,3	70	60	60	63,3
3	40	20	70	43,3	60	70	80	70
4	70	70	90	76,7	30	20	30	26,7
5	70	50	60	60	40	60	50	50
6	40	70	60	56,7	40	50	60	50
7	60	10	90	53,3	50	90	10	50
8	70	50	60	60	80	90	100	90
9	60	80	90	76,7	60	40	30	43,3
10	40	80	80	66,7	50	40	60	50
11	50	40	70	53,3	80	80	80	80
12	80	70	50	66,7	40	20	60	40
13	30	10	30	23,3	90	100	100	96,7
14	40	70	90	66,7	50	30	20	33,3
15	40	30	40	36,7	80	90	70	80
16	60	60	60	60	30	50	50	43,3
17	10	10	0	6,7	100	100	100	100
18	40	40	50	43,3	30	40	30	33,3
19	70	60	10	46,7	40	60	80	60
Mean	51,6	51,1	56,8	53,2	57,9	61,6	61,6	60,4

B

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	10	40	20	23	90	80	40	70
2	40	20	30	30	100	100	100	100
3	10	40	10	20	80	70	90	80
4	60	70	80	70	50	30	60	46,7
5	10	20	10	13,3	90	90	100	93,3
6	50	0	10	20	80	100	90	90
7	50	20	0	23,3	40	90	100	76,7
8	0	10	40	16,7	90	80	90	86,7
9	60	70	60	63,3	60	70	40	56,7
10	0	10	0	3,3	90	90	100	93,3
11	50	80	20	50	30	50	80	53,3
12	10	0	0	3,3	90	100	100	96,7
13	10	0	20	10	100	100	90	97
14	70	50	80	66,7	50	30	70	50
15	20	10	10	13,3	90	90	100	93,3
16	50	90	70	70	60	20	50	43,3
17	30	40	0	23	90	100	70	86,7
18	0	0	10	3,3	100	100	100	100
19	30	40	20	30	60	60	60	60
Mean	29,5	32,1	25,8	29,1	75,8	76,3	80,5	77,5

C

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	40	60	30	43,3	90	80	90	86,7
2	50	50	50	50	70	70	70	70
3	40	30	20	30	70	70	100	80
4	80	70	40	63,3	50	30	40	40
5	10	10	40	20	70	80	100	83,3
6	50	30	40	40	90	50	80	73,3
7	40	90	100	76,7	40	10	0	16,7
8	10	10	50	23,3	100	100	100	100
9	50	40	60	50	60	60	50	56,7
10	50	30	40	40	70	50	70	63,3
11	40	20	30	30	70	70	90	76,7
12	90	90	60	80	40	50	60	50
13	20	30	10	20	100	90	100	96,7
14	50	60	40	50	80	70	100	83,3
15	50	30	30	36,7	80	80	100	86,7
16	10	40	30	26,7	80	80	80	80
17	10	0	0	3,3	100	100	100	100
18	30	60	70	53,3	60	50	50	53,3
19	30	30	40	33	100	70	80	83,3
Mean	39,5	41,1	41,1	40,5	74,7	66,3	76,8	72,6

Figure 6.5. Performance of the third session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases. A. for the cube. B. for the cup. C. for the clothespin.

If we are now interested in the result from one of the amputees that completed the three sessions (Fig 6.6), we can see that we are obtaining accuracies close to those of the able-bodied.

BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	50	30	20	33,3	60	90	100	83,3
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	30	30	40	40	60	80	60
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	50	60	70	60	70	40	50	53,3
BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	30	20	0	16,7	100	80	100	93,3
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	20	40	10	23,3	100	100	70	90
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	20	10	30	70	80	90	80,0

Figure 6.6. Performance of the second (top) and third (bottom) sessions for the amputee subject in the three runs of 10 trials for the Grip and Release phases.

Especially for the third session, the participant gets decoding performances of more than 80% with the three objects for the Release phase while the Grip performances are below 30%. This pattern of performance is also found for the BB object in the second session while for the CUP and CS objects we observe decoding performances close to randomness. It is interesting to see that between the second and third sessions the subject seems to have presented a bias toward the Open movement which would explain both a better performance during the Release phase but also the poorer accuracy during the Grip of the objects.

It is quite difficult to exactly pinpoint the reasons behind the low performance we obtained. One plausible explanation for now that we were able to find is that there are some differences in the EEG data that is recorded in real-time compared to the data recorded at the beginning of the session. It is known that there are within-sessions and between-sessions non-stationarities in the EEG signal, which are posing a threat to the deployment of EEG-based BMIs outside of the laboratory [222] but in our case we also think that hardware issues could add to those obstacles. Indeed, with the able-bodied subjects during the first step we are recording the EEG data using the PyCorder software while for the real-time control, as everything is happening in Matlab, we chose to use the Remote Data Access (RDA) module proposed by BrainProducts which allows receiving data from the amplifier over the network via a TCP/IP connection. We are connecting to the amplifier at the beginning of the GRIP and RELEASE steps and are

disconnecting right after, we are thus suspecting that we are not receiving the correct data from the amplifier or that some noise has somehow been introduced into the data. It is not the case with the OpenBCI system used with the amputees as there are no differences between the Recording and Testing periods in terms of functions used to access the EEG activity.

Another explanation, which sounds reasonable, could be that the subjects are too tired when they have to execute the movements during the real-time control, which would prevent them to generate the same brain activity patterns as during the EEG recording. Along the same line, which could explain why the generated patterns from the test are too different from the previously recorded patterns, could be that the EEG data is different because of movements of the EEG system on the head of the user or that the CSP filters that are computed when processing the data are overfitting and not generalizing well with upcoming data. In Fig. 6.7, we are plotting the features coming from both the offline recording and real-time recording for the Half/Open model for one able-bodied subject.

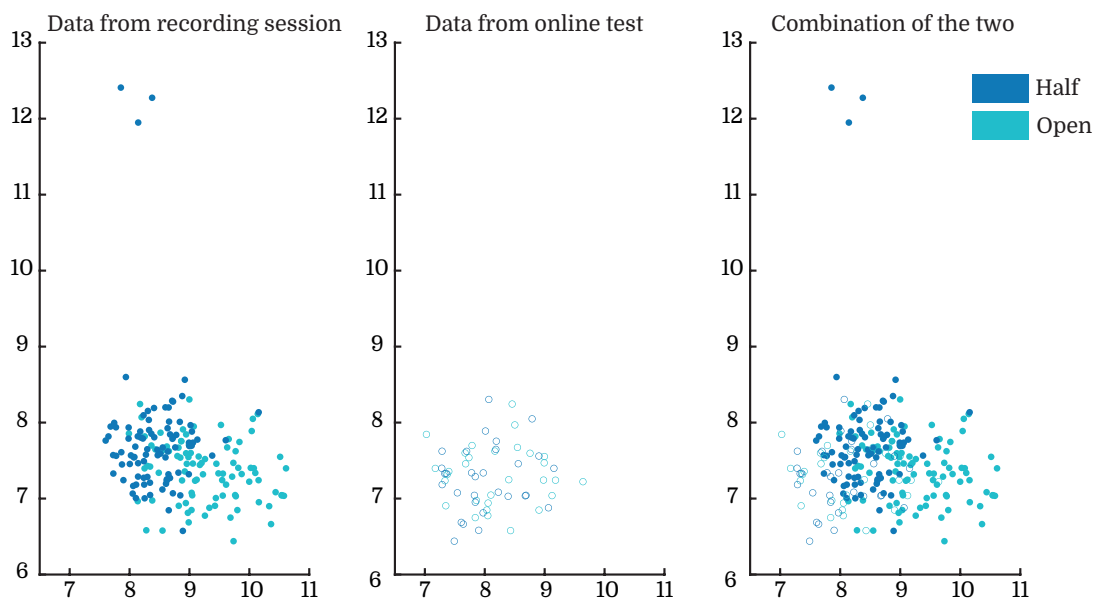


Figure 6.7. Graph of the input features for the movements Half (dark blue) and Open (light blue) with the data from the recording session (left), the online test (middle) and both combined (right).

While we observe a quite good separation of the two movements with the features from the offline recording, we can notice a shift in the feature space of those two movements with the features from the real-time control. More precisely we can see that the features computed during the test are shifted towards the “Open” features. We are still investigating the reasons for this shift and trying to understand if the problem is coming directly from the data or if it was introduced during the feature extraction. For this reason, we decided to also look at the results obtained when applying the Riemannian pipeline to the data, which we represent in Fig. 6.8 for the third session.

A

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	10	20	0	10	100	100	100	100
2	20	20	50	30	50	90	60	66,7
3	20	0	10	10	70	80	100	83,3
4	20	40	40	33,3	80	60	90	76,7
5	0	10	0	3,3	100	100	100	100
6	0	0	10	3,3	100	100	90	96,7
7	0	0	20	6,7	100	100	80	93,3
8	0	0	0	0	100	100	100	100
9	0	10	0	3,3	100	100	100	100
10	0	20	0	6,7	100	90	90	93,3
11	0	10	0	3	100	100	100	100
12	0	0	0	0	90	100	100	96,7
13	0	0	0	0	100	100	100	100
14	30	0	30	20	100	90	80	90
15	30	50	30	36,7	90	100	80	90
16	10	0	10	7	90	100	90	93,3
17	0	0	30	10	100	100	100	100
18	0	0	0	0	90	100	100	96,7
19	20	0	0	7	100	100	100	100
Mean	8,4	9,5	12,1	10,0	92,6	95,3	92,6	93,5

B

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	0	0	0	0	100	100	100	100
2	0	0	0	0	100	100	100	100
3	0	0	0	0	90	90	100	93,3
4	20	0	0	6,7	100	100	100	100
5	0	0	0	0	100	100	100	100
6	0	0	0	0	100	100	100	100
7	40	20	0	20	40	90	100	76,7
8	0	0	0	0	100	100	100	100
9	0	0	0	0	100	100	100	100
10	0	0	0	0	90	100	100	96,7
11	0	0	0	0	100	100	100	100
12	0	0	0	0	100	100	100	100
13	0	10	0	3,3	100	100	100	100
14	0	0	0	0	100	100	100	100
15	0	0	0	0	100	100	100	100
16	0	20	10	10	100	90	100	96,7
17	0	0	0	0	100	100	100	100
18	0	10	0	3,3	100	100	100	100
19	0	0	0	0	100	100	100	100
Mean	3,2	3,2	0,5	2,3	95,8	98	100,0	98,1

C

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	40	40	10	30	80	100	100	93,3
2	50	50	40	46,7	70	90	70	76,7
3	0	0	0	0	80	100	100	93,3
4	40	50	10	33,3	80	70	80	76,7
5	0	0	10	3,3	100	100	100	100
6	0	0	0	0	100	100	100	100
7	10	40	70	40	80	80	70	76,7
8	10	0	0	3,3	100	100	100	100
9	0	0	0	0	100	100	100	100
10	0	10	0	3,3	100	100	100	100
11	0	0	10	3,3	90	100	100	96,7
12	0	0	0	0	100	100	100	100
13	0	20	0	6,7	100	90	100	96,7
14	40	30	10	26,7	100	90	100	96,7
15	20	30	40	30	80	100	100	93,3
16	0	0	0	0	100	100	100	100
17	30	20	0	16,7	100	90	100	96,7
18	0	30	0	10	90	70	100	86,7
19	0	0	0	0	100	100	100	100
Mean	12,6	16,8	10,5	13,3	92,1	93,7	95,8	93,9

Figure 6.8. Performance of the third session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases with the Riemannian pipeline. A. for the cube. B. for the cup. C. for the clothespin.

Here we see that the results are even more biased towards one of the two movements with, for most of the subjects, performances of almost 100% for the Release phase with the three objects while the performances are close to 0% for the Grip phase. We observed the same trend of results for the second session.

BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	20	0	0	6,7	100	100	100	100
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	30	0	10	13,3	100	90	90	93,3
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	10	0	0	3,3	100	80	100	93,3
BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	20	20	10	16,7	80	100	90	90
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	30	10	10	16,7	100	100	90	96,7
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	40	0	10	16,7	80	90	100	90

Figure 6.9. Performance of the second (top) and third (bottom) sessions for the amputee subject in the three runs of 10 trials for the Grip and Release phases with the Riemannian pipeline.

Moreover, as seen in Fig 6.9, applying the same pipeline with the results from the Amputee gave the same biased performances.

We are still thinking of solutions that can be applied to possibly improve the decoding performance during the test. One of them would be to update all the parameters that are used for the online control: the classification models, the CSP filters, and the parameters used in the normalization. This updating could happen at the end of every trial or after every few trials while potentially removing older EEG data that are too different from the recently recorded ones. Another solution would be to align in some ways the data from the real-time test to the data from the recording period, which is applied in the Riemannian framework [221]. This could help to alleviate the non-stationarities and get rid of the shift happening in the feature space for some of the movements between the training and testing sets.

What we are using with the TS SVM from the Riemannian pipeline is the projection of the spatial covariance matrices on a common reference, which is here the identity matrix, with the following affine transformation:

$$C'_i = \bar{C}_i^{-1/2} \times C_i \times \bar{C}_i^{-1/2} \quad (\text{VI.1})$$

Where \bar{C}_i is the Riemannian mean for the covariance matrices of one of the pair of movements (Close/Open for example). To obtain the results with the offline data during the 5-fold cross-validation, the projection on the reference is done both for the training set and the testing set with the computation of \bar{C}_{train} and \bar{C}_{test} . As explained in [222],

during the online test the testing set that we need to compute \bar{C}_{test} is not fully available. Here, in our implementation, we naively used the \bar{C}_{train} matrices computed with all the data from the recording session as the \bar{C}_{test} for the projections. Nonetheless, Kumar and colleagues in [222] proposed to update this reference along with the acquisition of upcoming data with this adaptation scheme:

$$\bar{C}_{i,\text{test}} = \begin{cases} \bar{C}_{\text{train}} & i = 1 \\ C_{i-1} & \text{for } i = 2 \\ \gamma(\bar{C}_{i-1,\text{test}}, C_i, \frac{1}{i-1}) & i \geq 3 \end{cases} \quad (\text{VI.2})$$

with

$$\gamma(\bar{C}_{i-1,\text{test}}, C_i, \frac{1}{i-1}) = \bar{C}_{i-1}^{-1/2} \times (\bar{C}_{i-1}^{-1/2} \times C_i \times \bar{C}_{i-1}^{-1/2})^{i-1} \times \bar{C}_{i-1}^{-1/2} \quad (\text{VI.3})$$

For the first trial of the test, \bar{C}_{test} corresponds to \bar{C}_{train} and we note a shift once the second trial is happening, as the new \bar{C}_{test} will then be considered as the covariance matrix of the first trial. For more than two trials, the Riemannian mean for the upcoming trial will be estimated “using a weighted geodesic interpolation between previous estimates and each ongoing covariance matrix” [222]. Here we applied this method and obtained the following results (Fig 6.10) :

A

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	50	40	0	30	50	100	90	80
2	50	10	30	30	50	90	60	66,7
3	20	0	10	10	80	80	100	86,7
4	50	30	30	36,7	40	70	100	70
5	20	10	10	13,3	70	100	100	90
6	0	10	10	6,7	100	100	80	93,3
7	0	0	0	0	80	100	100	93,3
8	10	30	70	36,7	100	90	90	93,3
9	0	20	10	10	100	90	80	90
10	40	50	0	30	50	70	90	70
11	20	50	20	30	70	100	100	90
12	10	10	20	13,3	90	100	90	93,3
13	10	20	70	33,3	100	100	90	96,7
14	10	0	40	16,7	100	90	80	90
15	40	50	40	43,3	90	90	80	86,7
16	20	10	30	20	90	90	90	90
17	50	20	40	36,7	60	80	80	73,3
18	0	0	0	0	80	90	90	86,7
19	30	0	0	10	100	90	100	96,7
Mean	22,6	18,9	22,6	21,4	79	91	89	86

B

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	0	10	0	3,3	90	90	70	83,3
2	70	20	40	43,3	80	100	90	90
3	0	20	10	10	90	90	100	93,3
4	30	0	10	13,3	100	100	90	96,7
5	0	10	0	3	100	100	90	96,7
6	10	0	10	6,7	100	90	100	96,7
7	20	20	0	13,3	50	90	100	80
8	10	50	50	36,7	100	90	100	96,7
9	0	30	30	20	100	90	90	93,3
10	0	0	0	0	90	100	90	93,3
11	0	0	0	0	100	90	90	93,3
12	20	20	20	20	100	100	80	93,3
13	0	60	50	36,7	100	100	60	86,7
14	30	0	0	10	90	90	80	86,7
15	0	10	10	6,7	80	90	100	90
16	50	40	10	33,3	70	70	100	80
17	20	20	10	16,7	100	100	100	100
18	0	10	10	6,7	100	100	100	100
19	10	0	20	10	80	90	100	90
Mean	14,2	16,8	14,7	15,3	90,5	93	91,1	91,6

C

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	60	40	20	40	40	100	100	80
2	50	40	30	40	60	90	70	73,3
3	0	0	10	3,3	80	70	90	80
4	60	30	10	33,3	50	80	80	70
5	20	0	30	16,7	100	100	100	100
6	0	0	0	0	100	90	100	96,7
7	10	50	70	43,3	90	70	60	73,3
8	30	50	60	46,7	90	80	90	86,7
9	30	50	20	33,3	80	90	70	80
10	20	40	50	36,7	90	60	100	83,3
11	10	10	10	10	90	100	90	93,3
12	0	40	30	23,3	90	80	80	83,3
13	20	40	30	30	90	90	80	86,7
14	10	30	30	23,3	100	70	100	90
15	30	30	40	33,3	80	100	80	86,7
16	30	20	30	26,7	80	80	60	73,3
17	30	50	30	36,7	90	70	70	76,7
18	0	40	0	13,3	90	70	100	86,7
19	40	30	30	33,3	80	90	90	86,7
Mean	23,7	31,1	27,9	27,5	82,6	83,2	84,7	83,5

Figure 6.10. Performance of the third session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases in the Riemannian pipeline with the adaptive method. A. for the cube. B. for the cup. C. for the clothespin.

