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Human-Machine Co-Learning: interactive curriculum generation for the acquisition of motor skills

Vaynee Sungeelee

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Thèse

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par
Vaynee Sungeelee

pour obtenir le diplôme de
Doctorat de Sorbonne Université

HUMAN-MACHINE CO-LEARNING:
Interactive curriculum generation for the acquisition of motor skills

Soutenue le 27 septembre 2024

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Abstract

Motor skill acquisition is the process by which someone is able to perform a movement more accurately. In this context, practice plays a crucial role. However, practice is not always adapted to each learner's needs and learning journey. Generating personalized instructions manually is time-consuming and therefore impractical. Creating personalized practice sessions automatically is one way to alleviate this problem. Adaptive strategies that structure training, i.e., the sequence of tasks executed, according to task difficulty and skill level have the potential to facilitate motor skill acquisition. This dual process of a machine learning the sequence of tasks adapted to a human learner is what we call Co-learning. In this thesis, we study human-machine Co-learning in the context of motor learning. In this process, learning sequences are generated at the same time as the human learns to perform the motor task.

Machine learning algorithms can analyze the learning tendencies of individual learners and adapt training instructions accordingly. They can be used to create adaptive training tools, for example in the context of rehabilitation, to help humans adapt their movements. In this thesis, we leverage Machine Learning to facilitate the acquisition of motor skills. However, the use of Machine Learning to achieve this goal involves challenges : (i) few data is available to train the algorithms, (ii) the interactive nature of the system requires rapid training of machine learning algorithms (iii) the effectiveness of the algorithms depends on a precise assessment of the learner's skill level, which is difficult to measure in practice and (iv) the degree of control provided to humans when training the machine learning model can impact learning.

The aims of this thesis are twofold: (i) to develop a strategy for structuring the learning of motor tasks (ii) to study interactive systems that can adapt to and be adapted by the learner, to provide guidance during practice. Through two studies, we explore different strategies to

sequence motor learning tasks. In the first study, we evaluate the accuracy and smoothness of movement execution during the performance of a visuo-motor task. The second study explores how to train a machine learning algorithm in a prosthesis control task. We evaluate both the recognition accuracy of gestures provided by participants as well as participants' understanding of the system.

Our results contribute to the field of adaptive learning of motor skills and Human-Computer Interaction. They demonstrate that adapting motor tasks to the learner has advantages in terms of participants' performance and understanding of the task. These results provide insights for creating training protocols and facilitating their transition to applied contexts.

Keywords: Motor skills learning · Adaptive learning · Curriculum-based learning · Interactive Machine Learning

Resumé

L'acquisition de compétences motrices est le processus par lequel une personne est capable d'exécuter un mouvement avec plus de précision. Dans ce contexte, la pratique joue un rôle déterminant; elle contribue à améliorer les performances de l'apprenant, mais n'y est pas toujours adaptée. Un moyen de personnaliser l'apprentissage est de créer des séquences d'apprentissage qui conviennent à l'apprenant. Cependant, créer ces séquences manuellement demande du temps, ce qui rend cette démarche peu pratique. La génération automatique de séquences d'apprentissage peut remédier à ce problème. Les stratégies adaptatives qui structurent l'entraînement, c'est-à-dire la séquence de tâches à effectuer, en tenant compte de la difficulté de la tâche et du niveau de compétence de l'individu ont ainsi le potentiel d'améliorer l'apprentissage moteur. Ce double processus d'apprentissage par une machine de la séquence adaptée à un apprenant humain est ce que nous appelons le Co-apprentissage. Dans cette thèse, nous abordons le Co-apprentissage humain-machine dans le cas de l'apprentissage moteur. Dans cette approche, les séquences d'apprentissage sont apprises en même temps que l'humain apprend à faire la tâche motrice.

Les algorithmes de Machine Learning sont capables d'analyser les tendances d'apprentissage de chaque apprenant et ainsi adapter les consignes d'entraînement en fonction de ses besoins. Ils peuvent donc être utilisés afin de créer des outils d'entraînement adaptatifs, par exemple dans un contexte de réhabilitation où l'humain apprend à adapter ses mouvements. Dans cette thèse, nous utilisons le Machine Learning afin de faciliter l'acquisition d'habiletés motrices. Cependant, une approche fondée sur le Machine Learning se heurte à de nombreuses exigences : (i) peu de données sont disponibles pour entraîner les algorithmes, (ii) la nature interactive du système implique un entraînement de courte durée (iii) l'efficacité des algorithmes dépend d'une évaluation précise du niveau de compétence de l'apprenant, qui est difficile à

mesurer en pratique et (iv) le degré de contrôle que l'humain exerce sur l'entraînement du modèle de Machine Learning peut impacter comment l'humain apprend la tâche.

Les objectifs de cette thèse s'articulent autour de deux axes principaux: (i) élaborer une stratégie pour structurer l'apprentissage de tâches motrices (ii) étudier les systèmes interactifs capables de s'adapter à, mais aussi d'être instruits par l'apprenant, pour optimiser les performances motrices. À travers deux études, nous explorons différentes stratégies d'élaboration de programmes d'apprentissage pour effectuer des tâches motrices. Dans la première étude, nous évaluons la précision et la fluidité du mouvement lors de l'exécution d'une tâche visuo-motrice. La seconde étude explore le contrôle de prothèse fondé sur la technique de reconnaissance de formes. Elle évalue à la fois la précision de reconnaissance des gestes par un algorithme de Machine Learning et la compréhension du système par les participants.

Nos résultats contribuent aux travaux dans le domaine de l'apprentissage adaptatif des habiletés motrices ainsi qu'à l'interaction humain-machine. Ils démontrent qu'adapter les tâches motrices à l'apprenant présente des avantages en termes de performance des participants et de leur compréhension du système. Ces résultats offrent des perspectives pour créer des protocoles d'entraînement et faciliter leur implémentation dans un contexte appliqué.

Keywords: Apprentissage d'habiletés motrices · Apprentissage adaptatif · Apprentissage de curriculum · Machine Learning interactif

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Introduction

Motor learning and development have long fascinated scientists, likely due to their biological, psychological, social, cultural, and evolutionary significance to humans [46]. Understanding how motor skills are acquired and developed is of great importance in a number of fields such as sports, rehabilitation or music. When acquiring a motor skill, individuals learn and refine coordinated patterns of movement that are necessary to achieve a specific goal, e.g. to develop timing skills in music. A pertinent question which arises is how to train motor skills, given that there is considerable inter-individual variation in people's abilities to learn new motor skills [197].

Recently, the use of Machine Learning to solve real-world problems, such as identification of spam or image recognition, has gained much interest. Machine Learning (ML) is a branch of Computer Science that focuses on creating systems or algorithms which learn from data. ML has also been embedded in intelligent tutoring systems to provide feedback that is tailored to individuals' skills and learning goals. In a motor learning context, ML has been used to provide personalized, adaptive, and data-driven approaches to training, rehabilitation, and performance analysis. Research in ML applied to motor learning has the potential to create more effective methods for acquiring motor skills, leading to better outcomes [35].

In this thesis, we study how humans can learn motor skills with the help of adaptive algorithms which schedule tasks. In particular, we are interested in *Co-learning*, the mechanism whereby both human and machine learn through and with each other.

1.1 Context

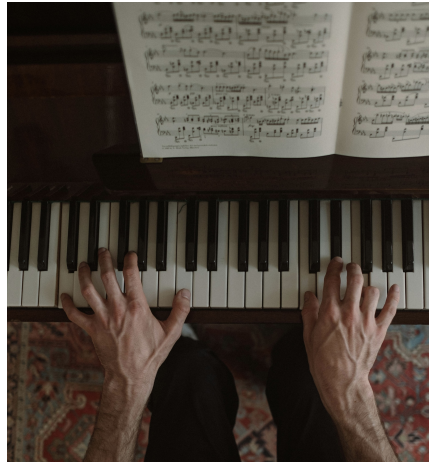
Learning is a fundamental aspect of human cognition and behavior, which influences how individuals acquire knowledge, develop skills, and modify their attitudes and beliefs. Humans have a remarkable ability to learn from and adapt to their environment through interaction. Learning occurs through various modalities, including visual, auditory, kinesthetic, and tactile experiences. Research on the specificity of learning has shown that we do not acquire motor skills in the same way that we learn language or mathematics [55]. For example, compared to cognitive tasks like solving an algebra question, mastering a tennis serve may require less explicit knowledge, and more understanding of how to coordinate thought and action.

The acquisition of human motor skills involves intricate processes that engage higher cognitive functions. Motor skill learning is predominantly associated with procedural memory, implying that movement-related knowledge is largely implicit (e.g. riding a bike or rollerblading). In contrast, cognitive skills are linked to declarative memory, which relies on the conscious recall of factual information [208]. Thus, theories of learning applicable to general cognitive skills might not be relevant to the acquisition of movement skills.

Practice and repetition are essential for the consolidation of motor learning, facilitating the building of neural connections and enhancing skill retention. In fact, practice is often considered as the single most important factor in motor learning. The act of repeatedly practicing movements, even without purposeful training, can lead to adaptation and improvement. However, deliberate practice is known to be more effective [62]. Consider a person who aspires to play the piano fluently and in the shortest time possible. Simply practicing various pieces of music daily may make the learner better at playing them, but will not make the latter a better musician. To train a large array of skills

optimally, it would be more effective for the learner to engage in effortful, performance focused practice, commonly referred to as deliberate practice.

Fig. 1.1: Motor skills, e.g. playing the piano, can be improved through practice and repetition. Source: [1]



One way to practice purposefully is for the learner to make decisions him/herself, for example, by deciding how frequently they want feedback from the teacher or when they need a demonstration of finger movements on the instrument. Learner control of training aspects is known as self-controlled practice. Other terms, such as self-regulated or self-directed practice have been used in the literature. Self-controlled practice has been associated with improved motor learning, even in scenarios where the factors controlled by the learner were not directly related to the task at hand, such as the order and repetition of practice sequences [106, 158]. However, the freedom of choice over these factors can add cognitive load that may counteract the benefits of self-controlled practice in certain conditions [48].

To engage in deliberate practice, the learner can seek the help of a music teacher, as has been traditionally done. The teacher can plan training sessions which are tailored to them, while considering their strengths and weaknesses. For example, the teacher may identify a subset of skills to improve over a period of time. However, designing

individualized practice and monitoring each learner presents significant challenges for teaching. This complexity arises from the diverse learning styles and paces exhibited by learners. The repetitive nature of learning tasks and the impracticality of supervising every learning trial further exacerbate these difficulties.

Online learning tools for training cognitive skills have effectively supplemented traditional classroom instruction to address these issues. Using computational approaches to automatically provide learning tasks and assess learners may free up the time of the teacher to concentrate on higher level goals or specific weaknesses. In other words, it can lead to a change in the role of the teacher from instructor to mediator. Nowadays, online learning is gaining relevance in education, and there is a high likelihood that it will endure even beyond the COVID-19 pandemic. In light of these technologies, learners may benefit from similar tools, which plan motor learning practice based on appropriate measures of learning. How can learner-adapted practice be enhanced with the help of machine learning?

Suggesting tasks which are appropriate to the learner is a problem which has been thoroughly studied in the development of intelligent tutoring systems. Clancey et al. [43] characterized an Intelligent Tutoring System (ITS) as being adaptive to the learner, being able to interact with the learner and having domain-specific knowledge. ITS research has studied how to recommend learning activities based on difficulty level, by predicting performance on certain tasks.

To teach cognitive skills, an ITS typically consists of modules, dedicated to personalizing the learning experience. For example, the student module evaluates the learners' knowledge. It supposes that a model of the learner can be created to assess the latter. Teaching motor skills through ITSs poses many challenges which are not straightforward to solve. For example, an ITS has to account for physiological factors, both in terms of interaction and assessment of skill. Identifying

the skill level of a learner and generalizing the transfer of learned skills to different environments or more complex scenarios, are among the issues that complicate motor learning through ITSs.

In this specific context, we consider a human learner whose goal is to acquire motor skills through computational approaches. Engaging the learner and an adaptive system in a closed-loop mutual learning environment can improve the learning speed as well as outcomes. We call this concept of mutual learning, *Co-learning*. *Co-learning* refers to the interaction between the human learner and the tutor in an ITS. However, our goal is not so much to create an intelligent tutoring system which can be readily used for acquiring knowledge, but rather to explore *Co-learning* through learning interventions which may favor skill acquisition.

Closely linked to *Co-learning* is *Co-adaptation* which is described by Mackay as phenomena in which the environment influences human behavior in a closed-loop: the environment is itself simultaneously being influenced by the human [134]. This two-sided adaptation is particularly important in the context of learning to control a body-machine interface, e.g. to optimize the translation of the user's commands into the machine's actions. We consider that *Co-learning* encompasses *Co-adaptation*, with the more specific goal of learning a new skill (as opposed to adapting a behaviour). We can also make a parallel to motor adaptation compared to motor learning. In the Motor Learning literature, learning is generally discussed as acquiring new movement patterns over time, while adaptation is referred to as making adjustments to an already acquired movement pattern [185]. Thus, the term *Co-learning* can be distinguished from *Co-adaptation* by focusing on the aspect of learning, rather than adaptation. In the context of this thesis, the objective of *Co-learning* is to enhance the user's motor skills, by improving the interaction between learner and machine.

1.2 Problem Statement

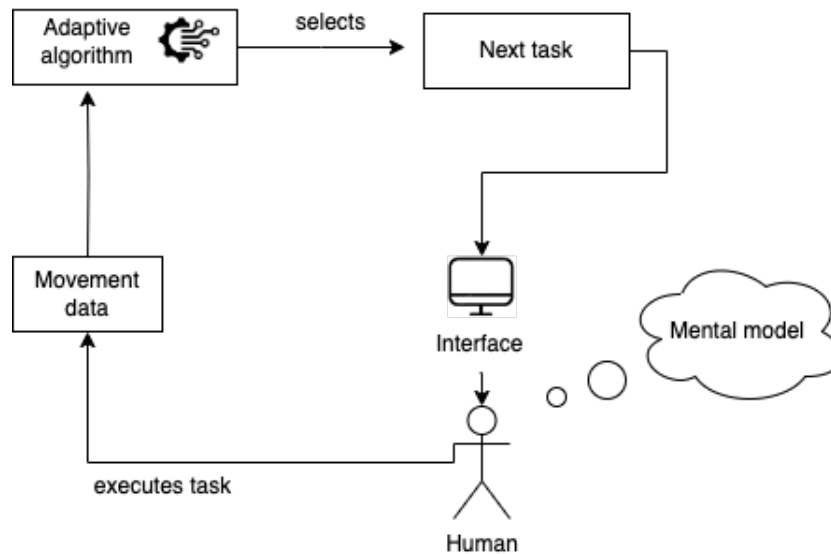
To ensure that *Co-learning* occurs, it is important to consider both parties in the learning loop. Engaging humans with machine learning systems necessitates that they acquire a fundamental understanding of how machine learning operates, enabling them to effectively train and debug the system. The system should be designed to enhance the human’s ability to accurately predict its behavior, ensuring that the human’s expectations align with the system’s actual functionality. This raises a number of questions, such as how to design the interaction between the two parties and how to enhance the human’s understanding of the system.

Figure 1.2 displays an illustration of the movement task setup used in this research. The human receives instructions on a screen and performs a movement task. A sensor records movement data, which is sent to the system. The role of the system is to run an adaptive algorithm which selects tasks, i.e. generates a curriculum for the human. To select (finite) learning tasks, the algorithm relies on estimates of performance derived from the movement data. In this setting, machine learning can be leveraged to achieve different goals. For example, ML can be used to propose the next task or learn to classify human movement. Besides learning to execute movement tasks and observing the feedback, the human also builds a mental model of the system. This mental model helps the human reason and predict the behavior of the system. Building a mental model of ML not straightforward, especially if the system is difficult to understand (e.g. a black box).