With the three objects, we note a drop in performance in the Release phase of 6 to 13%, but the decoding accuracy is still above 80% for almost all of the subjects. On the contrary, for the Grip phase when compared to the previous results, the use of the adaptive method is bringing a mean increase of 16,9%, 13,4%, and 18,5% for BB, CUP, and CS respectively. While these new decoding accuracies are still well below the chance level it is quite interesting to observe how the modification of the common reference used during the processing can have an impact on the decoding performance, slightly improving it.

BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	50	60	20	43,3	50	70	90	70
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	60	20	46,7	90	90	70	83,3
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	70	30	53,3	60	40	90	63,3
BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	70	60	50	60,0	30	70	60	53,3
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	30	40	10	26,7	100	90	60	83,3
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	20	30	36,7	80	60	90	76,7

Figure 6.11. Performance of the second (top) and third (bottom) sessions for the amputee subject in the three runs of 10 trials for the Grip and Release phases in the Riemannian pipeline with the adaptive method.

If we look at the results for the Amputee (Fig. 6.11), we can observe a similar trend with a loss of decoding accuracy for the RELEASE phase with for most of the objects an

accuracy above 70%. For the GRIP phase, for all the objects and the two sessions we see an increase in the performance from 10% up to 50%. Yet there is no clear increase improvement along the runs within a session or between sessions 2 and 3. The use of such an adaptive method requires thus a deeper investigation and may be adjustments because in its current implementation we are only updating the models Close/Open for the BB/CS objects and Half/Open for the CUP object. The idea would thus be to have a function running continuously in the background which would be in charge of updating the parameters either whenever a new EEG activity has been recorded or after a short calibration phase when the user would have to perform a few movements in a database.

Finally, by potentially focusing on just a subset of electrodes as we presented in the results from the second study we might be able to generalize better with upcoming data, with a feature space more homogeneous between the recording and testing periods. We investigated this particular point with the data from three subjects and looked at the performance of two smaller subsets of electrodes centered around the motor cortex and contralateral motor cortex (combinations 1 & 2 from the Chapter 5).

A

BB	Grip				Release			
Subject	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
2	40	70	50	53,3	40	50	60	50
18	40	20	30	30	90	80	70	80
19	30	50	40	40	20	80	70	56,7
Mean	36,7	46,7	40	41,1	50	70	66,7	62,2

CUP	Grip				Release			
Subject	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
2	20	40	40	33,3	100	100	90	96,7
18	40	20	20	26,7	90	100	80	90
19	10	10	30	16,7	90	80	70	80
Mean	23,3	23,3	30	25,6	93,3	93,3	80	88,9

CS	Grip				Release			
Subject	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
2	30	60	30	40,0	60	40	100	66,7
18	30	20	0	16,7	100	100	100	100
19	50	50	40	46,7	60	80	70	70
Mean	36,7	43,3	23,3	34,4	73,3	73,3	90	78,9

B

BB	Grip				Release			
Subject	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
2	90	80	50	73,3	20	50	20	30
18	50	50	50	50	60	30	60	50
19	50	20	50	40	30	50	80	53,3
Mean	63,3	50	50	54,4	36,7	43,3	53,3	44,4

CUP	Grip				Release			
Subject	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
2	0	0	20	6,7	100	100	90	96,7
18	30	30	60	40	70	70	70	70
19	60	40	40	46,7	40	100	80	73,3
Mean	30	23,3	40	31,1	70	90	80	80

CS	Grip				Release			
Subject	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
2	60	90	40	63,3	40	30	80	50
18	50	70	50	56,7	60	40	50	50
19	30	30	50	36,7	70	80	80	76,7
Mean	46,7	63,3	46,7	52,2	56,7	50	70	58,9

Figure 6.12. Performance of the third session for three able-bodied subjects in the three runs of 10 trials for the Grip and Release phases with two combinations of electrodes.

A. Combination 1. B. Combination 2.

The results in Fig. 6.12 show the same trend we presented in the table gathering all the subjects that is: subjects usually perform better at either the Grip or the Release but not at both. This is present in the two electrode combinations that we tested. Moreover, we notice that, when comparing combination 1 and combination 2, we observe an improvement in the decoding performance for most of the three subjects with an increase of around 3 to 20% for the Grip phase. As expected, we see the opposite pattern with the Release phase, with a drop in performance when going from combination 1 to combination 2. We also observed similar results when processing and decoding the EEG activity with the feature extraction and classification algorithms based on Riemannian geometry.

d. Control Strategy and modification of the results

It is not difficult to notice that the results we obtained are quite different from the ones obtained during the offline training part. We have tried to explain some reason behind this drop in performance and presented some solutions in an attempt to obtain better results, by updating or changing the processing pipeline or by looking at subsets of electrodes. Nonetheless, this is not enough to guarantee a daily-life use of the system, this led us to investigate different ways of improving the performance of the system without acting on the processing or decoding techniques that we were using.

In particular, fruitful discussions with the thesis committee brought us to consider the concept of finite-state machine (FSM) to act on this issue. A state machine is composed of two items that are called states and transitions. A state refers to the situation of the system after it received inputs, then the system is waiting for other inputs to switch to a different state which is referred to as a transition. In our system here we consider that the states are the positions that can take the prosthesis: Close, Half, or Open. The transitions are the outputs given by the classification algorithms which are indicating the future state of the prosthesis, and, if the output of the algorithm is the “movement” Rest it means that the system will stay in the same state as it currently is. This type of state machine is defined in the literature as a deterministic finite state machine, which means that there is only one transition for any given input, in other words, the transition from Open to Half is only possible if the output of the algorithm is Half.

We represent here the finite-state machine related to the prosthesis in Fig. 6.13:

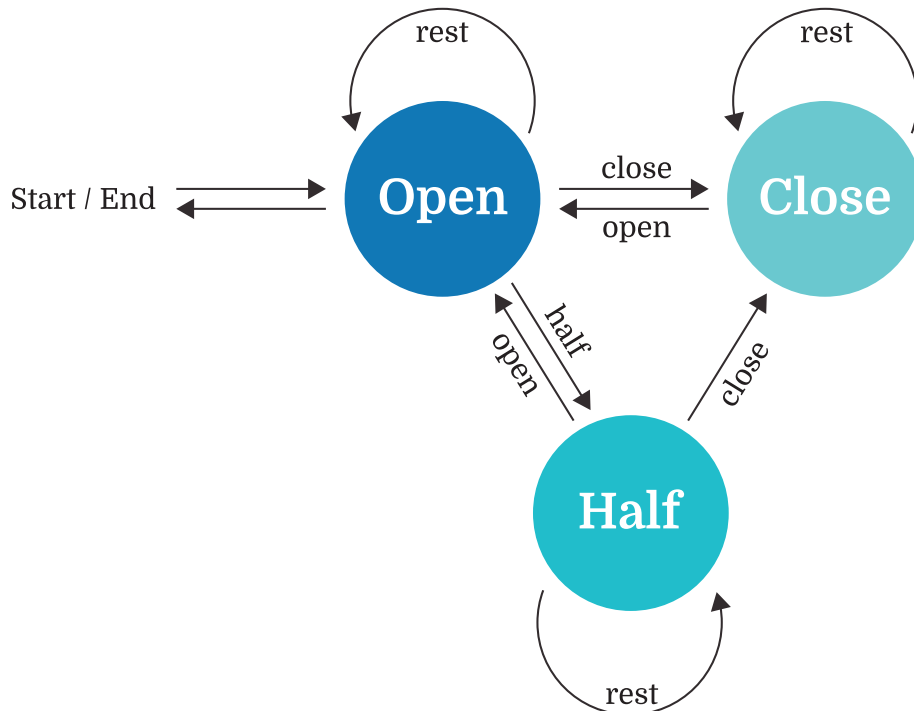


Figure 6.13. Schematic representation of the Finite-State Machine for the system. When starting the BMI system, the prosthesis will be open and then, based on the classification output, different movement can be triggered on the prosthesis which will change its state.

We are considering here, for simplification reasons, that the start of the system is putting the prosthesis in the Open state. We can also simplify the system by saying that when the prosthesis is closed there are little to no reasons to transition to the Half position and that this position can be reached by going back to Open before transitioning to Half. It is not the same when the prosthesis is half closed as the user can decide to either switch to the Open position or the Close position.

This concept of state machine is translated inside the software and scripts by the use of a variable that represents the state of the prosthesis, this allows for the choice of the one-vs-one models to be compared, and this variable is thus updated after each transition.

By using the FSM we can also see what are the differences brought in the results obtained during the real-time tests. Moreover, we can also implement two different difficulty levels on the control strategy similar to what we previously explained. For the first level we are still comparing a movement vs. Rest:

- Close vs. Rest and Half vs. Rest for the GRIP phase of “BB & CS” and “CUP” respectively
- Open vs. Rest for the RELEASE phase

And for the second level:

- Close vs. Half for the GRIP phase with the three objects
- Open vs. Rest and Open vs. Close for the RELEASE phase of “BB & CS” and “CUP” respectively

This takes into account that the prosthesis is limited either to the Half or Close position when it is Open, but also limited to Open or Close when at the Half state and finally can only go back to being Open when it is closed.

We will thus present the results with the second level for the second and third sessions:

A

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	90	100	70	86,7	100	90	100	96,7
2	40	50	60	50	100	100	100	100
3	90	70	40	66,7	100	100	100	100
4	70	50	40	53,3	100	100	100	100
5	30	50	60	46,7	100	100	100	100
6								
7	70	60	50	60	100	100	100	100
8	80	50	20	50	100	100	100	100
9	70	60	50	60	100	100	100	100
10	90	50	90	76,7	100	100	100	100
11	40	70	60	56,7	100	100	100	100
12	100	90	100	96,7	80	50	60	63,3
13	20	20	50	30	100	100	100	100
14	80	60	70	70	100	100	100	100
15	10	10	10	10	100	100	100	100
16	30	70	40	46,7	100	100	100	100
17	50	20	10	26,7	100	100	100	100
18	30	60	40	43,3	100	100	100	100
19	100	90	80	90	100	100	100	100
Mean	60,6	57,2	52,2	56,7	98,9	96,7	97,8	97,8

B

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	10	0	10	6,7	50	0	60	36,7
2	20	10	70	33,3	50	40	70	53,3
3	0	0	0	0	50	90	50	63,3
4	20	30	30	26,7	50	60	100	70
5	0	0	10	3,3	50	40	70	53,3
6								
7	20	50	80	50	10	40	90	46,7
8	60	90	100	83,3	50	80	90	73,3
9	10	20	100	43,3	60	50	60	56,7
10	60	40	80	60	100	80	90	90
11	60	40	10	36,7	90	90	50	76,7
12	0	0	0	0	0	0	0	0
13	0	0	0	0	40	60	90	63,3
14	40	50	30	40	80	60	80	73,3
15	90	100	100	96,7	90	80	80	83,3
16	80	60	30	56,7	80	80	60	73,3
17	70	70	70	70	90	90	100	93,3
18	10	10	0	6,7	50	50	50	50
19	0	0	0	0	20	60	30	36,7
Mean	30,6	31,7	40	34,1	56,1	58,3	67,8	60,7

C

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	100	100	100	100	90	100	100	96,7
2	50	80	90	73,3	100	100	100	100
3	100	100	100	100	100	100	100	100
4	100	70	60	76,7	100	90	100	96,7
5	100	100	100	100	100	100	100	100
6								
7	60	80	20	53,3	80	100	100	93,3
8	90	20	30	46,7	100	100	100	100
9	80	10	60	50	100	90	100	96,7
10	60	60	90	70	70	100	90	86,7
11	70	40	80	63,3	100	100	100	100
12	100	100	100	100	30	10	10	16,7
13	100	100	100	100	100	100	100	100
14	70	90	70	76,7	100	100	100	100
15	50	80	90	73,3	100	100	100	100
16	80	30	50	53,3	100	100	100	100
17	50	40	50	46,7	100	100	100	100
18	100	90	100	96,7	100	100	100	100
19	100	100	100	100	100	100	100	100
Mean	81,1	71,7	77,2	76,7	92,8	93,9	94,4	93,7

Figure 6.14. Performance of the second session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases with the Finite-State Machine. A. for the cube. B. for the cup. C. for the clothespin.

From Fig. 6.14, starting with the Grip phase, we obtain similar results with BB compared to the original strategy we employed in the first results with a mean performance of the subjects of about 57%. For the CUP the performance is still very poor but still about twice the previous performance, with a mean of around 34%. This result means that when comparing Close vs. Half, most of the EEG activity will be classified as being a Close movement, in practice during the experiment this would not be an issue to perform the sequence as the glass that the subjects are supposed to grasp is quite thick. If we think of a daily-living activity this would pose a problem if the users were grasping a thin plastic glass filled with water for example. We also see an increase in the performance with the CS object, with the accuracy going from 48% to 77%. What is interesting to note is that even though the GRIP phase of both the BB and CS objects is considered to lead to Close, the performance with the CS object is way better than that of the BB. One possible reason behind this is that because subjects have to apply a higher force to grasp the clothespin compared to the cube it could lead to a more distinct pattern of EEG that is less close to the one generated for the Half movement [223].

Moving to the Release phase we observe similar results for the BB and CS objects, with an accuracy of about 30 to 40% better, almost reaching 100% accuracy. Nonetheless, we see the opposite trend for the CUP object, with a drop of 30% in performance, but still reaching a mean of 60% in accuracy. These impressive results for BB and CS can be explained by the use of the Open vs. Rest model during the decoding of the EEG activity. From the articles presented in Chapter IV, we saw that the one-vs-one models where a movement is compared to the Rest all gave accuracies of close to 100%. The performance of the CUP object can also be linked to the results from the articles as the performances from the Close/Open model were the lowest of the 6 decoding models, with an accuracy of about 70%.

A

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	80	90	30	66,7	100	100	100	100
2	100	90	100	96,7	100	100	100	100
3	100	100	90	96,7	100	100	100	100
4	80	70	80	77	70	100	70	80
5	100	100	90	96,7	100	100	100	100
6	100	90	80	90,0	100	100	90	96,7
7	70	30	100	66,7	60	90	50	66,7
8	100	90	100	96,7	100	100	100	100
9	80	90	80	83,3	100	100	100	100
10	100	100	100	100	100	100	100	100
11	70	80	70	73,3	100	100	100	100
12	100	100	70	90	100	100	100	100
13	40	40	50	43,3	100	100	100	100
14	70	60	90	73,3	100	100	100	100
15	80	100	90	90	100	100	100	100
16	60	70	90	73,3	100	100	100	100
17	30	20	10	20	100	100	100	100
18	100	100	80	93,3	100	100	100	100
19	80	100	80	86,7	100	100	100	100
Mean	81,1	80	77,9	79,6	96,3	99,5	95,3	97

B

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	70	70	70	70	80	100	90	90
2	20	0	20	13,3	90	90	60	80
3	80	100	40	73,3	90	90	70	83,3
4	10	20	70	33,3	70	60	90	73,3
5	30	50	70	50	100	90	70	87
6	30	20	30	26,7	70	70	80	73,3
7	0	0	10	3	0	20	80	33,3
8	0	40	60	33,3	90	90	90	90
9	0	90	40	43,3	80	100	100	93
10	30	50	40	40	80	90	100	90
11	30	70	20	40	60	60	80	66,7
12	0	0	0	0	50	50	30	43,3
13	40	40	50	43	90	90	90	90
14	50	30	50	43,3	70	60	80	70
15	60	50	10	40	100	100	90	96,7
16	50	80	100	76,7	100	70	80	83,3
17	90	70	70	77	100	80	80	86,7
18	30	10	10	16,7	20	70	70	53,3
19	50	40	20	36,7	40	40	60	46,7
Mean	35,3	43,7	41,1	40	72,6	74,7	78,4	75,3

C

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	50	90	100	80	100	100	100	100
2	100	90	90	93,3	100	100	100	100
3	80	100	90	90	100	100	100	100
4	70	70	80	73,3	80	10	10	33,3
5	90	60	90	80	100	100	90	97
6	100	90	90	93,3	100	90	100	96,7
7	100	100	100	100	80	30	30	46,7
8	70	50	90	70	100	100	100	100
9	70	70	50	63,3	100	100	80	93,3
10	100	100	90	96,7	100	100	100	100
11	80	90	50	73,3	100	100	100	100
12	100	100	90	97	100	100	100	100
13	40	40	40	40	100	100	100	100
14	60	90	40	63,3	100	100	100	100
15	100	100	100	100	100	100	100	100
16	0	0	20	6,7	10	30	50	30
17	30	20	20	23,3	100	100	100	100
18	100	90	70	86,7	100	100	100	100
19	70	30	90	63	100	100	100	100
Mean	74,2	72,6	73,2	73,3	93,2	87,4	87,4	89,3

Figure 6.15. Performance of the second session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases with the Finite-State Machine. A. for the cube. B. for the cup. C. for the clothespin.

If we look next at the performance for the third session (Fig. 6.15), we see a noticeable improvement compared to the second session but also compared to the previous control strategy. Indeed, for the GRIP phase of both the BB and CS objects we obtained decoding performances of more than 70% (79.6% and 73.3% respectively). The accuracy is also slightly improved for the CUP object with a mean of 40% across all the subjects. We observe similar results to those obtained in the second session for the RELEASE phase, with performances in the same range of about 90% for the BB and CS objects. We also note an improvement for the CUP object compared to the second session, with a performance increase from 60 to 75%.