1.3 Research Questions

To investigate how learning tasks can be scheduled in the context of motor skill acquisition, we turn to the literature on motor learning,

Fig. 1.2: Illustration of the general movement setup used in this research. We investigate how to schedule motor tasks for a human learner in an interactive setting and how to enhance people’s mental models of Machine Learning systems.



which can provide insights into the factors responsible for achieving a high degree of proficiency. Since the focus of this thesis is on generating curricula, we seek to understand how motor skills can be developed as a result of manipulating practice conditions. Research has emphasized the importance of supplementing training with learning theories, e.g. Schmidt’s schema theory ¹, to plan practice [127, 128, 164]. If we consider the piano learner again, this means that appropriate practice can improve autonomy and may help the learner reach proficiency in a shorter timeframe. This can reduce frustration and increase engagement in learning, which is an important factor in motor learning. We ask the following research questions:

RQ 1 How can adaptive scheduling help a learner develop motor skills? To answer this question, we must first understand how to design algorithms which adapt to the learners’ skill level.

¹The schema theory supposes the existence of a motor program or schema, which can be built or refined for each new movement, thus reducing the storage problem. Variable practice is thought to be more effective for schema development

We then explore a second use-case, which is independent of the first research question. In this use-case, the human learns to control a prosthetic arm by conveying movement concepts to a machine-learning algorithm. To better explain the context, consider a rehabilitation patient who lost an arm. The patient is fitted with a prosthetic arm which relies on pattern recognition to classify movement. However, given the learning curve involved with these kinds of prostheses, the patient would benefit from techniques which make learning to control the prosthetic arm more seamless. In addition, the prosthetic arm requires retraining when movement patterns of the remaining limb change over time. Thus, the patient should also be able to train the machine learning system and diagnose any classification errors which might occur. This requires the patient to build an accurate mental model of the Machine Learning system.

In this second research work, we ask the following question: **RQ 2** How do people build mental models of these adaptive systems?

1.4 Research Methods

This section reports our general research methodology. To assess the state of works in the domain and motivate the research questions presented, we conducted literature reviews. To answer the first research question, we reviewed previous works to explore existing assistive motor learning systems and challenges in their implementation, as well as machine learning algorithms which have been successfully used to propose learning tasks. To answer the second question, we explored how training protocols have been designed and which user- training approaches of a pattern recognition-based prosthesis were most promising. The goal was to find solutions adapted to each problem and uncover gaps in each research field.

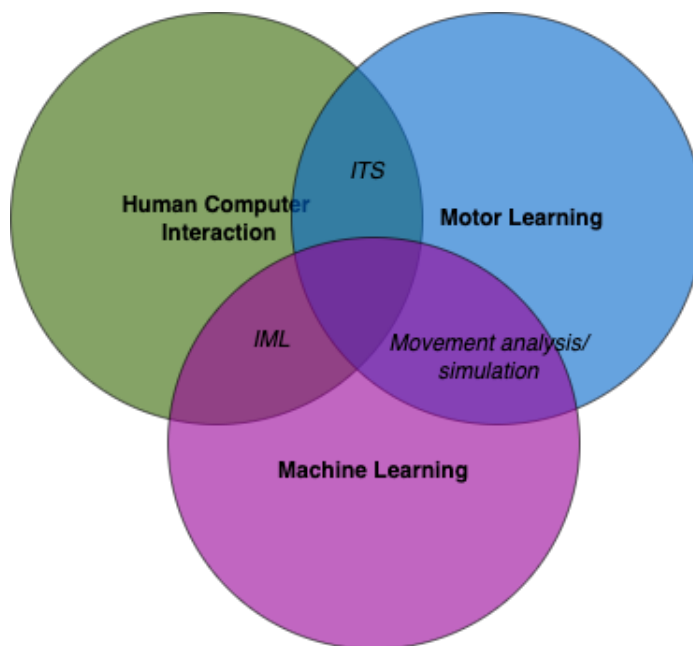
Our first research questions relates more to motor learning performance, but we also studied people's perception of the learning algorithm. The second research investigates human factors more explicitly, such as human agency in learning with the system and how humans understand the system. To address each research question, we conducted experiments to study the relation between relevant variables. For both experiments we conducted, we adopted a mixed method approach, consisting of qualitative and quantitative methods. We employed pre-test and post-tests to measure learning after practice. Our approach to design adaptive algorithms consisted of either identifying main metrics which were relevant to the task being used or suitable algorithms which meet the criteria of the scenario being investigated. We then implemented the algorithms and adjusted them based on a pilot study with participants. For instance, in the study presented in Chapter 4, one way to measure human learning for upper-limb rehabilitation tasks is to assess the quality of electromyography (EMG) patterns. Among the metrics used in the literature, the separability of patterns has been thoroughly used. We thus made the choice to use this metric to select the next task to schedule.

1.5 Contributions

This thesis explores *Co-learning* of humans and adaptive systems and users' mental models of these systems. The domains of interest are (1) Human-Computer Interaction (HCI), (2) Motor Learning and (3) Machine Learning (see figure 1.3). We contribute to knowledge in the fields of HCI and Motor Learning. In particular, we make contributions to the field of adaptive systems for Motor Learning and to Interactive Machine Learning.

We conducted two studies that highlighted the effect of: (1) adaptive learning on lowering the performance variability of movement smoothness among participants and (2) different interactive machine learning strategies to create a curriculum on learning rate, gain in accuracy and mental model soundness. This thesis motivates future research in adaptive algorithms and mental model evaluation, with the aim of making learners more autonomous and help them better understand the system through training.

Fig. 1.3: Domains of interest of this thesis: Human Computer Interaction, Motor Learning and Machine Learning.



1.6 Thesis Overview

In this chapter, we presented the motivation, context and contributions of this research. The remainder of this thesis is organized as follows.

Chapter 2 provides background knowledge on the main concepts employed in this research. It presents concepts and advances in learning

systems grouping the three main fields of interest: Human Computer Interaction, Motor Learning and Machine Learning.

Chapter 3 presents a study to understand how an adaptive algorithm which uses an exploitation-exploration strategy to select movement tasks to practice, can impact motor performance at post-test and 24 hours after training.

Chapter 4 presents a user study to investigate the impact of different interactive Machine Learning strategies on the Machine Learning accuracy and users' mental model. We study a more complex task, which involves classifying gestures to control a prosthetic arm.

In Chapter 5, we discuss some lessons learnt and the limitations of the research conducted.

Chapter 6 concludes this thesis, with implications of this research and perspectives for future work.

1.7 Publications and collaborations

Chapters 3 and 4 include papers that were published in a journal and presented at an international conference, respectively. The citations are provided below.

Sungeelee, V., Loriette, A., Sigaud, O., & Caramiaux, B. (2023). Co-Apprentissage Humain-Machine: Cas d'Étude en Acquisition de Compétences Motrices [191].

Sungeelee, V., Loriette, A., Sigaud, O., & Caramiaux, B. (2024). Interactive curriculum learning increases and homogenizes motor smoothness. *Scientific Reports*, 14(1), 2843 [192].

Sungeelee, V., Jarrassé, N., Sanchez, T., & Caramiaux, B. (2024, March). Comparing Teaching Strategies of a Machine Learning-based Prosthetic Arm. In Proceedings of the 29th International Conference on Intelligent User Interfaces (pp. 715-730) [[190](#)].

Background and related work

In this section, we present the purpose and scope of this thesis. We begin with an introduction to Motor Learning and how practice conditions affect Motor Learning. We then present research on how to build a curriculum to adapt tasks to the learner in real-time. We close this chapter by presenting works which have investigated how to transfer knowledge between humans and machines, for skill acquisition.

2.1 Towards adaptive Motor Learning approaches

First, we turn to the Motor Learning literature to better understand how to develop adaptive learning approaches for motor skill learning.

2.1.1 Mechanisms of motor learning

Motor Learning, the learning and performance of motor skills such as riding a bicycle, walking, or running, encompasses processes such as motor adaptation, skill acquisition, and decision-making [112]. Motor Learning is a set of mechanisms through which we can incrementally improve our ability to perform movements faster, better, and more accurately [59, 113]. It is a result of complex processes in the central nervous system and leads to relatively permanent changes in our movements.

At a more profound level, researchers have investigated how different mechanisms impact the development and improvement of motor

skills. Our motor learning capabilities are dependent on learning mechanisms which can proceed simultaneously or individually. These mechanisms include sensorimotor adaptation and trial-and-error learning for motor skill acquisition [109, 133, 126].

On the one hand, sensorimotor adaptation is an error-reduction process in which the nervous system learns to predict and cancel the effects of a novel environment on movements we already know, e.g. when you switch to a new tennis racket, you also adjust your swing accordingly. On the other hand, trial-and-error learning benefits motor skill acquisition, which concerns the practice and appropriation of new movement patterns. Feedback about the task is leveraged to improve the movement. This feedback encourages us to explore different movements and select the ones that are likely to be most successful [193].

At the level of the motor system, performance improvements in motor learning are characterized as a reduction in motor variability [114]. It was initially believed that motor exploration was an implicit process, which happened due to inherent variability in movement. Recent research suggest that exploration is intentional, to search for actions which are necessary for successful movements [58, 126]. Part of the motor system attempts to reduce execution noise to increase movement accuracy while another mechanism is responsible for motor exploration, which is conducive to learning.

Other research used these findings to investigate how variability affects learning in a reinforcement learning-based setting [210, 58]. For example, Wu et al. [210] studied how trial-to-trial variability affects learning. They showed that variability along relevant dimensions of the task helps the learner discover how to perform the task faster.

We will now look at how practice has been organized in previous studies on motor skill acquisition.

2.1.2 Practice organisation

In the Motor Learning literature, practice has been designed in many ways, e.g. by changing the type of skill practiced, exploring movement variations and changing task parameters. The most straightforward way to practice is for the learner to control practice parameters him/herself. This is called self-controlled practice. For example, the learner can decide which task to practice or when to increase the difficulty of the task. Compared to imposing the task difficulty, giving control to learners has been shown to improve acquisition, foster long term retention of skill [11] and improve the rate of learning [130]. Self-controlled practice is also requires active participation in the task, which can benefit learning. The benefits of controlling practice oneself, have been partially attributed to heightened motivation to achieve the motor task goals [175].

While self-controlled practice brings many advantages, it may require more cognitive load from the learner, compared to externally controlling certain aspects of practice. It might also not suit all learners, especially if the task is complex. There could be more efficient ways to learn, which learners may not be aware of. For these reasons, other ways of designing efficient practice have been investigated.

Variability during practice

Motor learning research has studied the effect of varying motor tasks in learning schedules. Varying the tasks during practice can be beneficial, as it promotes the exploration of a larger space of motor commands. This requires balancing variability and repetitions in the sequence of tasks involved in practicing new movements. To achieve this balance, practice can be planned to introduce variability. One way of introducing variability during practice is through *Contextual Interference* [186]. *Contextual interference* occurs when skills or variations of a skill are

interleaved within a practice session.

To induce different levels of contextual interference, studies have manipulated the order of practice tasks (see [89] for a more detailed review). The highest level of contextual interference typically occurs with random practice, in which the sequence of tasks is scheduled pseudo-randomly. The lowest level of contextual interference occurs with blocked practice, where all trials of one task are completed before moving to a different task. A third strategy is serial practice, which induces intermediate levels of contextual interference: the task changes after each trial but in an order which repeats throughout practice. Figure 2.1 illustrates the differences between random, blocked and serial practice.

Fig. 2.1: Varying the level of contextual interference. The boxes represent task scheduling in blocked, serial and random strategies.



A general finding is that high levels of contextual interference increase learning retention and improve transfer to other tasks, i.e., promote a relatively permanent change in behaviour. This is known as the contextual interference (CI) effect. However, high levels of contextual interference are detrimental to acquisition performance, when performance is assessed shortly after practice. If we consider a skill as consisting of distinct tasks which need to be mastered, the implication of CI is that practicing several tasks or variations of a task in one practice session can be beneficial for motor learning. This phenomenon has, for instance, been established for simple tasks with movement time constraints, as well as aiming and tracking tasks [102, 125, 211, 216].

Schmidt's theory of a Generalized Motor Program (GMP) [180] attempts to explain this phenomena. The GMP refers to a set of motor commands that is planned before executing an action. Schmidt's theory posits that these motor commands are retrieved and adapted to a particular situation. This way, alternating tasks with different motor programs, i.e. requiring a different set of parameters, such as in the case of tennis, when one changes from a backhand to a serve, causes interference which slows down skill acquisition. On the other hand this interference seems to favor retention of skills. Two theories have been put forward to explain this effect: (1) the elaboration hypothesis [186] and (2) the action plan reconstruction hypothesis [124]. The elaboration hypothesis supposes that random practice allows a learner to develop more distinct motor programs, which leads to a better understanding of each skill. On the other hand, the action plan reconstruction hypothesis supposes that each new trial of a different task requires the forgetting of its motor program and the reconstruction of a new one. This encourages a greater memory agility, speeding up retrieval of information.

Other studies varied the level of contextual interference during practice e.g. by mixing random and blocked practice or gradually increasing the level of contextual interference. Some of these studies reported superior retention performance with the mixed strategy, compared to either blocked or random practice [122, 157], while others found no significant differences [75, 56]. These mixed findings make it difficult to determine the impact of changing the level of contextual interference throughout practice.

The contextual interference effect has also been shown for some complex tasks such as executing a volleyball serve [198] or practicing music [15]. Other studies have contested the applicability of the Contextual Interference effect to complex skills [6, 213] or different levels of expertise [93]. Based on evidence of mixed results in several studies [83, 22, 199], Wulf et al. [213] argued that high levels of contextual

interference in random practice could be advantageous for simple tasks when tested for retention and transfer, but not for complex skills such as sports, where a higher cognitive load would be required. Another study showed that learners' skill level may play a role in how variability affects performance. Learners with poor skills performed better in a blocked practice than highly-skilled learners in a high contextual interference schedule [93]. Thus, the effectiveness of contextual interference could depend on task complexity and skill level. The type of skill targeted in a complex task should also be considered. For example, Caramiaux et al. [34] showed that random practice improved transfer of motor skills but not timing skills in a piano task.

Adapting task difficulty

One factor which distinguishes novices from experts is their information processing abilities. An experienced performer has a greater capacity to process information regarding the task than a beginner. Thus, they should not be challenged at the same level of task difficulty. The more difficult the task, the larger the gain in information from the task. However, skill level determines the capacity of the performer to interpret the information. A hard task provides a lot of information to a beginner, but they can only process part of that information.

Predictions of how information gain changes with task difficulty have been made by the challenge point framework. The challenge point framework suggests that task difficulty should be adapted to each learner with respect to his/her level of skill [86]. Figure 2.2a shows the relationship between information gain and task difficulty. The challenge point framework distinguishes between two types of difficulty : nominal and functional task difficulty. Nominal difficulty is independent of skill level and denotes the inherent complexity of the task. Of interest here is the functional task difficulty, which considers the impact of skill level and environmental factors on the overall challenge. Changing the

task parameters can make a task more difficult, e.g. varying the timing between actions. Contextual interference can also be manipulated to influence task difficulty. High CI, respectively low CI, can make a task more difficult or easy. According to this framework, there exists an optimal challenge point (functional difficulty level) which is conducive to learning. In other words, the task should not be too simple or too complex. It should be noted that this optimal challenge point does not coincide with maximal practice performance, since this is likely to happen at low levels of functional difficulty. Figure 2.2a illustrates this.

The challenge point framework can be leveraged to develop approaches to motor skill learning by manipulating task difficulty, e.g. through contextual interference [106, 104] or feedback, to match the learner’s current abilities. For example, the challenge point framework has been employed in adaptive learning approaches for motor learning [41, 203], in rehabilitation research [149, 57] and in sports training [85].