When comparing the performance of the second and third sessions for the Amputee with the FSM we similarly observed an improvement in the performance for both the GRIP and RELEASE for the three objects. Nonetheless, it is quite difficult to notice an improvement of the subject between the second and third session except for the CUP object where we note around 20% of increase for the two phases.

We also obtained interesting results when combining the FSM with the Riemannian

pipeline for processing and classifying. The results are almost identical for Sessions 2 and 3 with an almost perfect Grip and Release decoding for the BB and CS object. Moreover, the results are different with the CUP object with an accuracy of more than 90% for the Release phase while it is close to zero for the Grip phase, except for subject #10 for whom we observe 70% mean accuracy for the three runs of 10 trials.

BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	70	20	50	100	100	100	100
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	70	50	40	53,3	100	100	100	100
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	70	70	50	63,3	100	100	100	100
BB	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	20	40	20	26,7	100	100	100	100
CUP	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	60	90	60	70	90	100	90	93,3
CS	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
	80	80	40	66,7	100	100	80	93,3

Figure 6.16. Performance of the second (top) and third (bottom) sessions for the amputee subject in the three runs of 10 trials for the Grip and Release phases with the Finite-State Machine.

With the Amputee when comparing the results without the FSM applied we note a slight improvement (Fig 6.16) to the already good decoding performances obtained for the RELEASE phase as well as an increase of 30% to around 70% for the decoding in the GRIP phase. Nonetheless, this can be contrasted by the fact that for some of the performances that have been improved it only brings them around chance level.

We finally also tested a modified version of the adaptive method presented in 1.c. which might be at risk of introducing some overfitting. The idea is to combine both the Finite-State Machine concept we mentioned but also the adaptation of the reference used to adjust the trial in the Riemannian framework. Here the first step was to load all the data recorded from the test phase and use them to compute an updated version of the mean covariance matrices. In particular, as we had more GRIP data related to the Close movement (60 trials in total with the objects BB and CS) compared to the data related to the Half movement (30 trials with the object CUP) we selected 15 trials out of the 30 for both BB and CS and, along the 30 trials from CUP, used them to compute the new mean covariance matrices associated with the comparison Close/Half, which is used for the GRIP phase with the three objects. Similarly, the other mean covariance matrix that we could update was the one used during the RELEASE phase for the CUP object which is the Close/Open one. For this one, we selected the 30 trials from the GRIP phase for both BB and CS and randomly selected 20 trials from the 30

for the three objects. For the mean covariance matrix associated with the comparison Open/Rest that we are using for the RELEASE decoding of both BB and CS, we kept the original matrix obtained during the processing of the data from the EEG recording. Once the mean covariance matrices were obtained, the next step is to compute the common reference following equation VI.1 in 1.c. with \bar{C} being the matrices updated previously. Here the risk of overfitting/data leakage is present for some of the trials as the covariance matrices used in the equation might have been used for the computation of the mean matrices.

A

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	90	90	60	80	100	100	100	100
2	90	90	80	86,7	100	100	100	100
3	90	90	100	93,3	100	100	100	100
4	70	50	50	56,7	100	100	100	100
5	100	100	80	93,3	100	100	100	100
6	80	40	70	63,3	100	100	100	100
7	100	100	90	96,7	100	100	100	100
8	100	80	100	93	100	100	100	100
9	90	90	80	87	100	100	100	100
10	100	100	100	100	100	100	100	100
11	80	80	60	73,3	100	100	100	100
12	90	70	60	73,3	100	100	100	100
13	90	90	70	83,3	100	100	100	100
14	80	90	90	86,7	100	100	100	100
15	80	100	90	90	100	100	100	100
16	80	90	100	90	100	100	100	100
17	100	90	70	86,7	100	100	100	100
18	100	80	80	86,7	100	100	100	100
19	80	90	90	87	100	100	100	100
Mean	88,9	84,7	80,0	84,6	100	100	100	100

B

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	30	50	30	36,7	60	90	90	80
2	40	20	20	26,7	60	100	90	83,3
3	80	90	80	83,3	90	100	90	93,3
4	30	0	10	13,3	40	30	80	50
5	20	40	40	33,3	80	100	100	93,3
6	50	0	20	23,3	90	100	90	93,3
7	10	10	0	6,7	50	90	90	76,7
8	20	20	70	36,7	80	100	90	90
9	0	20	20	13,3	90	100	100	96,7
10	60	80	80	73,3	70	100	100	90
11	20	30	20	23,3	90	100	90	93,3
12	20	40	50	36,7	80	80	60	73,3
13	0	40	10	16,7	70	90	80	80
14	30	10	40	26,7	90	100	80	90
15	90	60	50	66,7	90	90	100	93,3
16	30	40	20	30	80	60	100	80
17	0	70	0	23,3	50	50	80	60
18	0	10	10	6,7	90	100	100	96,7
19	60	40	30	43,3	80	100	100	93,3
Mean	31,1	35,3	31,6	32,6	75,3	88	90,0	84,6

C

Subject	Grip				Release			
	Run 1	Run 2	Run 3	Mean	Run 1	Run 2	Run 3	Mean
1	100	100	100	100	100	100	100	100
2	70	80	70	73,3	100	100	100	100
3	90	100	100	96,7	100	100	100	100
4	100	80	70	83,3	100	100	100	100
5	70	60	80	70	100	100	100	100
6	80	80	60	73,3	100	100	100	100
7	100	80	70	83,3	100	100	100	100
8	40	30	50	40	100	100	100	100
9	100	90	70	86,7	100	100	100	100
10	100	100	90	96,7	100	100	100	100
11	80	90	70	80	100	100	100	100
12	80	80	80	80	100	100	100	100
13	100	90	80	90	100	100	100	100
14	80	90	60	76,7	100	100	100	100
15	100	90	100	96,7	100	100	100	100
16	50	20	90	53,3	100	100	100	100
17	70	80	80	76,7	100	100	100	100
18	100	90	80	90	100	100	100	100
19	50	50	90	63,3	100	100	100	100
Mean	82,1	77,9	78,4	79,5	100	100	100	100

Figure 6.17. Performance of the third session for each able-bodied subject in the three runs of 10 trials for the Grip and Release phases with the Finite-State Machine and the Adaptive method from the Riemannian pipeline. A. for the cube. B. for the cup. C. for the clothespin.

By looking at the results obtained using this combination of the methods for the able-bodied subject's data of session 3 (Fig. 6.17) we can note that the decoding accuracy in the RELEASE phase for both BB and CS is not different from the results obtained without the adaptive method, for the CUP object we note a drop of performance from 93,3% to 84,6%. For the GRIP phase of BB and CS, we also observe a loss of decoding accuracy of about 14% compared to the previous results while we see the opposite effect on the GRIP phase of the CUP object with an increase in the decoding performance of 23%. The drop for BB/CS and the increase for CUP shows that the adaptive process which is possibly working as the Close/Half model will be less biased in classifying almost all the trials as belonging to the Close movement which is what was obtained in Fig. 6.8. While the addition of the adaptive method has been done in a really fast way in our scripts, the fact that we still obtain results way above chance level for most phases and objects, as well as an improvement of the performance where the worse results were obtained is showing that such a solution is worth investigating more deeply. It is also worth noting the computation cost of such methods during the online test is transparent as the computation of the covariance matrices does not require extensive resources on the computer. Nonetheless, it would still be something to take into consideration for the move from a control software on a computer to its equivalent on a smartphone or any smaller device.

The fast and easy implementation of the State Machine in the BMI system is thus giving promising results regarding the decoding performance of the four movements. Nevertheless, there is still room for improvement as we are still quite distant from the results obtained by the classification algorithms during the offline training. We raised some of the causes for those differences for which we will be trying to find answers, in the hope that they can be explained by hardware issues.

2. Going from a synchronous to an asynchronous control: an investigation

The presentation of the results we obtained is giving us an idea of the performance of the system but it was only one part of the first principal functions we introduced in Chapter 3, the second part being about the need to have a reliable system. Of course, the performance can be linked in a way to the reliability, as an unreliable system will likely have a low performance. Moreover, from what we displayed we can easily argue that, as of now, the system is not reliable enough to be used daily. Indeed, during the tests the decoders sometimes considered the recorded EEG activity to be associated with a movement the user is not intending to perform. By using the state machine, we are limiting the movements the prosthesis can execute by considering its current state rather than feeding the EEG activity directly to the decoders and hoping that somehow the correct movement will be performed on the prosthesis.

As such, one addition to the BMI system which could make it more reliable would be the possibility for the user to first either start or resume the system from an idle state and second to be able to stop a movement from being executed on the prosthesis. Specifically, we mentioned in the second chapter the use of “brain-switches” in the literature which are a type asynchronous BMIs continuously receiving brain activity and triggering an output whenever a specific pattern is detected from the activity. In his Ph.D. thesis [150], Alexandre Barachant reminds us that a brain switch does not rely on a cue, there is no indication for the user to generate the specific activity. He also adds that the task recognized by the brain switch should be independent of the other tasks used in the control of the BMI system.

Implementing such a brain switch in our system will be necessary if we want to successfully move from a synchronous to an asynchronous control of the BMI. Making the system asynchronous would mean that the user is in charge of generating the right EEG pattern to perform the movement. Nonetheless, there is no need to have the system active at all times as this would come at the risk of triggering unwanted movements on the prosthesis. With the brain switch, the user would thus also have the control of activating or deactivating the system whenever required.

We did not add any brain switch yet to our system as we are still reviewing the options at our disposal. One of the recent works we did was to investigate the use of Event-Related Desynchronization and Synchronization (ERD/ERS) as markers indicating movement onset/offset. As explained by Neuper and colleagues in [224], this desynchronization is mostly present in the alpha and beta bands (around 10 and 20Hz respectively) over the sensorimotor areas. More specifically, the ERD especially appears in alpha activity in the contralateral areas during movement planning and bilaterally with movement execution or imagination. The twin of ERD is the ERS which is characterized by an increase in the alpha band in the areas that are not involved in the task, this synchronization is said to be linked with an idling cortical activity, an inhibition of the cortical networks that are not engaged in the task. After movement offset, the sensorimotor areas will also display an ERD, with the activity going back to its original state. Moreover, the ERS is not only found in the beta band as what has also been a source of research is the so-called “Beta rebound” which is a very fast recovery and burst of the beta activity that appears after movement offset in the sensorimotor cortex. The idea was thus to use ERD and ERS for example as markers activating, before movement, and deactivating, after the movement, the BMI system, allowing it to move from a synchronous to an asynchronous interface.

To do this, we squared the amplitude of bandpass-filtered EEG signals of electrode C3 over the alpha (10-13Hz) and beta (16-20Hz) for several right-handed subjects. We remind that electrode C3 is located over the contralateral motor cortex for these subjects. We then averaged this activity for all the trials and computed the ERD% by choosing a reference period in the sequence. Specifically, we chose some data in the

first fixation cross before the “Go” instruction appears on the screen.

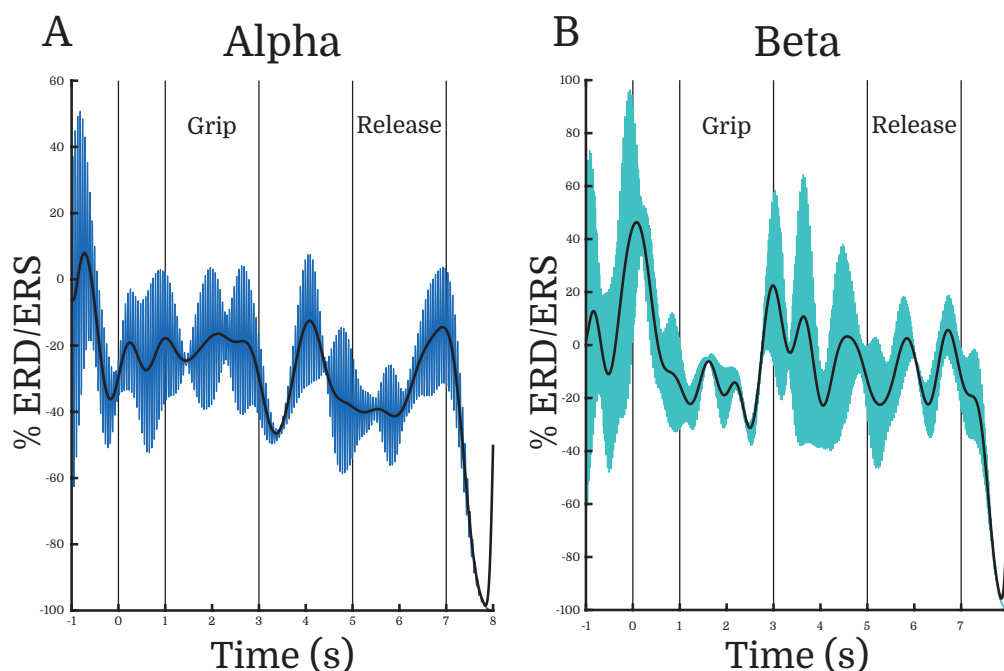


Figure 6.18. Representation of the ERD/ERS percentage for the cube and clothespin object combined. Zero represent the display of the “Go” phase on the screen. Each subsequent vertical lines represent the onset of a phase of the sequence. A. Signal for the alpha frequency band. B. Signal for the beta frequency band.

Fig. 6.18 A. represents the averaged amplitude of the EEG signal for the alpha frequency band. Here we wished to observe an ERD with a decrease of the EEG power before movement onset and during the execution of the movement. Nonetheless, we can note that the ERD% values are well under the values from the reference period and, during the Grip and Release phases, we observe a drop followed by an increase of the ERD% value. Similarly, in Fig. 6.18 B., which represents the power change of the EEG signal for the beta frequency band, we were expecting to see an ERD followed by the beta rebound with a fast increase in power after movement offset. Here, we do not observe precise beta rebounds in the GRIP and RELEASE phases although we do note a drop in ERD% just after the instruction followed by an increase after more than 500msec. The fact that we are not observing the expected changes in activity might come from the fact that the sequence of movements that we recorded presents too many different tasks for the user in a short interval of time. Pfurtscheller and Lopes da Silva recommended in [225] to have an inter-trial interval of at least 10s for voluntary limb movement studies which is not what we have currently as the sequence of movement takes about 10s in total.

This investigation was revealed to be inconclusive and we hypothesized other ways of implementing the brain switch in our system. Although we were not able to test it, we were especially interested in using eye blinks as a way to activate/deactivate the system. In Chapter 2, we briefly mentioned the work of Choi and colleagues [135] about the control of an exoskeleton with an asynchronous BMI, the monitoring of triple

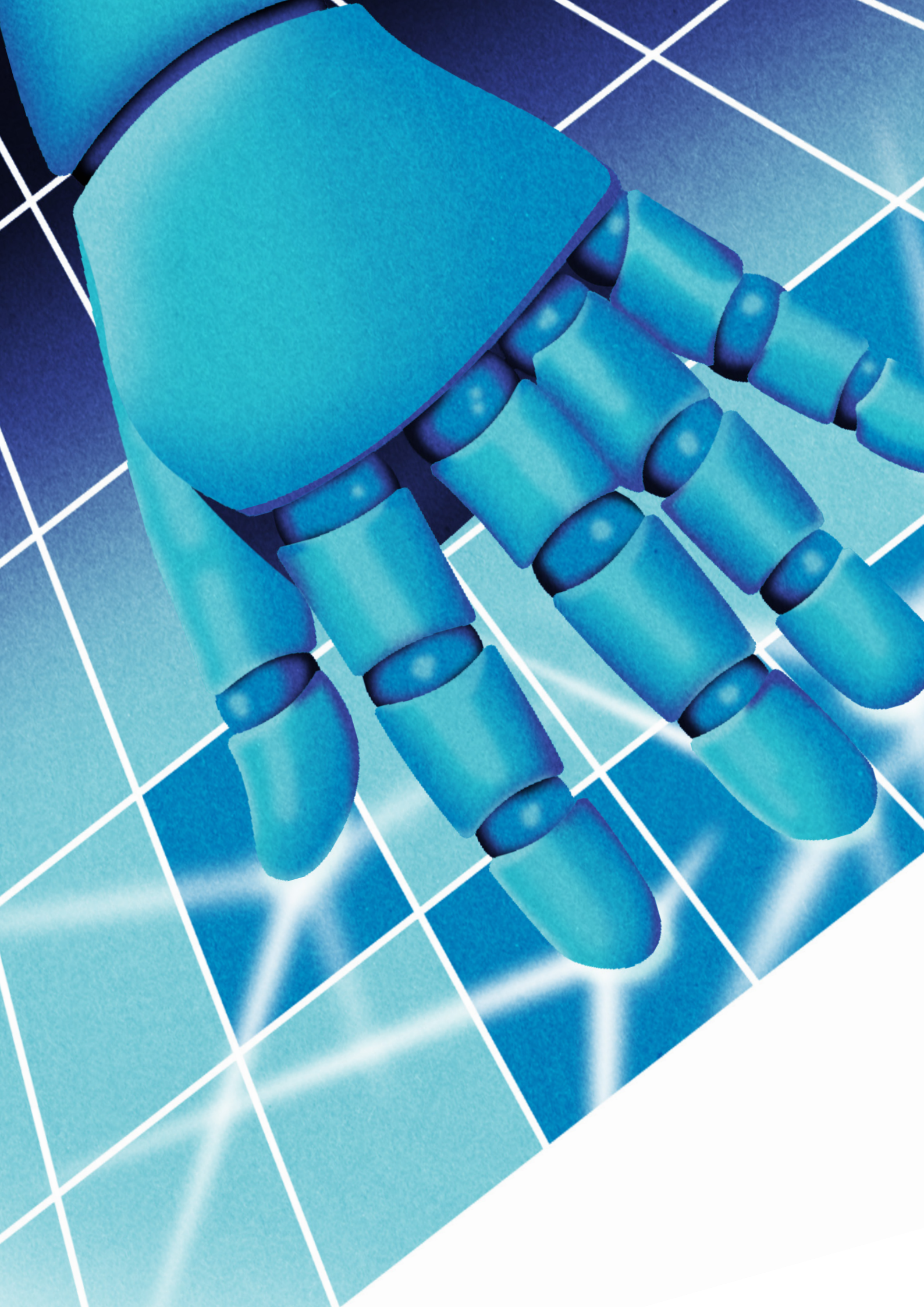
eye blinks on the EEG activity allowed for the recording of the EEG and the activation/deactivation of the decoders. To do so they used the activity of the two prefrontal electrodes, Fp1 and Fp2, filtered the signal, and counted the peak to distinguish between the unusual triple eye blinks and the occasional single or double blinks. One of the next steps in the development of the system will thus be to implement the detection of triple blinks and see if it could be used in our system. Nonetheless, this detection would still require the presence of prefrontal electrodes which is relatively incompatible with the use of the system during the daily-life, as the electrodes would likely be visible and not hidden in a cap of some sort. Other solutions could include again the monitoring of ocular activity but through an eye tracking device and not with the EEG system, we indeed see that some eye tracking glasses are available for research purposes and could therefore be used to track the blinks. Moreover, we will also look if it is possible to record residual muscle activity with EMG electrodes that would allow us to authorize the execution or not of a movement

Those additions would thus be another step to make the system easily usable as well as more reliable, yet it is required to keep in mind that adding the brain switch or the monitoring device should respect the primary and constraint functions we presented in Chapter III and it should also be integrated smoothly within the system, with potential communication between the devices and the smartphone, prosthesis or EEG system.

3. Run-down and Conclusion

During this chapter, we presented the test that the two groups had to do during their second and third sessions, as well as the architecture of the control software with the different functions we implemented and the choices we made regarding the various possibilities of control. Then we introduced the results we obtained with the subjects depending on the processing methods that were used. We also attempted to explain the possible reasons behind the low decoding performances while also providing some leads to improve it, by updating parameters or by only selecting subsets of electrodes. Moreover, we have also shown how the implementation of a control strategy, using the concept of Finite-State Machine, could reveal beneficial for the decoding performances.

Finally, the last part of the chapter focused on what can be done on the system to change the control from synchronous to asynchronous, which is the only type of control that could truly make the system be used daily. Here we particularly insisted on the notion of brain-switch and how it is relevant to the system.





VII

**The proposed system with
sensory feedback**

1. The use of sensory feedback in prosthesis: a short review

When we went through the various factors leading to prosthesis abandonment, we mentioned that the lack of sensory feedback coming from the prosthesis to the users was one of the main reasons leading amputees to remove their prosthesis. Even today, there are only a few marketable devices to target that need, with most of the research hardly escaping the laboratories, and this despite being a topic of interest for several decades (see [226] for historical background on the subject).

With upper-limb amputations, we note the deafferentation of the nerves that are connected to the hand. This loss of nerve fibres conveying information leads to a lack of touch or proprioceptive information returning to the prosthesis user. Indeed, with this loss, the connection to the cutaneous mechanoreceptors is lost and the tactile information can no longer move back from the Peripheral Nervous System (PNS) up to the Central Nervous System (CNS). There are four types of mechanoreceptors which respond differently to tactile stimuli, some only elicit action potentials during the phases when the skin starts or stops touching a surface or an object. Other mechanoreceptors send a response as long as the skin is touching the surface/object. Similarly, the proprioceptive information comes from proprioceptors that are located in the muscles, tendons and joints. Those located in the muscles or tendons provide information about the characteristics of the muscle: its length, the force exerted on it or the velocity at which its length is changing. The joint receptors are in charge of sending information about the position of the limb in space as well as the force and information about the movements performed.

To adapt to those changes with their prostheses, the amputees need to develop strategies allowing them to aggregate other sensory information: they will rely mainly on vision for most of the movements but they can also train to recognize the sound made by the prosthesis (specifically by the motor) under different circumstances or sometimes use proprioceptive information coming from the stump. What is also interesting to highlight is that the sensory feedback is not only needed to get the sense of touch or proprioception back but it is also of importance for the issue of embodiment of the prosthesis. Indeed, we saw in Chapter I that visual information is not the main component to keep the body schema intact and that exteroceptive and proprioceptive information are two important points for a good integration and embodiment of the prosthesis.

Yet, developing sensory feedback allowing the user to feel touch or to know the position of the joints of the prosthesis remains a challenging task, we can find different solutions in the literature to tackle this issue. Nonetheless, before looking at the methods to give sensory feedback for upper-limb prostheses it is interesting

to see what sensory information can be retrieved with a prosthesis (other than the ones we mentioned earlier). Nowadays, recent prostheses can have several sensors at their disposal but most of them are internally used for the control of the prosthesis without the information accessible to the users. In most cases in research articles, what we see is that the prosthesis is fitted with a variety of sensors which will serve to record touch or proprioception information, like the pressure applied on an object for example. The information has then to be encoded in a form that the prosthesis user will be able to understand. As explained by Raspopovic et al. [227] or Stephens-Fripp and colleagues [228], this question of encoded information is crucial. They remind us that, for the users, optimal or effective feedback should elicit the same sensations as what they were feeling with their biological hand. Not only does the feedback have to be modality-matched (also referred to as homology), meaning that pressure on one finger of the prosthesis should trigger a pressure sensation, but it also has to be somatotopically-matched, with the pressure on the finger eliciting a sensation on the same finger in the phantom limb of the user.

Similar to the way brain activity can be recorded, we can find invasive or non-invasive sensory feedback methods in charge of sending the information back to the CNS. Along with differences in the way the feedback is sent to the user, we will also note for both methods a different encoding of the information.

a. Invasive methods

With invasive methods, we can distinguish between two types of stimulation to transmit the information, the first one will be passing by stimulation of the PNS while the second type will consist in direct stimulation of the CNS.

i. Peripheral Neural Interface

This type of stimulation takes advantage of the presence of the nerves that were, before the amputation, connected to the mechanoreceptors and especially their end organs in the hand. There exist two kinds of interfaces that can be used to stimulate the nerves, called extraneural and intraneural interfaces. In extraneural interfaces, the electrodes that are used to stimulate the nerves circle around them but they are not inserted in the nerves. Their invasiveness and the damage they can cause to the nerves thus remain limited. Nonetheless, these electrodes suffer from poor selectivity as they cannot target individual fascicles or sub-fascicles in the nerve and mostly those located on superficial levels. To act on this issue without increasing the invasiveness of the electrodes, flat interface nerve electrodes (FINE) have been developed which are compressing the nerve and allow for better access to the fascicles as they are now spread out, offering a larger surface.

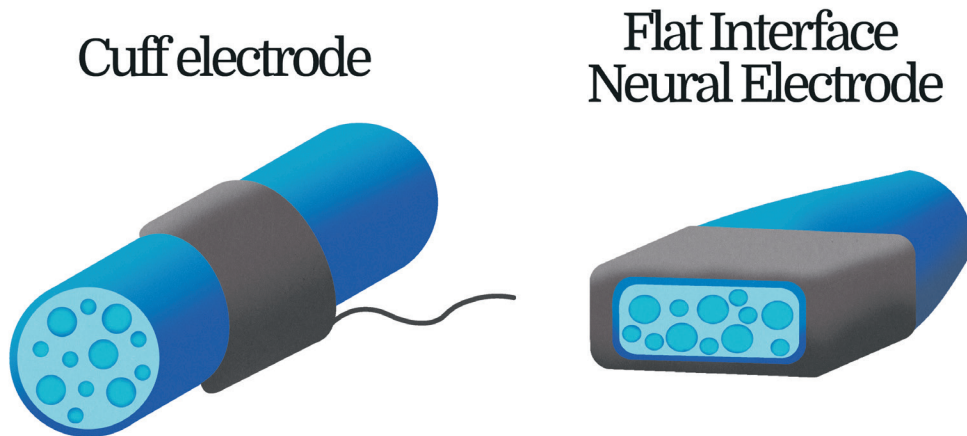


Figure 7.1. Two types of extraneural peripheral interfaces.

Going inside the nerves with the intraneural interfaces, they present a better selectivity as they can have access to both superficial and deep fascicles in the nerves, with the risk of creating some damage to them. The first type of intraneural electrode is the longitudinal intrafascicular electrode (LIFE). They can be inserted, as the name implies, longitudinally into individual fascicles. Then we find electrodes that are implanted transversely in the nerves for example the transverse intrafascicle multichannel electrode (TIME) which contains multiple electrodes capable of stimulating through several fascicles compared to LIFE. Evolving from the TIME and LIFE, the self-opening intrafascicular neural interface (SELINe) contains several wings with electrodes that will open once inserted into the structure of the nerve; the electrodes located on the wings can then penetrate inside the fascicles. The last type of intraneural electrodes that we will present are multielectrode arrays (MEA) previously mentioned in Chapter II. The Utah slanted electrode array (USEA), which can be found in the literature, presents around a hundred recording sites and target multiple levels of the nerve. Indeed, the electrodes are slanted on the array following the distal-proximal axis, allowing access to a large variety of fascicles in the nerve. Nonetheless, the transverse electrodes and the MEAs are the interfaces more prone to damaging the nerve, especially with the latter as the structure of the array is quite rigid.

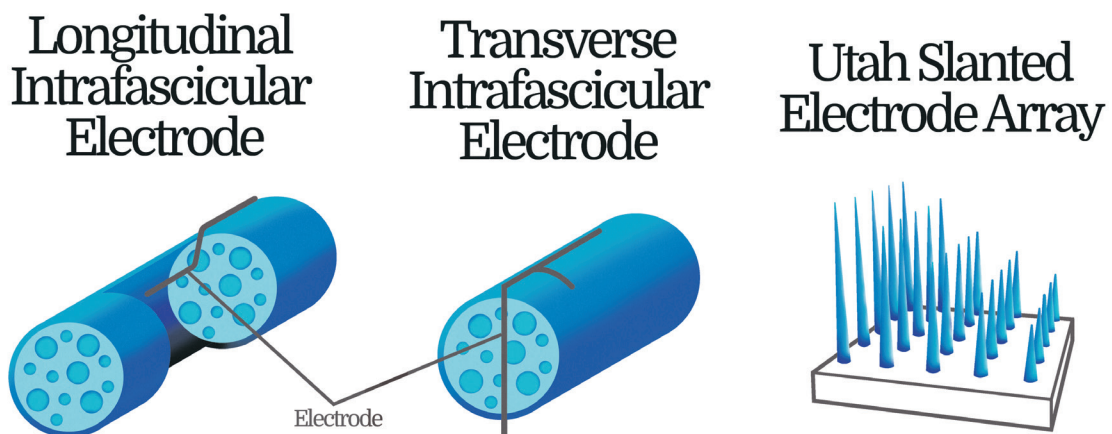


Figure 7.2. Three examples of intraneural peripheral interfaces.

Another concern with those peripheral neural interfaces is their stability over time. With extraneural electrodes, studies from Polasek et al. [229] and Ortiz-Catalan et al. [230] showed stability in the stimulation of the classical cuff electrodes in humans for at least 37 months after implantation for the first study and 3 to 7 years for the second study. Because of the damage to the nerve when using intraneural electrodes, especially with transverse electrodes, it is possible to observe the apparition of connective tissue surrounding the implants over time. The fibrosis induces an increase in the threshold needed to stimulate the nerve. Raspopovic and colleagues [227] explain that studies on rats showed a long-term implementation of TIME electrodes over time for up to six months (with a reminder from the authors that one rat month corresponds to about three human years). They also add that, concerning UESA electrodes, studies showed implantation of 3 to 6 months with a stability of the stimulation over time in cats [231] and humans [232]. Interestingly, another study using the classical Utah MEA instead of the UESA by Warwick et al. [233] showed a decline in the functionality of the MEA with only 3 electrodes working out of 22 at the end of the 96-day study. However, this drop was not due to the silicone electrodes but because of the mechanical fatigue of the connection wires.

Studies showed how the use of neural interfaces could be successfully used to encode sensory feedback, with elicitations of tactile and proprioceptive sensations. In particular, Tan et al. [234] showed that the use of cuff electrodes in two upper-limb amputees to stimulate the peripheral nerves allowed them to feel tactile sensations which could be controlled in size (the size of the area) or strength, by increasing the intensity or the frequency of the stimulation respectively. The subjects also reported that the sensory feedback on one hand reduced both the need for visual feedback and the phantom limb pain they had while; on the other hand, it increased the embodiment of the prosthesis. The subjects indeed pointed out that when the sensory feedback was active, the prosthesis and the phantom hand were making one while the prosthesis was considered a tool when the feedback was turned off. Finally, while the users describe feeling natural pressure sensations with a modulation of the stimulation intensity, constant intensity stimulation triggered “an unnatural sensation of paresthesia”, this advocates for a need for different stimulation patterns and find the one matching both in modality and somatotopically. Zollo and colleagues [235] presented results with an amputee equipped with both cuff electrodes and a ds-LIFE (a polymer-based LIFE); the user reported a natural sensation of slippage during the task, and the user could also perform the tasks in less time when the feedback was applied all the while presenting both better success rates and an increase in the force needed during the task. It is also interesting to note that the sensations elicited by the electrodes changed over time, going from movement sensations to tactile sensations. We also note similar results with tactile and proprioceptive sensations with subjects implanted with UESA electrodes [236] although it was noted that there was a decrease in the number of electrodes eliciting sensations over the five weeks of experiment which also came with an increase of the stimulation threshold. Finally, several studies using TIME electrodes

pointed out how the stimulation could be used to modulate grasping force [237] and elicit a large variety of sensations: object shape and compliance or surface recognition for example [238][239].

ii. Intracortical stimulation of the somatosensory cortex

The second type of interface we will present for the invasive methods is the intracortical stimulation of the somatosensory cortex. This technique is applied when access to the peripheral nervous system is not possible, like after a spinal cord injury for example. Similar to the invasive recording of the brain activity, here an array of electrodes is implanted in the somatosensory area that corresponds to the region of interest with respect to the somatotopic map. Bensmaia and colleagues [240] report two types of implants that are commonly used in research: the first one is the Utah electrode array (UEA), which is similar to the UESA we presented in the peripheral interface and presents 100 active sites, the second one is the floating microelectrode array (FMA) with 32 electrodes. The FMA presents the advantage of having microelectrodes with custom lengths depending on the needs, compared to the UEA whose length of electrodes is set at 1.5mm; this difference allows the FMA to target deeper brain structures in the cortex and potentially follow closely the somatotopy.

Successful applications of Intracortical microstimulation (ICMS) using such implants have been reported in the literature in both non-human primates and humans. As one can imagine, it is impossible to know for sure what kind of sensations this type of stimulation elicited in primates. Nonetheless, as shown in a study by Klaes et al. [241] where a monkey was trained to move a virtual robotic arm to perform several tasks, the use of ICMS and the sensory feedback it is creating is beneficial for the completion of the tasks. In particular, for the handbag task where the monkey has to find a target in a virtual handbag, the performance with the feedback was significantly better than in the no-feedback condition. In [242], Callier and colleagues trained three monkeys to discriminate between the frequency of the ICMS from 10Hz to up to 200Hz. This indicates that a range of discriminable perceptions exists when the frequency of stimulation is modulated; this range could be even more increased with changes in the amplitude of stimulation. However, the authors point out that “frequency and amplitude can never be completely dissociated” and that further investigation is required. The work done on humans is quite recent with a steady increase in the last few years with tetraplegic patients being implanted with MEAs. In an ongoing experiment, Flesher and colleagues [243][244] were interested in the bi-directional control of a BCI to control a robotic arm; a tetraplegic received four MEAs, two of them being located in the somatosensory cortex and for which the stimulation elicited sensations in the palm and fingers. The stimulation was encoded from the torque measurements of fingers on the robotic hand. Specifically, the index finger torque was in charge of eliciting index sensations while the middle finger torque was in charge of the sensations for the middle, ring and pinky fingers. The patient was then asked to perform different

functional tasks to evaluate both the control of the robotic arm but also the sensory feedback. The authors highlight that the performances with ICMS-evoked tactile feedback were higher than with only the visual feedback, and the time taken for the subject to grasp the object was also reduced with the use of the ICMS feedback. Moreover, the participant presented an increase in the performance of a functional test after the implementation of the feedback, and this effect disappeared as soon as the feedback was removed, showing the results were not due to training for the task but mainly attributed to relevant feedback provided to the subject. From the same team, Hughes et al [245] showed that the electrodes on MEA responded differently to changes in pulse frequency of stimulation. They divided the electrodes into three categories, those giving the highest intensity response for either the lowest pulse frequency (LFP), intermediate pulse frequency (IFP) or highest pulse frequency (HFP). They found that those three categories were leading to different perceptual qualities, for example, at a low frequency the stimulation elicited sensations of pressure and tapping in LFP and IFP electrodes. They also suggest that those perceptual responses were spatially organized in the cortex, with a clustering of some electrodes from the same category; yet more investigation is needed to identify the size of the clusters.