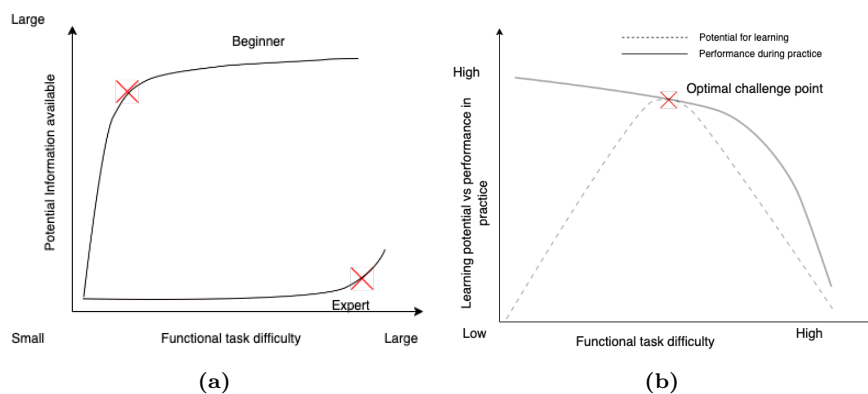
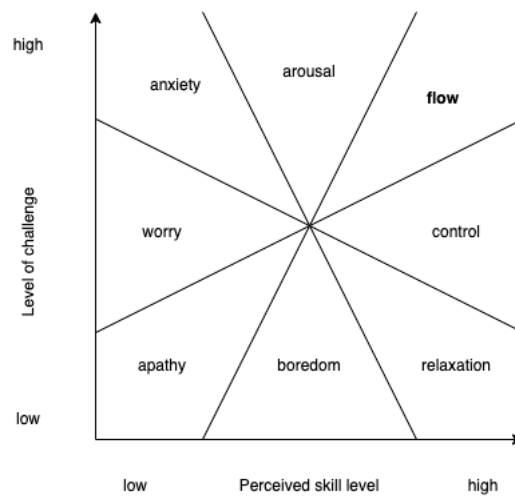


Fig. 2.2: Optimal challenge points based on functional task difficulty (a) Relationship between challenge point and task difficulty for different skill levels: beginners are more easily challenged at lower functional difficulty than experts. (b) Performance versus learning (retention) curves for different functional task difficulty levels. High performance in practice is likely to occur at low levels of functional task difficulty but the highest potential for retaining the skill occurs when the task difficulty is neither too low nor too high. Figure adapted from Guadagnoli et al. [86].

In the field of psychology, the level of challenge has been linked to

motivation, a key factor for successful learning. Flow is the experience of being completely engaged in a task, so that it is given full attention. The flow model was first introduced by Csikszentmihali [49]. Facing different levels of challenge can result in different emotional states, which influences motivation. For example, a task which is not challenging can give rise to boredom. Conversely, a task which is too complex for the individual can result in anxiety. Figure 2.3 illustrates the flow model.

Fig. 2.3: Flow model. Figure adapted from [49]



Adaptive motor learning strategies

More recently, approaches have been developed to optimize practice for the learner, using rules or algorithms. For example, Choi et al. [41] adapted visuo-motor task difficulty to the learner based on an error reduction rule which considered performance in the last trial. They showed that adapting practice led to superior performance compared to a random practice. Wadden et al. used individualized challenge points to adapt the amount of contextual interference [203]. They concluded that adaptive practice, when coupled with high levels of contextual interference improves motor learning compared to low levels of

contextual interference. Simon et al. proposed an approach called win-shift-lose-stay, which involved switching to another task only when it was successful [189]. The results showed that win-shift-lose-stay strategies were comparable to either random or blocked practice in terms of acquisition and retention in a key-press timing task. Another approach involved excluding tasks with good performances further along training, based on the premise that time should not be spent on easy tasks, but on tasks with high error rates, to reduce uncertainty of practice outcomes [97]. This work showed that excluding easier tasks led to poorer retention. Thus, research suggests that adapting the challenge to the learner yields better retention results than a random strategy. In addition, maintaining a range of difficulties rather than practicing only the most difficult tasks seems to be beneficial for learning. We will now see how motor learning can be evaluated.

Measuring motor learning

Evaluation techniques have been devised to measure the progress or effectiveness of practice over time, based on performance indicators such as time, distance and frequency. For example, performance curves can be plotted by logging a performance variable which characterizes skill across time. They are indicative of (1) consistency across trials and (2) improvement by inspecting the direction of the curve [45]. Performance curves follow patterns, the most common one being a negatively accelerating curve (see figure 2.4b). This shape can be explained by the Power Law of Practice, which states that learners improve fast initially, slowing down with time. The shape of the Power Law curve is a negatively decelerating curve, with practice time on the x-axis and number of trials on the y-axis (see Figure 2.4a).

The general form of the Power Law of Practice is as follows [146]:

$$T = A + B(N + E)^{-\alpha}$$

where:

T is the time to perform a task. A is the asymptotic value of performance. B and E are prior experiences before the start of practice. and α is the learning rate.

The Power Law can be transformed into a linear function by plotting the logarithm of time taken to perform the task against the logarithm of the number of trials. This can be practical to compute performance measures, such as the learning rate, in human experiments.

A simpler version of the Power Law can be written as follows.

$$T = B * N^{-\alpha}$$

$$\log(T) = \log(B * N^{-\alpha})$$

$$\log(T) = \log(B) - \alpha * \log(N)$$

$$\log(T) = b - \alpha * \log(N)$$

The linear function of the Power Law has intercept $b = \log(B)$ and slope α .

While it is a popular method to track progress, performance curves have some limitations. First, the measures of performance are computed during practice and do not represent permanent changes in skill, but rather temporary effects of skill acquisition. Second, the power law may not hold for all tasks, e.g. its use has been questioned in the context of training complex perceptual-motor skills [168].

A better indicator of learning is a retention or a transfer test, which evaluates an individual's ability to consistently perform a specific task over time (retention) or in various contexts (transfer). To assess learning, most studies use a delayed retention test, which measures long-term changes in skill or performance on the practiced tasks. The learner

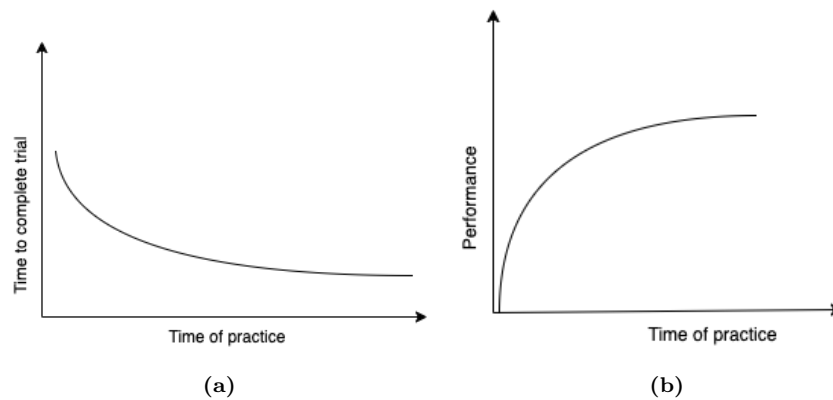


Fig. 2.4: (a) Power law characterized by sharp improvements in time taken to complete a trial at the start of practice, followed by a decelerating improvement. (b) Performance curve showing decreasing rates of improvement in performance with time.

withholds practice for some time before performing the retention test. For laboratory studies, this period of no practice usually lasts 24 hours or more. Generalisation to another task or skill can be tested by changing the task parameter that was varied during practice or by changing the skill. For example, in tennis, if the racket width was manipulated during practice, a novel width not seen during practice can be tested.

Motor Learning models

To provide more concrete knowledge and tools for coaches and clinicians to design practice, researchers have developed motor learning models which describe the different phases of motor skill acquisition. These models are based on theories of cognitive and motor learning. The two main motor learning models were proposed first by Fitt and Posner and later by Gentile.