In a similar study where a patient has been implanted with two stimulating MEAs in S1, Armenta Salas et al. [246] showed that the electrodes were presenting a variety of evoked perceptions in the upper arm, forearm and fewer in the hand with a “coarse somatotopy” between the two arrays, stimulation of the medial array leading to more sensations in the anterior upper arm while stimulating the lateral array elicited more sensations in the posterior forearm. The possible reason giving for a not clear somatotopy might be the locations of the implants in the upper arm and forearm areas, with a “less established somatotopic map”. Nonetheless, the sensations reported by the subject were natural, covering both cutaneous/touch sensations and proprioceptive ones with a dominance of the former over the latter. The authors highlighted that higher amplitudes of stimulations were leading to more proprioceptive sensations, one potential reason might still reside in the location of the implants, with the upper-arm/forearm areas receiving more proprioceptive signals than cutaneous compared to the hand area. Moreover, the authors reported a positive correlation between the intensity of the sensations and the amplitude of the stimulation, with the subject mainly considering that the duration of the perception was short, only lasting briefly at the onset of the stimulation.

Finally, Bensmaia et al. reported in [240] the potential importance of learning in neuroprosthetics. In particular, they explain that ICMS is evoking unnatural patterns of neuronal activations in the cortex, which is an insurmountable barrier to pass if researchers are trying to evoke the same activation patterns as with a normal limb. Yet, they are quite confident in the ability of future users to learn to use new sensory mappings, arguing that biomimicry is not necessarily needed to achieve optimal sensory feedback. However, it is not yet possible to give an answer on the level of

complexity that can be reached as more studies are needed to assess the limit in learning and the adaptation of the brain to new sensory modalities.

b. Non-invasive methods

As with invasive methods, we find a variety of stimulation techniques for sensory feedback using non-invasive methods. We will not review all those methods but only present the most commonly found in the literature.

i. Electrotactile

The first non-invasive technique that we will mention is the electrotactile; as the name implies it consists in stimulating the skin with an electric current to elicit sensations. We find two different types of electrodes, they can be either epidermal, in which case the electrodes are located on the skin, or subdermal, where electrodes are made of microneedles penetrating the upper layers of the skin. Given the relative invasiveness of subdermal electrodes, the most used remain epidermal ones. To elicit the sensations, it is possible to play on various parameters of the electrical current such as the waveform of the pulse, usually set as a sine or square wave, or more classic parameters like the width, amplitude or frequency of the pulse. The modulation of the pulse width and amplitude act on the perceived intensity of the sensation while the pulse frequency modulates the perceived sensations.

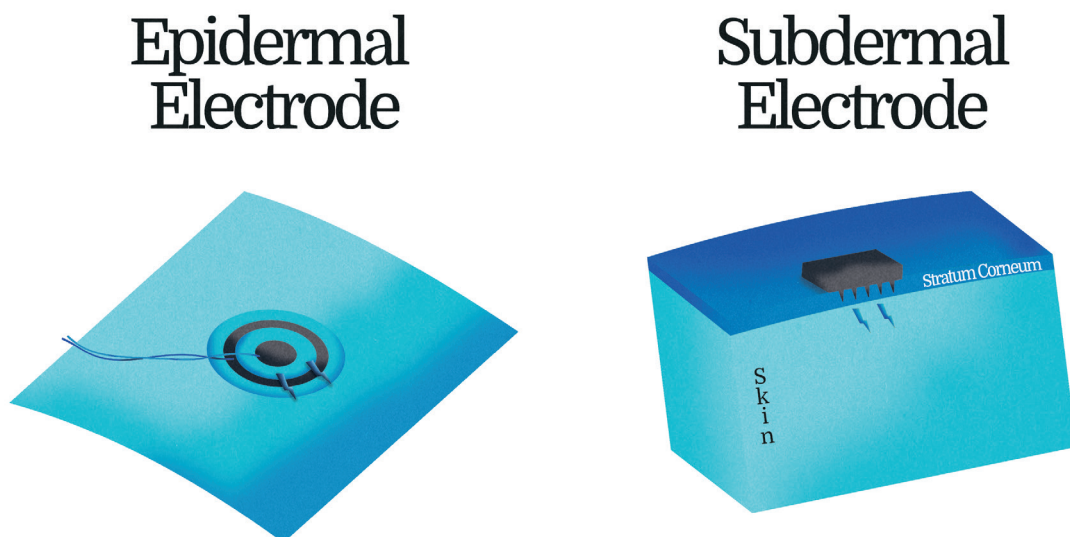


Figure 7.3. Two types of electrotactile electrodes. The epidermal electrode is at the surface of the skin while the subdermal electrode goes through the Stratum Corneum, the outer layer of the epidermis.

Nonetheless, one has to take into account the location of the electrodes before use. Indeed, putting the electrodes on thick skin leads to higher impedance and lower sensitivity to electric stimulation. This calls for the need for a proper calibration process

which will be used to define the low and high threshold of the stimulation, respectively the minimal stimulation to feel a sensation and the highest stimulation before feeling pain or discomfort. Much like the EMG electrodes, the electrotactile electrodes will more or less suffer from the same disadvantages; for example, the sensations will be altered with fluctuations of the skin like sweat or movement of the electrodes on the surface of the skin. This means every time the electrodes are moved out of their original location (even slightly) the calibration needs to be run again. This calibration is an ongoing research topic, in particular, the team of Isaković et al. [247] presented a method for optimizing the calibration of a multichannel electrotactile feedback system, by using a priori knowledge to guide the process. The question of the location of the electrodes can also be linked to the aim of having somatotopic feedback. Zhang et al. [248] investigated this topic by conducting experiments on amputees where they would either present feedback with the electrodes following the phantom map on the stump of the subject or with a non-somatotopic mapping of the electrodes around the forearm. The authors showed that, when the subjects were asked to distinguish between different electrotactile sensations in terms of position, type and strength, the somatotopic feedback was significantly better than the non-somatotopic one in both accuracy and faster response times. These results can either be explained by a stimulation of the phantom digits in the case of the somatotopic feedback or because the subjects are not trained enough to recognize the non-somatotopic mapping they were presented with.

Another concern that comes with electrotactile electrodes is the potential interaction of the stimulation with EMG electrodes on the prosthesis. The stimulation electrode is indeed generating interferences because it is inducing a voltage difference between the two sites of the EMG electrode. This effect can be alleviated by moving away the two kinds of electrodes but, if not possible, the noise from the stimulation can be reduced by reducing the size of the stimulating electrodes. In [249] Yang et al. propose the design of a concentric electrode with the intent of reducing the interference. The design is made of two concentric circular electrodes with opposite polarities to have mutual noise cancellation effect. Other studies are focusing on processing techniques rather than hardware modifications, in particular, Hartmann et al. [250] were interested in using artefact blanking (i.e. the removal of the data samples affected by noise) during the processing of the EMG data; Shuang et al. [251] proposed an adaptive filtering technique to remove the electric stimulation signals from the EMG signal.

Nonetheless, in a review from Kourtesis and colleagues [252], the authors highlight that most of the studies on electrotactile feedback are eliciting sensations on the forearm and very few on the upper arm and the studies are mainly focusing on healthy subjects or with amputees that are not controlling their prostheses. They stress the importance of having studies with patients using the prosthesis but also with electrical stimulation on the upper arm to have a closed-loop system. Such studies could help find if the feedback might have beneficial effects on the control of the prosthesis.

Specifically, they mention the work of Strbac et al. [253] and Cheng et al. [254] which are advocating that the use of electrotactile feedback shows promising results, even more when the subjects were able to learn to use the feedback after multiple days of experiments. Finally, electrotactile stimulation has also been combined with BCI control in a study by Achancaray et al. [210] yet the stimulation did not present any significant improvement over visual feedback; further investigations are thus needed to prove the benefits of sensory feedback produced by this technique.

ii. Mechanotactile

Mechanotactile feedback might be one of the only non-invasive techniques that allow for modality-matched feedback (with potentially the temperature feedback presented in the review from Stephens-Fripp et al. [255]). Indeed, the user is informed of the applied pressure on the fingertips of the prosthesis by applying the pressure on the skin on the forearm or upper arm. In their review [256], Schofield and colleagues present different devices that can be used for eliciting sensations. The mechanotactile devices mainly consist of either pneumatic bladders and pressure cuffs or servomotors. The first type of device works by inflating the bladder with air, the bladder will then put pressure on either small parts or around a large area of the forearm/upper arm. The second type relies on tactors actuated by servomotors; the movement of the motor is used to move the tactors and apply pressure on the skin.

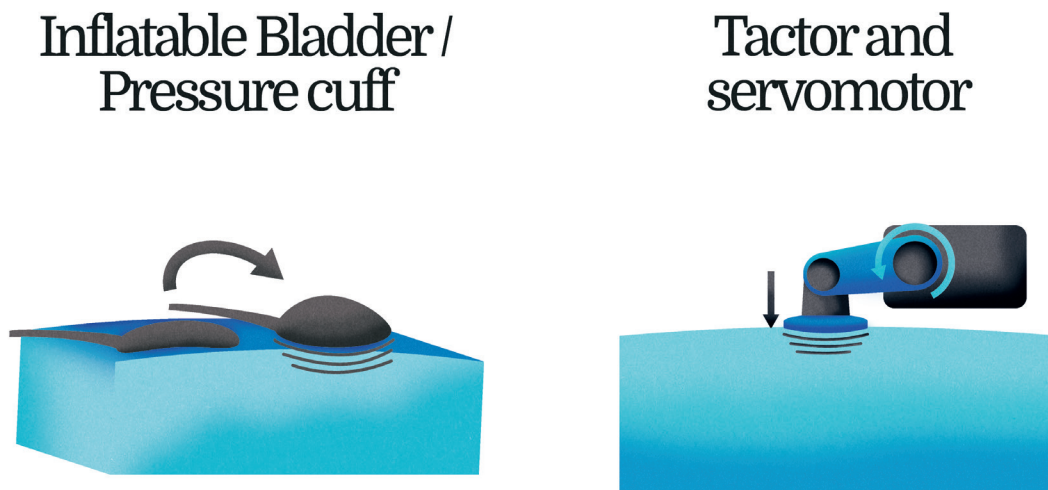


Figure 7.4. Two ways for mechanotactile feedback. Left : with bladders that inflate and put pressure on the skin. Right : with a tactor actuated by a servomotor whose rotation pushes the tactor on the skin.

Like with the electrotactile feedback, the mechanotactile devices can be set either by following or not the phantom map. For example, in a study by Wijk et al. [257], during the first meeting with the amputees the position of the phantom hand digits was marked and used to create a custom-made socket of the prosthesis containing five actuators, silicon bulbs which would apply the pressure on the skin. The new prosthesis socket, also containing sensing bulbs on the fingertips of the prosthesis, allowed the subjects

to do most of the tasks they were able to do with the original socket except when required to handle small objects or for heavy activities, as the subjects were not risking damaging the sensors. While there were no significant differences with and without feedback between the performances of the subjects in the two functional tests of the study, subjective responses in the questionnaire subjects had to fill showed that they considered the feedback as close to real tactile sensations which increased the feeling of body ownership of the prosthesis. However, the authors noted the reports from the patients, suggesting that the feedback needed to be stronger when they were using the prosthesis, as the contraction from the muscles was masking the feedback sensations. The appearance of the device was also not satisfactory for the subjects as the sensor bulbs added to the bulkiness of the prosthesis glove. Most of the patients chose to only use the prosthesis at their home because of a lack of confidence, which can be linked to what we have discussed in the chapter about amputation and prosthesis use. Nonetheless, this study presented the advantages of being set up in an ecological environment for the subjects where they were able to perform daily-life activities at their home and learn how to use the added information from the sensory feedback.

Borkowska et al. presented in their study conducted on able-bodied subjects [258] with a sleeve containing mechanotactile feedback made with a motor whose rotation was tightening the sleeve and compressing the forearm. The sleeve also contained EMG electrodes that allowed the subjects to control a prosthetic hand with force sensors on its fingertips; the pressure information detected by the sensors was then sent to the feedback device in the sleeve. The subjects then had to perform three different types of grasp, weak, normal or strong grasp, with the instruction of not breaking or dropping the cup. Results are showing that performing the tasks with the added sensory feedback was leading to a significantly higher grasp rate and, interestingly, there were no differences in the visual+haptic feedback compared to the haptic feedback-only condition. The authors are implying that either the subjects were relying less on vision to perform the task or that there was less delay in the transmission of the haptic feedback to the user. By studying the EMG traces from the three types of grasp they also showed that there was a correlation between haptic feedback and lower energy expenditure, pointing toward the fact that the EMG amplitude was significantly lower for the haptic feedback condition compared to the other two. This is interesting in the case of a closed-loop control which strives for the economy of energy when performing a movement. Nonetheless, the authors are well aware that the results they obtained might not be translatable to the amputee populations as they might not be able to perceive the same sensations if they were to use the haptic sleeve. Moreover, compared to amputees, the subjects of the experiments still had a sense of proprioception which could explain partly the results that were obtained. Future investigations from the team will require experiments with amputee subjects to see if the haptic sleeve can be used in the same way.

In a different experiment but still tested on able-bodied subjects, Shehata et al. [259] showed similar results to the study from Wijk and colleagues presented earlier. In this work, the subjects were going through two different tests: a passive and an active prosthesis test. A myoelectric prosthesis was fitted on the arm of the subject using a brace whose other purpose was to stimulate the thumb, index and middle fingers on the hand of the subject with mechanotactile tactors. During the experiments, the subjects could only see the prosthesis with a box and black sheet covering the hand and the brace. The passive prosthesis test consisted of four different conditions: first the synchronous or asynchronous brushing, where two brushes are used to touch the fingertips of the prosthesis and the intact hand, either with a delay or not. Then the synchronous or asynchronous tapping consisted of the experimenter applying pressure on the fingertips of the prosthesis, with sensors transmitting the information to the mechanotactile devices with a delay or not. For the active prosthesis test, there were 3 conditions: synchronous and asynchronous tapping, and no feedback. During the tapping, the participants were grasping different objects and the feedback was applied to the fingertips with or without delay. For the two experiments, the authors looked at the proprioceptive drift and filled questionnaires, the drift assessed if the subjects were more biased towards the prosthesis or their normal hand. Results showed an increased feeling of embodiment during the active task with the synchronous feedback being above both the asynchronous and no feedback conditions. The subjects also presented a prosthesis drift towards the prosthesis for the three conditions, but once again higher with the synchronous feedback. For the passive task, there were no significant differences between synchronous touch or brushing and the feelings of ownership and location were only present with the synchronous conditions. The system could thus be used to modulate different aspects related to embodiment, but as in the previous study, further investigations will be needed to evaluate the effects on amputees. The authors also question the need for quantitative measures regarding embodiment and its aspects like ownership or agency, especially during active tasks as a large part of the literature was dedicated to the measure during passive tasks.

The mechanotactile feedback is showing promising results but one concern that was raised in the different studies is the fact that mechanotactile devices present the disadvantages of being bulkier and heavier than other techniques. Moreover, and especially with the servomotors, they sometimes require more energy to be used which is an obstacle to their use.

iii. Vibrotactile

The last non-invasive method we will present in this review is also the one we ended up choosing during the PhD thesis. Like the electrotactile method, vibrotactile feedback is a sensory substitution technique that is not modality-matched as it will use vibrations on the skin to elicit the sensations. As explained by Stephens-Fripp and colleagues [255], most of the time in the literature the feedback is conveyed using small vibrating motors which will activate some mechanoreceptors in the skin of the subject. Using force sensors or other sensors on the prosthesis, the force/pressure information will be translated into vibrations on the upper arm or forearm of the subjects. Nonetheless, as we will see, the vibration motors are also used to provide not only tactile sensations like the grasping force but also more kinaesthetic information.

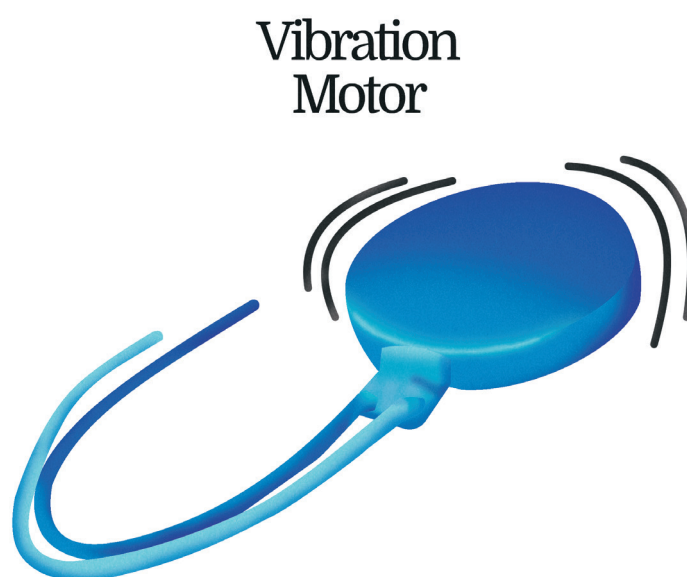


Figure 7.5. Vibration motor used for vibrotactile feedback. Represented here is a coin vibration motor.

In their 2015 study, Witteveen et al. [260] were interested in the discrimination of both grasping force and hand aperture levels using vibrotactile feedback. The subjects, with upper-limb loss, were looking at a virtual hand on a screen which was grasping objects of various sizes and weights. The grasping force feedback was either fed through a single tactor on the stump or with an array of coin motors on the forearm. For the hand aperture feedback, only the array of motors was used, and the motors could follow two different configurations, either transversal or longitudinal meaning that they were either placed around the forearm or along the forearm. The hand aperture task was split into two sessions with the first session having both visual and vibrational feedback while the second session only had vibrational feedback. In the grasping force task, the results showed that the presence of the vibrotactile feedback increased significantly the performance of the correct grasping force compared to the no feedback condition. There were no differences between the tactor and the array of motors. Moreover, the task durations between the different configurations were not different. For the hand

aperture task, without surprise, the performance on the task was significantly better with the combination of visual and vibrational feedback compared to only vibrational or no feedback. There were also no significant differences between the two configurations of the array of motors. The authors were also able to compare the performance of the amputees to the results obtained in previous studies with able-bodied subjects for the same two tasks. They showed that with visual feedback, the able-bodied subjects had significantly higher performances and reduced duration time in the hand aperture tasks compared to the amputees. Reasons could be that the able-bodied subjects were less naïve to computers and experimental studies than the subjects with upper-limb loss, and were also less aged which could explain the lower duration times. Nonetheless, in the absence of visual feedback, there were no significant differences between the two groups.