Fitt and Posner were the first to develop a model of motor skill acquisition with three stages [71]. When learners start out, they are in the cognitive stage. This stage involves understanding and memorizing instructions. As they progress, learners start to refine skills, with

less dependence on external instructions. This is called the associative stage. Finally they are able to perform skills autonomously, with less reliance on conscious cognitive processes. They are in the autonomous stage of learning. Task variables and practice structure play a key role in determining whether learners will reach the autonomous stage. Coaches and clinicians often rely on these three stages to know when to switch to other exercises or to another difficulty level.

Gentile proposed a model with two stages, which consider different goals [78]. The first stage involves understanding the task and exploring strategies to perform it. The goal is to acquire a movement pattern by also adapting to the environmental context. For instance, when a rehabilitation patient is learning to pick up an object, they concentrate on recruiting the appropriate muscles necessary for lifting the object. The size and weight of the object are also considered. The outcome of this stage is a concept of movement which is neither consistent nor efficient. In the second stage, the goal is to enhance the ability to adapt movements and execute the task with greater consistency and efficiency. The clinician identifies practice variables to improve the learner's consistency in solving the motor problem.

In the next section, we will explore the role of machine learning in developing learning interventions. The section is structured into two parts: Curriculum Learning strategies to teach artificial learners (e.g. RL agents) and curriculum-based approaches to schedule learning activities for humans.

2.2 Curriculum-based learning

As seen in the previous section, insights in motor learning suggest that adapting practice to the learner could be essential for enhancing skill acquisition efficiency. As humans, we learn by means of curricula as

early as infants, e.g. we learn to crawl before learning to walk. We continue to do so as we acquire a formal education. Curriculum-based learning consists of structuring learning by starting with an easier problem and incrementally increasing its difficulty. It has been shown to be important in many human learning domains. Its implication for practice is that the order in which tasks are presented to the learner is important.

The predominant way to create curricula in education is to seek an expert to manually design schedules for learning tasks. However, this process is time-consuming and does not scale well; catering to the learning pace and preferences of each learner is difficult. When it comes to designing curricula for motor learning, in addition to the latter challenges, one also has to consider the effect of various practice conditions on learning. To design adaptive practice automatically, Machine Learning can be useful.

Machine Learning is a branch of Computer Science that focuses on creating systems or algorithms which learn from data. The three main types of machine learning algorithms are Supervised Machine Learning, Unsupervised Machine Learning and Reinforcement Learning.

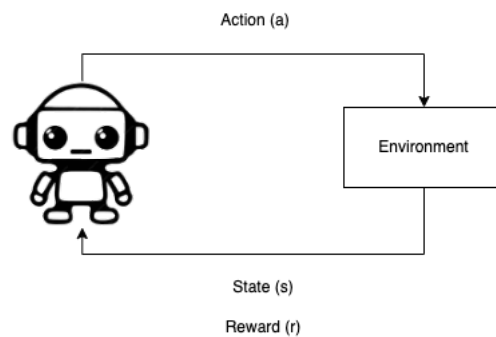
Supervised Learning algorithms are used to identify concepts by learning from available data. A supervised learning setting consists of a dataset, with features which characterize the data, and correct labels (usually labeled by a human). This allows a machine learning algorithm to learn a mapping between features and labels. The trained model can then be used to make predictions on unseen data. Examples of supervised learning algorithms include linear and logistic regression, multi-label classification and support vector machines.

Unsupervised Learning on the other hand relies less on human guidance. It learns to identify complex patterns in unlabelled data. Examples of unsupervised learning include k-means clustering and principal

component analysis (PCA).

Reinforcement Learning (RL) is a framework for sequential decision-making, in which an agent learns by interacting with an environment through trial and error. The goal of RL is for the agent to learn an optimal behavioral strategy, called a policy, based on rewards obtained from the environment. The agent starts in a given state and by taking actions, moves to other states in the environment. The dynamics of the environment is defined by a transition function, which computes the probabilities of starting from one state and ending in another state. The agent receives a reward, which allows it to evaluate the degree of success of the chosen action. This reward is computed from a function called the reward function. Figure 2.5 illustrates the RL-framework.

Fig. 2.5: RL framework: At each time step, the RL agent takes an action in an unknown environment. The agent reaches a new state (s) and the environment produces a reward (r) for the agent based on the optimality of the action (a) taken.



The goal of RL is to maximize the long term reward by attempting to balance between exploration of new actions to discover which ones yield the most reward and exploitation of known actions currently yielding high rewards.

Below, we describe a technique, called Curriculum Learning, which is used to order training examples or experiences in machine learning, with the goal of solving complex tasks and/or speeding up training.

2.2.1 Curriculum Learning for artificial agents

Just as structuring learning tasks for humans leads to better and more efficient skill acquisition, similar techniques have successfully been applied to train a machine in supervised learning settings. Previous works have trained machines to learn skills by incrementally adapting the difficulty of training examples [19, 84]. Bengio et al. [19] ordered the training examples from easy to hard, in a shape recognition task before presenting them to the model. The model learnt from the easier features first and then learnt the harder features. To increase difficulty, they added variability to the shapes, considering the standard shapes as easy samples and the variants as hard ones. This approach is known as *Curriculum Learning*.

In Bengio et al.'s work, the order of difficulty of samples was decided by the authors. However, in many real-world problems, this ordering is not straightforward. Thus, in other research, different ways of measuring difficulty or the usefulness of a sample have been proposed. For example, instead of assuming that some ordering of samples exist, one strategy is to consider the learning progress of the model to decide how to choose the next samples [121].

Reinforcement Learning (RL) agents have also benefitted from this technique to solve more complex tasks. Curriculum Learning for Reinforcement Learning is an active area of research, aiming to speed up the training of RL agents on a goal task by first training them through progressively more challenging tasks. It involves sequencing tasks or training data to optimize knowledge transfer between tasks which would otherwise be too complex to solve or too sample inefficient. Curriculum Learning approaches leverage transfer of knowledge between tasks. Instead of directly learning on a target task, the agent can learn on one or more simpler tasks and progressively transfer the knowledge required to solve the more complex target task. Transfer Learning in Curriculum Learning implementations explore how to transfer relevant information

from each task and how to group information from several tasks [143].

Manual curricula have been successfully employed in RL to achieve expert performance in games with sparse rewards, such as Go [188] or Dota 2 [2]. However, designing curricula manually is time consuming and requires domain knowledge. This has led researchers to explore automatic Curriculum Learning, where a teacher algorithm automatically generates a curriculum for the learning agent - the student. One such work [138] proposed a Teacher-Student Curriculum Learning approach (TSCL). TSCL considers two separate tasks in which both a teacher model and a student model are trained. In the Teacher-Student interaction, the teacher selects tasks for the student to practice, based on the premise that students should practice more tasks on which they progress rapidly. The teacher’s goal is to minimize training time for the student to succeed on a target task. To select tasks for the student, they used an online algorithm, with different ways of computing the learning progress. The learning progress is used here as a proxy to measure the current challenge offered by a task.

The notion of learning progress as intrinsic motivation for artificial agents was inspired from past research on learning robots [179, 150]. The authors postulate that keeping the learning progress high pushes the robot to become *curious* and learn new things. The idea of learning progress has been reused in several works using teacher algorithms for Curriculum Learning [156, 44, 73, 4].

In the Motor Learning domain, research in the control of articulated robots has investigated Curriculum Learning for skill acquisition [105]. The articulated robot learnt acrobatic skills incrementally, starting from the simplest skills and combining skills. The manual curriculum was decomposed into high-level and low-level curricula. The high-level curriculum specified the order of acquisition of skills, while the low-level curriculum favored exploration and gathered experiences

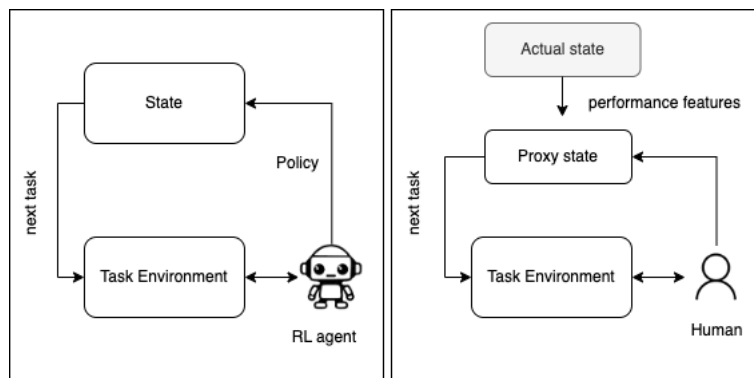
to perform a specific skill, with different parameter settings. The authors showed that the task sequences were learnt efficiently and that the curriculum generalized to different types of robot morphologies.