Once again with a partly virtual task, Raveh and colleagues [261] tested how vibrotactile feedback could impact user performance and visual attention in a dual task where transradial amputees had to realize a virtual task with their intact hands and perform different grasping tasks with their prosthesis. The aim was to look at the difference with and without feedback, which was given by four pairs of vibration motors. The feedback informed the subjects about the closure of the hand, indicated by different levels of pressure. The performance was calculated based on the time required to complete the task as well as the percentage of the total time when their car was off-road. Moreover, they evaluated the gaze behaviour by computing the time when the subjects focused their gaze on the screen and not on the prosthesis. Results showed that with the vibrational feedback, the total performance time was significantly shorter than without, but there was no effect of the feedback on the time off-road. The team highlighted that the use of the feedback did not affect gaze behaviour; they explain that it might be because the tasks performed required more attention and could not be performed easily. They argue that there is an immediate advantage of the feedback but it might require longer training to be fully integrated by the subjects.

Continuing with the same team, Raveh and colleagues [262] studied on able-bodied subjects the importance of vibrotactile feedback when visual feedback is disturbed. The subjects were performing a modified version of the box and blocks tests using a myoelectric prosthesis in three conditions: in full light, and a dark room with and without vibrational feedback. The authors showed there were no significant differences between the visual feedback condition (full light) and the vibrotactile condition but both conditions were different from the no vibrotactile conditions. Indeed, when the vision is disturbed, the addition of the vibrotactile feedback improved the performance while also reducing the number of errors, reaching performances close to those obtained in full light. Compared to the two studies we presented, here the authors highlight the importance of grasping real objects instead of virtual ones, questioning the generalization issues caused by virtual grasping tasks as they might not be translatable to real life.

Using vibrotactile feedback, Thomas et al. [263] wondered about comparing this feedback and joint-torque feedback under different conditions with a task performed by able-bodied subjects. They were asked to discriminate between blocks of different stiffness without visual feedback under three conditions: with vibrotactile or joint-torque feedback and without any feedback. The grasping of the blocks was made possible by a voluntary-closing prosthesis that the subjects were controlling based on the recording of EMG activity. They reported higher performances with the sensory feedback conditions compared to the no feedback one, yet there were no differences between vibrotactile and joint-torque feedback. The authors hypothesized that there were no differences in how the subjects were encoding the force information, with both tactile and kinaesthetic sensations leading to the same performance. Subjective surveys filled out by the subjects also allowed them to report that the presence of feedback led to less cognitive workload when performing the tasks, possibly by reducing the importance of having to rely on visual information. They also argue that with the presence of visual feedback, the performance could have been better as the subjects would have had the opportunity of seeing the block being deformed by the grasping. Moreover, one of the limitations that they report is that, because the feedback was given on the contralateral arm, the elicited sensations which are less natural probably reduced the performance of the subjects.

Finally, the work of Markovic and colleagues [105] was the one that inspired our team the most when working on the implementation of sensory feedback in our system. In their study, amputees were performing four different tasks over multiple sessions with and without vibrotactile feedback, which was given by a vibration bracelet with multiple motors located on the contralateral upper arm of the subjects. The four tasks, composed of the box and blocks tests, the cup relocation test, a block turn task as well as a clothespin relocation test presented increased complexity. Here the authors reported that the vibrotactile feedback was only useful for the more complex tasks as the performances in the simpler tasks were not affected by the feedback. They suppose that there is a possible redundancy of the feedback appearing with the training to the task as the subjects might not need the feedback as much when they are more experienced in the task. Nonetheless, they also hypothesize that for certain tasks the performance could get better as the subjects are learning to exploit the feedback. Interesting results were obtained by subjective reports from the amputees which showed that, even though it was not improving the overall performance, the addition of the vibrotactile feedback was always considered positive when performing the tasks. They indeed explain that the feedback was comprehensive and useful and that the embodiment of the prosthesis was significantly greater with the feedback condition even though its use led to an increased workload.

Some limitations and disadvantages reported in the studies concern the need for longer training for the subject to fully exploit the feedback. Studies also wonder about the potential addition of the vibrotactile feedback inside the socket of the prosthesis

which could raise the same issues as the EMG electrodes as well as possibly create interferences with the recording of the muscular activity. Moreover, the delay in the generation of the vibration, the limited bandwidth of vibration as well issues depending on how the vibration frequency is perceived if the motor is not tightly/too tightly attached are pointing out a need for more research to develop reliable sensory feedback.

c. Conclusion

As we have seen, not only does the sensory feedback have the role of conveying sensations that were lost after an amputation, which can be proprioceptive or exteroceptive, but those sensations can also either be somatotopically and/or modality matched. We presented different techniques allowing prosthesis users to feel tactile and other sensations. Similarly to the brain recording techniques, the invasive techniques are offering the most natural type of sensory feedback yet the required surgeries are obstacles to their widespread use. On the other hand, non-invasive techniques can be more easily scaled or integrated into prosthetic devices but yet there is still a need for deeper research to understand the benefits of the feedback in terms of prosthesis control. Nonetheless, other than the issues raised regarding objective measures, we have shown that many studies pointed out how the sensory feedback was crucial in how well accepted the prosthesis is by the user, with an increase in the embodiment of the device in presence of the feedback. Despite those potential advantages, the ambiguity of the objective benefits is slowing down the applications outside of research.

2. Development of the device

From the article of Markovic and colleagues [105], we retrieved the idea of making a sensory feedback bracelet with vibrating motors that could be used with both amputees and able-bodied subjects. The idea behind the addition of sensory feedback in our BMI system was to evaluate its contribution to the performance of the control of the prosthesis. We thus tried to develop a sensory substitution system that could be easily implemented on the prosthesis as an add-on.

a. From the first to the current version of the system

Right from the beginning, we were set on the idea of using a combination of several force sensors on the fingertips of the prosthesis that would each be connected to vibration motors located on the upper arm of the subject. The prototype was composed of a bracelet containing four vibration motors, the bracelet was itself connected to an Arduino Uno microcontroller as well as three force sensing resistors (FSR) that were located on the thumb, index and middle finger of the prosthesis. This first iteration of the sensory feedback system has never been used during experiments and was only used during demonstrations at the IRMA or in the lab (Fig. 7.6). There

were several limitations to the design that would have made it difficult to be used by subjects: first while working as expected, the bracelet was not comfortable for long time use. Secondly, the whole sensory feedback system was bulky and was only working with all the parts connected with cables. Third, the Arduino board had to be powered by a computer or through an electric outlet which made the system impossible to carry around.

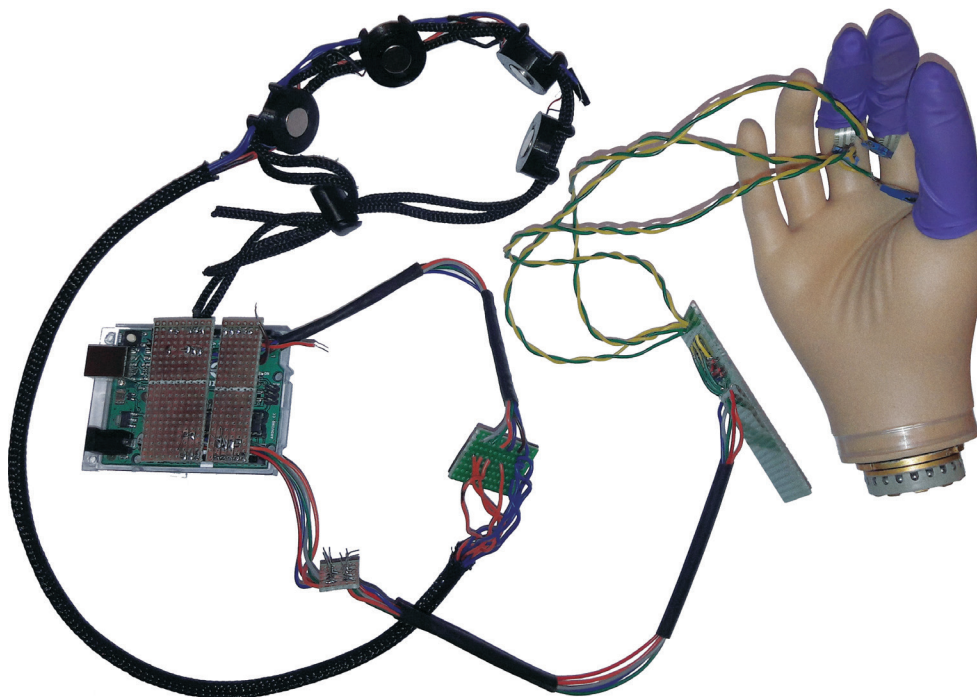


Figure 7.6. First iteration of the sensory feedback system. Vibration motors are located in 3D-printed shells and connected to an Arduino UNO board which is also used to connect to the force resistive sensors on the fingertips of the prosthesis.

The second iteration of the sensory feedback system allowed us to work on those issues and refine the system (Fig. 7.7). The second version of the bracelet was handmade and sewn in elastic fabric, the inner part contained several notches to fit the vibration motors and was used to hide all the cables needed for the connection to the Arduino. All the electronic parts were enclosed in a 3D-printed case, it contained a small PCB with components needed for the connection to the motors, an Arduino Nano 33 BLE with a built-in Bluetooth module and a rechargeable battery to power it all. The bracelet once again was composed of four vibration motors, three of them were connected to the fingertips on the prosthesis and, for the fourth one, we were trying to see what kind of information we could convey that was different from the force information. A suggestion we received from Dr Jose González-Vargas from Ottobock, but have not yet tested on the system, was to feed the classification result as a vibration to the user, indicating to them the movement that has been recognized. Other options we considered were to put different sorts of sensors on the prosthesis like temperature or proximity sensors and translate the information into vibration. Thanks to the Bluetooth connection with the Arduino board, we could get rid of the cabled connection between

the vibration bracelet and the force sensors. The second part of the system was thus the Arduino board, another Arduino Nano 33 BLE, connected to three force sensors going on the fingertips of the prosthesis. Like with the vibration bracelet, we also 3D-printed a case enclosure to fit the Arduino, the PCB as well as the battery.

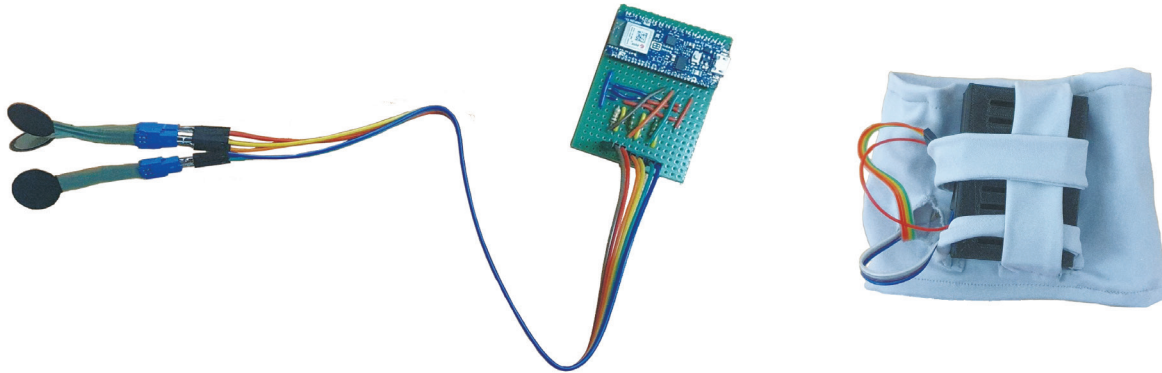


Figure 7.7. Second iteration of the sensory feedback system. Here the communication between the two parts is wireless and rely on two Arduino Nano 33 BLE boards. The vibration motors are located in a soft and extensible fabric.

The third and current version of the system is once again composed of two parts (Fig. 7.8). The vibration bracelet is made of two 3D-printed parts that can be connected: the first part is the bracelet in itself, it contains three notches to fit the vibration motors. Although all the cables from the motors are visible this design never suffered from any damage or malfunctioning contrary to the elastic bracelet in the second iteration. Indeed, due to the repeated extensions on the fabric, the cables tended to de-solder quite often. The second part of the bracelet is the 3D case with the microcontroller, the circuitry and the battery, it connects with the bracelet through an interlocking joint that is securing the assembly. The rationale behind the choice to split the bracelet into two parts was that, with the current design, any repair would be easier to proceed with. We also reduced as much as possible the form factor of the bracelet, the first part has only been made in one size and a Velcro strap was used to adjust to most of the subject's upper arms sizes.



Figure 7.8. Third and latest iteration of the sensory feedback system. The two parts are communicating using two Bluno Beetle boards from DFRobot.

There are nonetheless two limitations that we can highlight with this design of the bracelet, first for the thinnest arms the bracelet was sometimes hard to adjust, even with the Velcro strap being set to the tightest. Second, the thickness is probably too thin which can reduce the sensations coming from the motors, with the 3D-printed part also vibrating. Those two issues can make difficult the recognition of the vibrations by the subjects during the test. The second part of the system is similar to the previous iteration but with a smaller form factor. At first, the 3D enclosure was supposed to be combined with a 3D-print rigid wristband to fit on the socket of the prosthesis of the amputees or the intact wrist of able-bodied subjects. During experiments, we decided to tape the case to the device for able-bodied subjects or on the prosthesis which was more convenient and less burdening for the subjects. Because of issues with the Bluetooth connection and the need to reduce the bulk of the devices we also decided to change the microcontroller used in the two parts. Our choice fell on the Bluno Beetle boards which are much smaller in size than the Arduino Nano boards, the connection between the two boards is also more stable. Nonetheless, these boards only have two PWM outputs meaning that, without any modification to the PCB, we can only modulate the vibration of two motors maximum. This issue turned out to be not so restrictive as we were able to combine the force sensors of the index and middle fingers into only one because, on the Myobock prosthesis we used, those two fingers are linked to each other.

b. Future improvements

From the current version of the system, we can think of multiple leads for improvement that would bring it closer to a system usable during daily life. First, the force sensors would need to be integrated inside the glove of the prosthesis instead of being fixed directly on the fingertips. During the experiments we indeed had to change periodically the FSR as the repeated opening/closing and grasping movements were damaging the sensors. Specifically, with the clothespin object, the position of the sensors had to be adjusted because the pressure was making the sensors move out of their original position which might have affected in some ways the experiments. Ideally, if the sensors are integrated into the prosthesis, and because more advanced prostheses (especially polydigital ones) are now connected to smartphones, they could replace the need for the force sensors microcontroller and directly communicate with the vibration bracelet. With the sensors directly integrated inside the prosthesis, it will also be possible to consider using more sensors of different kinds, for example, to indicate the level of aperture of the hand.

Second, as raised by the issues we faced during the experiments, there is a need to modify once again the design of the vibration bracelet. The first change should be to make sure that the vibrations of the motors are not spreading too much on the bracelet. To do this we will either increase the thickness of the bracelet and/or add anti-vibration pads that will focus the vibration on the skin. Moreover, we also need to do some more

tests to verify how the contact with the motors is with different arm sizes, this might lead us to design several bracelet sizes that could guarantee a standardized position of the motors as well as elicit the same sensations in all the subjects. We will be testing out those solutions as soon as possible on several able-bodied and amputee subjects. Third, while we do not need more than two motors with the Myobock prosthesis we have used until now, this will change if we start doing some experiments with other types of prosthesis such as the Michelangelo or the i-limb. There are three possible modifications that we can do regarding this, the first would be to change the microcontroller we are using and find one with more PWM outputs. Yet, to our knowledge, we did not find any board with such outputs in a similar form factor. The second modification might be to buy a module with additional PWM outputs but this solution would likely require to increase the size of the enclosure, although we are striving for the opposite. The last solution is this time software-based and would consist in using Arduino libraries that are allowing to get a PWM signal from non-PWM outputs, by changing the pin from HIGH/LOW with varying frequencies. This solution is ideal in that there is no need to change the hardware or add any components yet there might be a risk of the code not running as smoothly if the resources allocated to the software PWM are too high. The first step will thus be to test those libraries and see if there is any additional delay in the vibrations.

Finally, another improvement will be to work on the general design of the vibration bracelet, which is ultimately the part that might not be integrated into the prosthesis socket. The primary change will be to hide as much as possible the cables from the bracelet by either masking them with the use of fabric all over the bracelet (the fabric could also be personalized from user to user if we think of a marketable device) or by adding cable feedthrough to the design. As of now, the total cost of the sensory feedback device is relatively low, less than 100€ to have a functional system, we aim at keeping the same limit in terms of price or even optimizing the price.

3. Analysis of the preliminary results

In Chapter III we mentioned that, for the development of the system, sensory feedback was part of the primary functions, with the need of it being informative and coherent for the user. To see if it is being integrated by the subject, we can look back at the results and see if there is a difference in performance with and without the feedback.

a. Comparison between the recording sessions

We can start by looking again at the evolution of the offline performance of the SVM RBF for the six one-vs-one classification models for the able-bodied subjects along the three sessions.