As mentioned earlier, organising practice of movement skills in an optimal way can enhance motor learning. Ordering tasks automatically could enhance the motor skill learning process for humans, while relying less on coaches or teachers. One way to do this could be to replace a general task by a target motor task and use RL to optimise performance on a subset of tasks before learning the target task. Figure 2.6 illustrates this idea. However, this raises a number of challenges, as we'll see below.

Recent research has suggested a Reinforcement Learning framework, as a first step towards the long-term goal of automatically generating curricula for human motor skill acquisition. Ghonasgi et al., [79] extended a framework designed for autonomous Reinforcement Learning agents to human learning.

Drawing on this framework for RL agents, the authors proposed a model, where the teacher is an artificial agent that trains a human agent to perform a task. In this setting, the goal of Curriculum Learning is to maximize performance on a final task. The RL teacher selects the next task from a set of simpler versions of the final task for the learner to train on. This model was developed with the intent of building a complete curriculum in advance (policy) to ensure efficient learning progress on a motor task. An optimal policy is learnt by considering future goals, for instance, maximizing performance on the final task. The authors defined a Curriculum Learning model to select the task which will maximally challenge the learner. Figure 2.6 illustrates the differences between Curriculum Learning for RL agent compared to Curriculum Learning for a human.

Fig. 2.6: Curriculum Learning to select motor tasks. To do so, the RL agent selects sub-tasks which will help the agent optimize scores on a target motor task. Adapted from Ghonasgi et al. [80]



Formalizing a motor learning task as an RL problem makes it possible to consider RL algorithms to create curricula. However, the challenges of replacing the student agent by a human learner are such that the framework remains theoretical for the moment. Given a policy in RL, it is possible to predict the agent’s behavior in each state. Replacing the RL agent with a human means that the state of knowledge of the human needs to be modeled. Accurately measuring skill level is not straightforward, since learning or changes in motor learning mechanisms are not directly observable. Thus, there is no optimal way to parameterize this model. Second, Curriculum Learning applied to humans presents a challenge in terms of the amount of training. While RL agents can be trained for extremely long periods of time, humans are subject to fatigue and cannot focus for extensive periods of time[80]. Other difficulties include computing transition functions for selecting actions from given states. This requires prior insights and experiments on the task and learners.

Below, we describe another line of research in Intelligent Tutoring Systems, which leverages Machine Learning in computational tools to tutor humans.

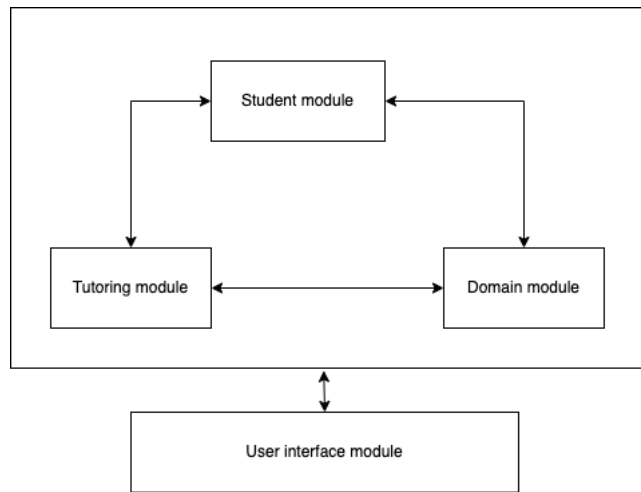
2.2.2 Intelligent Tutoring Systems

The development of systems designed for tutoring is a thoroughly studied research field. These systems are called Intelligent Tutoring Systems (ITS). ITSs have successfully been used to personalize and scaffold learning, resulting in rapid progress and improved performance. They have been defined as computer-based instructional systems which adapt to the learner, integrate teaching strategies and use domain knowledge [12].

An ITS typically consists of four components: (1) the domain module, (2) the student module, (3) the tutoring module and (4) the user interface module. Figure 2.7 shows the related modules. The domain module models the knowledge base, consisting of concepts, rules, facts, and other elements required to analyse how well a learner has understood the domain. In other words, it is a cognitive model of expert knowledge. The student module models learner's cognitive and affective states as they learn. It is usually implemented as a subset of the domain model. It keeps track of how knowledge and skills are learned through practice. For example, when the learner's solution deviates from predefined steps to solve a problem, this may trigger an error to alert on a potential misunderstanding of a concept. The tutoring module consists of a model representing a teaching strategy, which uses information from the domain and the student model to select pedagogical actions. It tracks the learner's progress to provide suitable feedback and instructions. Lastly, the user interface allows interaction between the learner and the ITS. It can be multi-modal, to allow different types of interaction and is usually designed to increase personalization.

Tutoring strategies involve varying the difficulty and ordering learning material to help the learner reach proficiency. Various techniques have been used to propose pedagogical tasks to the learner. Reinforcement Learning (RL) can be used to discover the best learning strategies, given a reward function [100, 163, 18]. However, its usage has been

Fig. 2.7: The 4 modules in a typical Intelligent Tutoring System: the student module, the tutoring module, the domain module and the user interface module.



restricted because of challenges involved in training the model. For example, in online RL, where a policy is generated as a result of agent interacting with the environment, the algorithm requires a large number of interactions to update the policy. Thus, training can be inefficient and not suitable for use in real-time. On the other hand, offline RL requires historical data to train on, which might not always be available [40, 136]. Other RL approaches are based on deep learning to deal with high dimensional states [14, 18]. Neural networks have also been used in other settings to learn student characteristics, which can be used to predict the right level of difficulty for a learner [205]. Other techniques include collaborative filtering, where data of multiple learners influence the content which is proposed [147, 103] and Multi-Armed Bandits, which leverage a simpler Reinforcement Learning paradigm to select actions [44, 182, 76, 181, 24], We discuss Multi-Armed Bandits in more detail later.

Advances in human motion sensors and Machine Learning have helped develop similar tools to support users in learning motor skills. A few studies implemented ITSs for teaching psychomotor skills. Psychomotor skills encompass both cognitive and physiological skills. For

example, golf putting involves both judgement and physical actions, like hitting a ball. Kim et al. implemented a physio-cognitive model based on ACT-R in an ITS to predict how breathing rate affects movement in a golf putting task [108]. ACT-R is an extension of the ACT model of cognition, developed by John Anderson. ACT is a computational model of human intelligence, encompassing perception, memory and reasoning. ACT-R made it possible to understand and predict how cognition can be decomposed into units at the level of the brain. It has been used to simulate cognitive learning and predict the difficulties that learners may face [9].

Another example of ITSs in learning psychomotor skills is Neagu et al.'s strength training system, called Selfit [145]. The authors implemented a movement ontology called *OntoStrength* to describe exercise characteristics. The student module used this knowledge to update the individual's training components when performing workouts. This required identifying parameters which influence training individualization and mapping exercises to movement types and to difficulty levels. However, the richness of the field made it impossible to map all parameters and they reported that this limitation could impact the system's reliability.

Most existing tools to teach motor skills do not follow the typical ITS architecture described in figure 2.7. For example, one research studied motor skill acquisition by changing the shape of training tools—in this case, the diameter of a basketball hoop [200]. They configured sensors and actuators to monitor a user's performance and adapted the difficulty accordingly. Other effective strategies include adapting the motor task to the mental states of the learner, e.g. stress level [171] or using real-time tactile feedback to supplement feedback from a teacher [129].