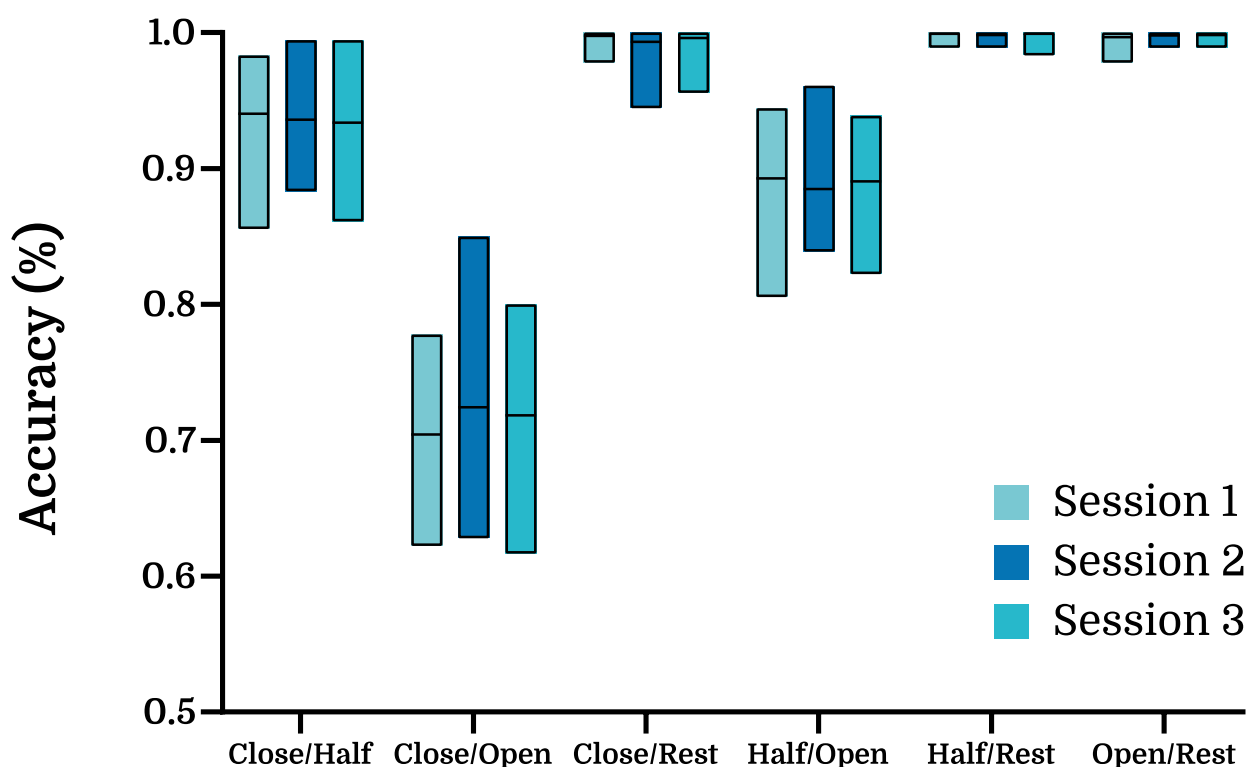


Figure 7.9. Accuracies of the SVM RBF algorithm for the six one-vs-one models of the able-bodied group in the Motor Execution condition along the three sessions. * indicates significant differences.

From Fig. 7.9, it is difficult to estimate if the results obtained are due to the training of the subjects for the task or if it is due to the use of sensory feedback. In Chapter IV, we explained that Wilcoxon tests on those performances showed no significant differences between the sessions for each of the models. At first, we could have hypothesized that the use of the prosthesis in session 2 could diminish the performances of the subjects as they are not trained to use this device, which might be reflected in the higher variance we can observe in some of the classification models. The fact that we are not observing any differences between the sessions can be explained by the task that was performed by the subjects which might not be designed to assess the need for sensory feedback, as they are not asked to discriminate between different levels of vibration or different objects. Here, the visual feedback was still the main feedback on which the user could rely, especially as the task consisted in grasping and moving repeatedly an object. Moreover, although the subjects were introduced to the sensory feedback system at the end of the second session, the training to understand the feedback was really short mainly due to the length of the recording sessions. It would probably require a few more sessions to see the effect of the sensory feedback over the no-feedback condition.

Although we could not test a large number of amputees, it is still possible to look at the trend of the results obtained with the subjects.

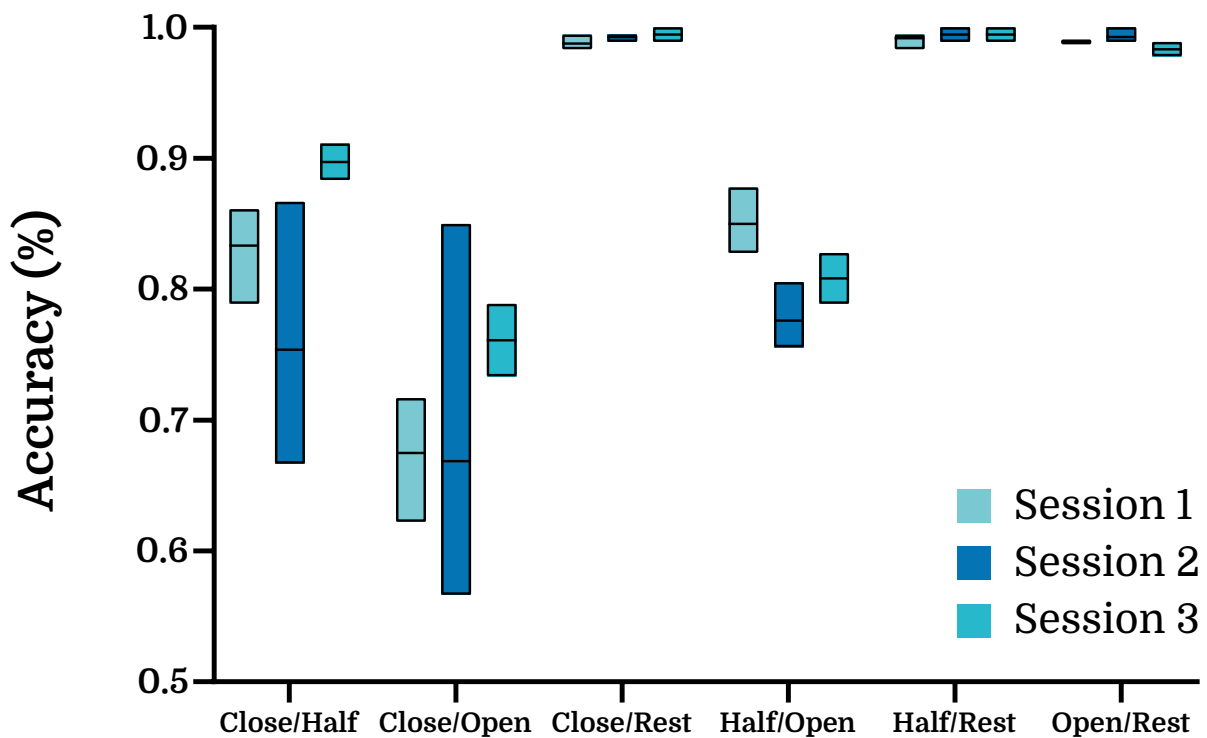


Figure 7.10. Accuracies of the SVM RBF algorithm for the six one-vs-one models of the amputee group in the Motor Execution condition along the three sessions. More data is needed for running statistical analysis.

Here is the trend regarding the evolution of the accuracy which is more along the lines of what we could expect (Fig. 7.10). During the first session, the subjects were using their original prosthesis, with which they probably developed alternative sensory feedback strategies that they are most comfortable using. In the second session, we changed the type of prosthesis, although they probably used a similar model of prosthesis in the past, the feedback strategies they might have been using until now were disturbed. We can suppose that this change of prosthesis is not only reflected in the drop in performance but as well as in the higher variance that we can observe for some of the binary models (Close/Half and Close/Open more particularly). What is also interesting is that in the third session we observe an increase in offline performance. This increase can be due to the familiarisation of the subjects with both the task and the change in prosthesis but it might also indicate the usefulness of the vibrotactile feedback for the subjects. It is still unclear if this feedback contributes to creating distinct brain activity patterns in the cortex of the subjects, and if the newly learned feedback is more efficient than the strategies the users might have developed over time with their original prosthesis.

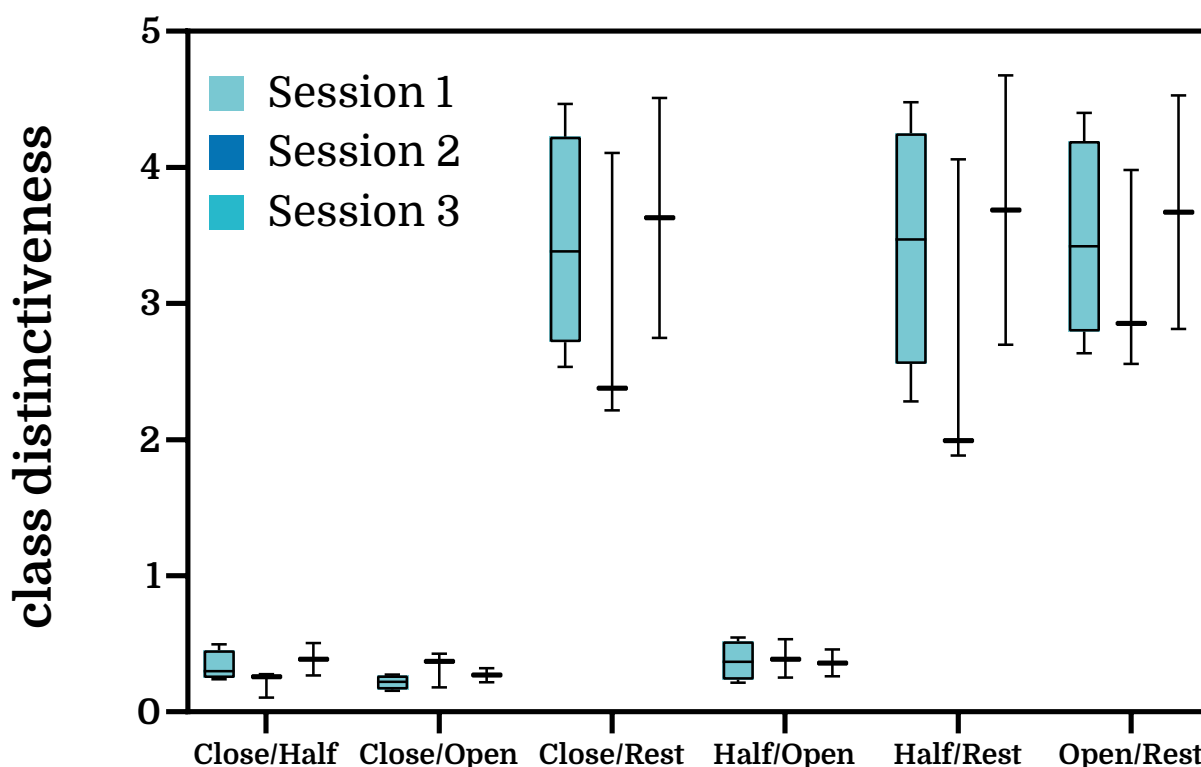


Figure 7.11. Evolution of the class distinctiveness metric for the six one-vs-one models of the amputee group in the Motor Execution condition along the three sessions. More data is needed for running statistical analysis.

If we indeed look at the class distinctiveness results for the three sessions (Fig. 7.11) it is quite impossible to rule in favour of more distinctiveness between the brain activity patterns for the movements. For some of the classification models, we observe an improvement for the third session over sessions one and two, but the lack of subjects does not allow us to go any further in the discussion. What was showing through from the discussions we had with the amputees was that they could feel that the feedback added another dimension to the task they were performing and that they could link the vibration to the pressure applied to the object. It was indeed especially tangible when the subjects had to grasp the clothespin, as the force needed to open it was triggering intense vibrations. These results are thus quite reassuring to see and can comfort the idea of pursuing the development of the sensory feedback system. Nonetheless, there is still the need of recruiting and passing the experiments with more amputees to confirm the trend.

b. Comparison between the testing sessions

We can not only compare the offline performance obtained during the recording sessions but it is also possible to look at the results we obtained during the test phase of the second and third sessions.

	Grip			Release		
	BB	CUP	CS	BB	CUP	CS
Session 2	56,7	34,1	76,7	97,8	60,7	93,7
Session 3	79,6	40	73,3	97,0	75,3	89,3
% Increase	40,6	17,4	-4,3	-0,8	23,9	-4,7

Figure 7.12. Mean performance for the 30 trials of the Online test with the three objects in the Grip and Release phases for the second and third sessions in the able-bodied group. Also represented is the percentage of increase between the two sessions.

Fig 7.12 represents the mean performance over the three runs of 10 trials for each of the objects in the GRIP and RELEASE phase using the Finite-State Machine strategy we introduced in Chapter V. Also represented is the percentage of increase or decrease between the two sessions. Here what we would expect is an increase in the performance between the second and third session mainly for the GRIP phase because this is where the feedback will have the biggest role compared to the RELEASE phase. We can observe an increase for both the BB and CUP objects during the GRIP and a slight decrease for the CS object. The difference in increase between BB and CUP could potentially find an explanation behind the fact that the feedback was much stronger when grasping the cube than when grasping the cup due to the locations of the force sensors on the fingertips. Nonetheless, this explanation does not hold up because of the decrease with a clothespin, for which the vibrations are higher than for the two other objects.

We can finally look at the same table but for the amputee that was able to do both of the testing sessions.

	Grip			Release		
	BB	CUP	CS	BB	CUP	CS
Session 2	46,7	46,7	73,3	100	73,3	100,0
Session 3	26,7	70	66,7	100,0	93,3	93,3
% Increase	-42,8	49,9	-9,0	0,0	27,3	-6,7

Figure 7.13. Mean performance for the 30 trials of the Online test with the three objects in the Grip and Release phases for the second and third sessions for the amputee. Also represented is the percentage of increase between the two sessions.

In Fig 7.13, we observe similarities in the results obtained with the able-bodied in the RELEASE phase but the trend is different regarding the GRIP phase, we can indeed note a decrease in the performance with the BB and CS objects between the two sessions and an important increase for the cup. We explained in Chapter V that the results might be explained by the general fatigue of the subjects who have to go through a lengthy EEG recording before doing the tests.

4. Run-down and conclusion

In this last chapter, we were interested in the topic of sensory feedback and we explained how crucial, yet underrepresented, it is for the control of prostheses. The first part allowed us to review some of the existing methods to elicit sensations, either by invasive or non-invasive techniques. As we are developing a system based on non-invasive techniques exclusively, we focused the review on the non-invasive method and specifically presented work done on vibrotactile feedback.

The second part was dedicated to presenting how we created the sensory feedback device that was used during the experiments but also present the future improvements that are needed to answer the functions we mentioned in the bill of specifications in Chapter III. The improvements are not only hardware-based, with a change of design or the use of different sensors but also software-based, with changes in the feedback script and how the information is translated into vibrations.

Finally, the last part of the Chapter was aimed at exposing the preliminary results obtained in the experiments, even though only a few amputees were able to do the three-sessions experiments, we decided to present the results we obtained with them as well as those from able-bodied subjects. What we saw from those results is that there is no big difference regarding the absence or use of the sensory feedback for able-bodied subjects; the results are different for the amputees and correspond to what we expect with an improvement of the decoding accuracy between the second and third sessions. These preliminary results are suggesting a potential benefit of the sensory feedback that could be lying in the brain activity patterns of the amputees.

Conclusion

1. Summary of the PhD work

During this PhD project, we aimed to offer a proof of concept regarding the control of upper-limb prostheses using a non-invasive Brain-Machine Interface. To develop this system dedicated to upper-limb amputees, the work revolved around three main axes:

- Selecting the signal processing techniques and classification algorithms
- Choosing a suitable EEG system
- Investigating the effect of sensory feedback on the control loop

To orientate our work toward a system that can be used daily, we have established a bill of specification grouping the functions that are required on the system. After three years of work, it is, of course, difficult to satisfy all the criteria of the interface, but, this preliminary work has nonetheless been essential as the criteria accompanied us along all the development phases that we faced thus far. In particular, they also guided us in the design of the experiments that we performed with amputees and able-bodied subjects, which were composed of a sequence of movements where the subjects had to grasp and release different objects. With those experiments, we aimed to classify the brain activity of four different movements that could be used to control the Myobock prosthesis from Ottobock. Although classifying four movements necessarily meant a simplification of the system, it was needful to build a strong base on which we were able to develop the system. Moreover, there were very few examples in the literature dedicated to the classification of unimanual movements to be used in a brain-machine interface. And this was an even more interesting challenge to tackle with amputees as even fewer studies in the BMI field were centred around them. As such, we did our best to include them in as many steps as possible during the development, along with the collaboration of Ottobock and the IRMA. Working with amputees has been decisive as they opened our eyes to many details that would have gone unnoticed. Nonetheless, working on this project has remained a challenging task as the experiments were required to be run simultaneously with the development work of the system, leading to evolutions of parts of the system along the way. But this joint development also proved to be beneficial, bringing the system to its actual state.

a. Selection of the signal processing techniques and classification algorithms

Before setting our choice on the current version of the processing and classification pipeline, we first compared different techniques and algorithms for the four-class classification problem that we obtained thanks to our experiments. In particular, we first started by comparing the classification performances of the system with different combinations of three well-known feature extraction techniques: Common Spatial Patterns, Wavelet Decomposition and Gram-Schmidt Orthonormalization. The

results we obtained with the two groups of subjects showed that the combination of CSP and WD yielded the best performance over the rest of the combinations. Always with the work presented in chapter IV, regarding the classification part, we aimed to highlight differences in performance between three algorithms: Artificial Neural Network, Support Vector Machine with a Linear Kernel and with Radial Basis Function Kernel. The results showed that there were no significant differences between the three algorithms although we highlighted better results with the RBF SVM.

In chapter V, we detailed the work using Riemannian geometry and more specifically, we got acquainted with other classification methods based on this concept that we compared with the widely used methods presented in chapter IV. Here we studied this alternative method that is exploiting spatial information contained in the EEG signal and applied it to the classification of the four upper-limb movements. In particular, we used two other classification methods, the first being applied directly on the Riemannian manifold while the second is applied on the tangent space to the manifold. With the first method, the MDM algorithm, we obtained performances close to or slightly lower than those with the widely used classifiers from the first study (on which we added a Linear Discriminant Analysis classifier). The second method allowed us to work with more advanced classification algorithms. In particular, we used a Tangent Space SVM for which we obtained significantly better performances compared to most of the other algorithms. The use of Riemannian geometry brought a new perspective to our work and on how we could process the EEG signal by looking at covariance matrices. Nonetheless, as reminded by Barachant in his conclusion [150], one has to be careful when using the tangent space method as it is more sensitive when the number of electrodes used is high.

b. Choice of the suitable EEG system

This last remark also resonated with one of the challenges in the development of the BMI system that stemmed from the specifications we established in Chapter III. For the experiments, we used two EEG recording systems: the first one was a medical grade system composed of a cap with 64 electrodes that we used on able-bodied subjects, and the second one was composed of a cap with 16 electrodes that was used with the amputees. Here to compare the results obtained with the two recording systems, the 16 electrodes of the 64-electrodes system which are in common with the 16-electrodes system were processed. While there is probably more at stake to fully compare the two systems, these first results were interesting to discuss the choice of an EEG system for this application. In particular, we highlighted that the performances obtained with the gold standard system were significantly better than the other system mostly when comparing one movement to another (Close vs. Half for example) while there were no differences between the two systems when comparing one movement vs the neutral/resting movement (Close vs. Rest). While those results showed that the gold standard system was still the preferred choice to achieve a better performance, the results also highlighted that reducing the number of electrodes to 16 could lead to

promising results regarding our application.

The reduction of the electrodes has also been one of the key points of the second work presented in chapter V. We studied several combinations of electrodes that were either centring around the motor cortex or focusing on other areas. We showed how this selection of electrodes led to a drop in the performance of the classification algorithms (with both state-of-the-art and Riemannian-based ones) while it was also improving (to various levels) the distinction between pairs of movements (by computing the class distinctiveness metric). Even though we observed this loss in the classification accuracy we then discussed the trade-off it constitutes: reducing the number of electrodes can make the EEG-based BMI system more suitable to be used for daily-life activities with an acceptable, slight decrease in performance. We first showed that splitting by half the number of electrodes was not significantly reducing the performance compared to the system with the full number of electrodes. Splitting the electrodes by four, to reach 16 electrodes, was here giving a loss between 3 to 5% compared to the original performance (depending on the feature extraction/algorithm pipelines and on the combination of electrodes). Those results suggest the necessity of defining a threshold for the number of electrodes while also exploring a larger variety of combinations of electrodes.

i. Comparison between conditions and between sessions

One of the main advantages of having EEG data from a multi-session experiment with different conditions is the possibility to look at the data from various angles. Our study has revealed that there were almost no differences between Motor Execution and Motor Imagery for the two groups of subjects. These results are particularly interesting as some differences could have been expected between the two conditions, especially in the Amputee group where Motor Execution is impaired. Those results also suggest that the proposed system could potentially be used by other groups of subjects such as tetraplegics with whom only Motor Imagery recordings are possible. Moreover, when looking at the evolution of the performance over the three sessions we showed that the performances remained stable over time without any significant improvement or loss in the classification accuracy. As we explained, those results are double-edged: On one hand, it was interesting and reassuring to note that there was no impact on the introduction of new devices for the subjects; on the other hand, we did not observe any improvement that could be explained by the fact that subjects got better at the tasks through learning. Here we suppose that seeing an improvement in the performance would require more than three sessions for the subjects to fully integrate the modified prosthesis and the sensory feedback devices.

ii. Modification of the prosthesis and real-time tests

In the fourth and fifth chapters, we reviewed how the prototype has been developed and how the subjects were able to use the BMI system during real-time tests which we presented in the sixth chapter.

Indeed, in parallel to the experimental sessions, we have shown how a commercially-available myoelectric prosthesis could be modified to be integrated as the end effector of a brain-machine interface. The challenge lies not only in the modification of the prosthesis but also in the use of this prosthesis in experiments with amputees and healthy subjects.

In chapters V and VI, we showed how the two groups of subjects were able to use the modified prosthesis in the second and third sessions both during the recordings and during real-time tests where they were in control of their BMI. For those tests, the processing of a one-second recording of the EEG activity triggered a movement on the prosthesis when subjects were performing the grasp sequence. We showed the results obtained for the two groups and the two sessions and they first highlighted that subjects were better at one phase of the sequence compared to the other (better at closing the hand compared to opening it for example) with some changes depending on the object they were asked to grasp. To explain the results, we offered multiple leads regarding the hardware used and the recording modalities as well as pointing out differences in the EEG data that was recorded during the test and at the beginning of the session. To work on those issues, we first proposed to apply an alignment of the data in the Riemannian framework which improved the performance for the phase with the lowest accuracy. Moreover, we studied how selecting only a subset of electrodes could here potentially improve the performance of the subjects.

Finally, we also looked at the results after applying the concept of the finite-state machine to our BMI system. By limiting the movements on the prosthesis based on an initial state, it is possible to simplify the control strategy of the prosthesis. This simplification also had an impact on the performances obtained during the real-time test, with overall a great improvement in the accuracy compared to the previous control strategy. The finite-state machine also proved to be easy to implement in the control software while also potentially offering a more natural control for the user.

To go further in the development of a daily-life system, we briefly investigated how a brain switch could be implemented in the BMI with the goals of starting/ending the control loop of the prosthesis but also stopping any unwanted movement from being performed on the prosthesis. While the primary tests did not yield satisfying results, we offered some leads with the use of eye blinks.

c. Sensory Feedback

In the last part of the manuscript, we addressed the question of the use of sensory feedback for the control of prostheses and specifically for the system we developed.

To this end, we first reviewed the literature to better understand the different ways of eliciting sensory feedback and especially when it is dedicated to the control of a robotic arm or a prosthesis. We focused on the different methods for having non-invasive feedback and explained the reasons for our choice of vibrotactile feedback for our system.

In the second part, we introduced the sensory feedback system and presented the various iterations to its design that led to the one we used during the experimentations. We proposed to use several force sensors on the fingertips of the prosthesis that were communicating wirelessly to vibrating motors integrated on a bracelet located on the upper arm of the subjects. While we can successfully use it during all the experiments, we also suggested several improvements to the design which could improve the sensations brought by the vibrations on the arm.

Finally, we presented some preliminary results we obtained during the experiments by focusing more specifically on the effect of the sensory feedback. In the able-bodied group, the results suggest that the addition of sensory feedback does not affect performance as it remained stable during the three sessions. In the amputee group, even though all the subjects were not able to pass the three sessions, the preliminary results show a potential improvement in the classification accuracy between the second and third sessions, suggesting a benefit brought by the sensory feedback. Yet the same results were not obtained when looking at the performance obtained during the real-time tests in the two sessions with contrasted accuracies depending on the object and the phase of the sequence.

2. Future work

Because we aimed to offer a proof-of-concept for the development of the BMI, there is still some work to achieve on different parts of the system.

Starting with the processing and classification unit of the interface, we think that future work should first be interested in the miniaturisation of the system. We envisioned that those parts could be integrated into a smartphone application whose role would be to connect all parts of the BMI-based system (prosthesis and EEG recording system). Consequently, the system would require both a wireless connection between the EEG system and the interface but also between the latter and the prosthesis, possibly through a microcontroller integrated into the socket of the prosthesis. The application would gather the training protocol, where the subjects could record some new data that would be combined with previously recorded ones and form a larger database and

improve the performance of the real-time control of the prosthesis. To adapt to the needs of the subjects and their prostheses, they would be able to add more movements to classify which would come along with the recording of new EEG patterns. Moreover, as we explained in Chapter III, we will also be interested in fostering the motivation of the users by adding a playful aspect to the application/software. A part of the future work will also be dedicated to the implementation of the brain switch, which is an essential feature for the final version of the system. We will thus focus on the use of eye blinks or other biological markers as a safeguard in the control of the prosthesis.

We are still quite far from a replacement of the classical EMG approach for the control of prostheses. It will be thus interesting to study how the combination of EMG and EEG could be used as an alternative control way. Nonetheless, working on the limitations of EEG will be key to the development of the system.

Concerning the prosthesis, along with the smartphone application, future work will consist of an increase in the number of movements that can be recognized by the system. One of the first addition will be to use the wrist rotation unit that can be added to the Myobock prosthesis. Moreover, we will study how we could control a larger range of opening/closing of the device without losing too much in the performance, this will allow us to find a limit on the number of fine movements that the system can classify. The next step must concern the use of a polydigital prosthesis like the Michelangelo model from Ottobock; this will allow us to tackle a larger array of grip types and movements.

Concerning the EEG recording system, future work will be interested in offering more leads and answer regarding the selection of electrodes for this specific application. In particular, we can wonder if it will be possible to offer a personalized configuration of electrodes for each user if it is found that there is no common configuration between them. Along this future exploration, we will be tackling how it can be translated with hardware and specifically look at the creation of EEG caps that can be integrated into more aesthetic hats.

Regarding the sensory feedback system, the first modification will consist in improving the design of the bracelet to elicit better sensations on the upper arm of the subjects. The future work will also consist in experimenting with more and different sensors on the prosthesis and encoding the information on the vibrating bracelet through the use of more vibrating motors. Moreover, we will also be looking on first, how to add the sensors directly inside the silicone glove of the prosthesis, and then, how to retrieve the information from the sensors already located in the prosthesis.

Finally, it will be interesting to conduct experiments with more subjects and especially more amputees. Having more data will allow us to evaluate more thoroughly the performances of the amputees compared to the able-bodied subjects while also having more complete answers regarding the multiple comparisons we did in our

studies. Moreover, gathering more data from real-time tests with the system will be crucial to explain the differences between those data and the data from the recording periods as we presented in chapter VI. It will also be interesting to study, for the same subject, the differences in performance when using the two EEG recording systems. Finally, it is difficult to evaluate the learning aspect behind the experiments, because of the limited number of sessions we are not seeing much effect of learning in the results we obtained. We would for example need more sessions with the sensory feedback device in order to see an effect on the performance. The same reasoning would apply with the real-time control of the prosthesis where subjects probably need more sessions to fully be trained to use the system.

3. Perspectives

a. Type of signal used

We chose to work with EEG signals during this PhD thesis as we aimed to create a system based on the non-invasive recording of brain activity. While we were able to show such a signal could be used to control prostheses, we wonder what would be the outcome if ECoG signals were used. Indeed, using ECoG could act on the spatial resolution limitation that comes with EEG, allowing it to target the motor cortex with more precision than traditional EEG systems. Moreover, using ECoG could also help with the non-stationarity we are faced with when using EEG. We presented in Chapter II how ECoG has been used for the control of robotic arms or exoskeletons but not yet for the control of prostheses on amputees. Of course, reaching this level would require the ECoG procedure to be more acceptable for patients and this state will not be reached until significant improvements in electrode design. Such research is currently underway with either a focus on developing biocompatible materials which could be used for long-term implantation [264] or on having better control of the inflammatory response caused by the medical devices in the body [265].

b. Bringing BMIs out of the lab

While it is easy to talk about the importance of testing BMI systems outside of laboratories, we can notice how difficult it is to implement such a practice in real-life. During this PhD, we have just scratched the surface of what can be done on the matter, mostly preparing the way for future work we discussed earlier. There are several facets to this: the first relates to the material that is used for the BMI system which is mostly bulky computers and EEG recording systems. Mridha and colleagues remind us in [266] that the “Mobility to Users” is one obstacle to the development of better brain-machine interfaces, arguing that they are not yet suited for real-world tests. Moreover, another facet of this issue is that BMIs require lengthy training from the subject to

improve their performance. This advocates a need to optimize the recording of the brain activity of the users, reducing the length of the sessions while also guaranteeing their engagement with an interface that is easy and entertaining to use. Finally, studies showed that, when used in more realistic environments, the performances of BMIs were dropping to reach low levels that were making them not usable anymore [221][267]. There is thus a need to encourage the recording of brain activity in an environment as realistic as possible, and ideally to let the users “tame” the BMI system at home and for daily activities. This is closely related to the material issue we presented as the first facet, indeed without miniaturized BMIs (or systems that could be fitted in laptops or smartphones), such tests are difficult to implement.

4. Final Word

This thesis work offered to bridge a gap between the industrial and academic worlds on the issue of prostheses and brain-machine interfaces. As we said in the introduction, it is easy to have tunnel vision and to totally ignore the problems arising from the other side, prostheses or BMIs. Moreover, we have had occasion to note that these areas are more complex than they seem. It is therefore essential to establish a dialogue between these different worlds in order to move them in the best possible direction. Being on the borderline between research and industry during this thesis has been particularly rewarding and challenging, especially when working on such an exciting and useful project. There is still a long way to go, but it is clear that there is still a lot to be done to best meet the demands of prosthesis users. I will certainly continue to evolve in this field, which I hope will help bring BMIs to users who need them.

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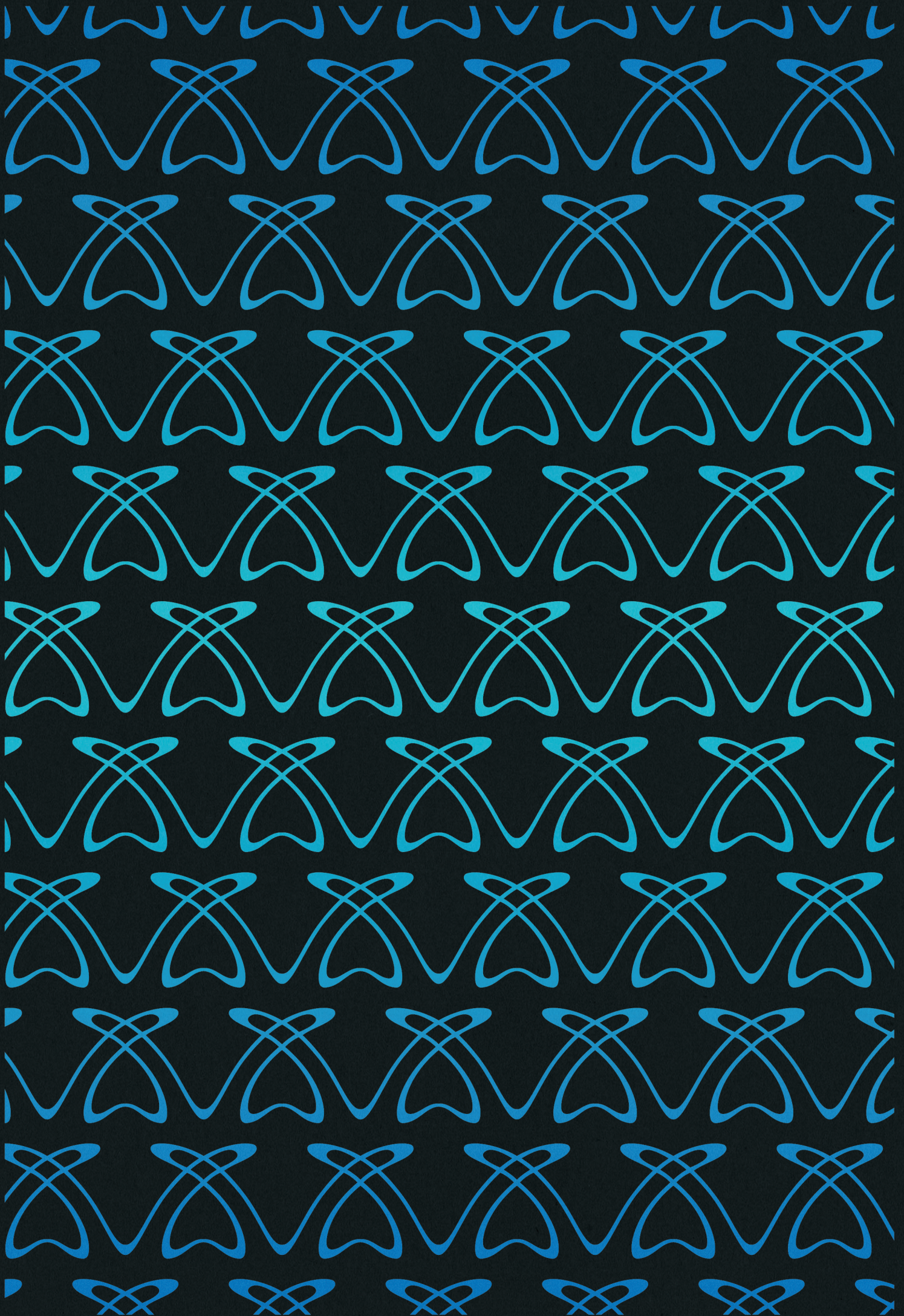
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Thank you for letting me see myself
Thank you for letting me be myself

(More than) Three years
of PhD





“In fact, ‘exceptional’ bodies have often proven to be more telling, more industrious starting points, than the ‘normative’, and have time and again been the impetus for theoretical and conceptual re-visioning.”

Cassandra S. Crawford