Another way to train motor skills is game-based training. It can provide feedback that is tailored to individuals' skills, learning goals

or preferences and can be done at home. Dynamic Difficulty Adjustment (DDA) is a method in serious gaming which aims to optimize the adaptation of task difficulty. This technique automatically adjusts game parameters, scenarios, and behaviors in real-time based on the learner's ability. In rehabilitation, this approach involves sequentially selecting the difficulty of tasks presented to the patient, ensuring they are optimally challenged. Several approaches have been studied, for example Reinforcement Learning to change game parameters [183], heuristic search to determine the sequence of tasks which satisfy several constraints [96], Bayesian approaches to adapt to the patient's capabilities [155] or Evolutionary algorithms to adapt the game's difficulty [10].

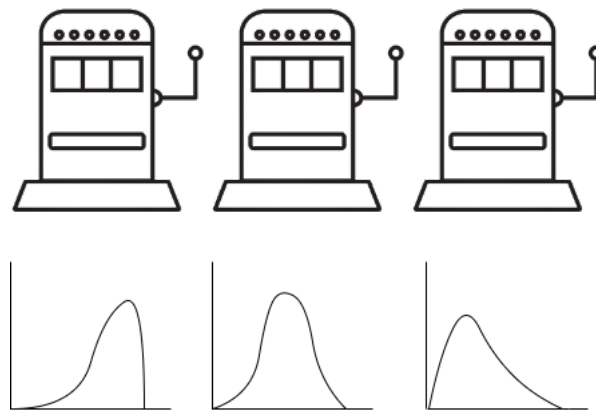
Other works have attempted to model the movement being learned to evaluate performance. Different approaches have been used, including gesture recognition using machine learning [5, 221] or use of virtual environments [52, 224] (see [176] for a more complete overview of movement modeling in learning systems). To assess the learner and provide feedback, the learner's movement is usually compared to an expert's [140, 166]. Some systems have also modeled users' bodies to assess performance or have employed user profiles to adjust the feedback modality [129, 166].

2.2.3 Multi-Armed Bandits for human learning

To solve some of the problems listed in section 2.2.1 and 2.2.2 regarding the challenges of using an RL framework to select tasks for human learning, some works have used simplified RL frameworks. For example, the Multi-Armed Bandit (MAB) framework supposes that there is only one state in the environment. Thus, the transition function (or the policy) need not be computed. In addition, online algorithms used to solve the MAB can be fast to train compared to RL algorithms, if the number of options to explore are not too large. MABs are based on

an analogy for a slot machine with many arms, where each arm has an unknown reward distribution (see figure 2.8). How can the highest long-term rewards be obtained when the rewards are not known in advance? Strategies to solve this problem involve different ways of selecting an arm through exploration - learning which arms provide the most rewards and exploitation - playing arms with high rewards obtained so far, to maximize cumulative rewards. A naive approach is to pull the same arm for a large number of trials to accurately estimate its reward probability. However, this is not an optimal strategy and does not guarantee the highest long-term rewards.

Fig. 2.8: Illustration of the Multi-Armed Bandit problem with 3 arms. The reward distribution of each arm is unknown. The probability (y -axis) that each arm yields an mean reward μ (x -axis) is estimated at each step. The problem consists of determining how much each arm should be explored and exploited to maximize long-term rewards.



Examples of bandit strategies include the ϵ -greedy algorithm and the SoftMax algorithm. The ϵ -greedy algorithm selects the arm which currently provides the highest reward and randomly selects an arm the rest of the time. The expected future rewards are estimated by computing an action value function, denoted as $Q(a)$, which is the expected return obtained for taking action a . To estimate the action value Q of pulling an arm a , the past rewards for arm a are averaged until time t as follows:

$$Q_t(a) = \frac{\text{Sum of rewards when action (a) taken before time(t)}}{\text{Number of times action (a) taken before time (t)}}$$

The Softmax algorithm is a more strategic way to assign probabilities to each arm. It uses a softmax distribution of the Q values. Compared to ϵ -greedy, which selects arms with a fixed probability determined by ϵ , the SoftMax selects arms based on softmax probabilities, which change based on the Q function. The Q function estimates the value of an action. Based on these probabilities, arms with a higher average reward are more likely to be selected (exploited).

$$P(a) = \frac{\exp(\frac{Q(a)}{\tau})}{\sum_i^{|A|} \exp(\frac{Q(i)}{\tau})}$$

where τ specifies the randomness of exploration, with higher values tending towards uniform exploration and lower values tending towards exploitation. The higher the Q-value of one arm, the higher its probability.

When applied to pedagogical action selection, each arm in the MAB framework is analogous to a task, the reward is defined to maximize the learning gains or other performance metrics for learners. Previous work have framed adaptive learning as a MAB problem. The main idea behind these works is that the learner should be challenged to his/her skill level i.e., provided with tasks which are neither too easy nor too difficult. This idea has several names, for example *Scaffolding* or *Zone of Proximal Development* [202].

Clement et al. [44] used the MAB framework to select actions in an intelligent tutoring system teaching kids how to count money. Using the MAB allowed them to not rely too strongly on a cognitive model

of learning - the algorithm computes estimates of the learner's knowledge directly through performance. The proposed algorithm, called Zone of Proximal Development and the Empirical Success (ZPDES), recommends tasks which the learner can do when provided with guidance. ZPDES incorporates a Multi-Armed Bandit problem to select tasks currently providing high learning gains. The algorithm computes the reward as the learning progress on a given task. Thus, when a task is already mastered or the learner is stuck on a task, the learning progress and reward is very small. To reduce the number of activities which need to be explored by the multi-armed bandit, the algorithm is steered using a prerequisites graph, which defines the order in which activities need to be visited.

Exploration is an important aspect of the algorithm- it enables the estimation of the learning progress on tasks whose rewards are not known or which have not been scheduled in a long time. The algorithm has potential to schedule a range of task difficulties, whose importance has been highlighted in the Intelligent Tutoring Systems and the Motor Learning literature. For example, Neagu et al. [145] found that allowing the bandit to explore a larger variety of exercises was more motivating (more users were likely to complete the practice sessions). Multi-armed bandits have also been used to help people practice non-technical skills, such as simulated driving [169, 24] or to provide adaptive feedback on gesture quality in a Calligraphy task [76].

After exploring how algorithms have been implemented for skill acquisition, one question which remains is how to design effective learning interaction with Machine Learning systems. In particular, we review how knowledge can be transferred between humans and machines and look at the human factors which should be considered during the interaction.

2.3 Knowledge transfer between humans and machines

Movement interactions are not always easy to design, since they can be tacit and difficult to represent. Nowadays, a great deal of human behavior is augmented by technology. Advances in Human Computer Interaction allow gestural interactions and more intuitive interfaces, which are personalized to conform to people's needs. Machine Learning can be leveraged to avoid explicitly programming rules which define the interactions. Building adaptive learning systems based on Machine Learning may also allow greater interactivity, feedback and personalization.

However, to ensure the effectiveness and long-term success of such systems, human factors such as motivation, degree of user control and users' understanding of the system need to be considered. For example, rehabilitation patients using a support system to move should have the freedom to navigate, interact and make choices within the system according to their capabilities and preferences.

We begin by exploring how to transfer knowledge between humans and machines. In particular, we look at how humans have taught robots to become more autonomous.

2.3.1 Teaching human skills to robots

In an attempt to understand how to transfer knowledge between humans and machines, we look at ways humans have taught robots to become more autonomous. Recently, the human robot interaction field (HRI) has shown increased interest in transferring skills of a human teacher to a robot using Machine Learning techniques such as learning from demonstration (LfD). Robot learning from demonstration (also

known as imitation learning) is a method to make robots more autonomous. Rather than requiring the user to program a desired behavior, the user shows the robot how to perform the task. LfD makes use of several observations of a human's performance to teach a new behavior, with the goal of generalizing performance to new settings. For example, Cakmak et al. [30] taught a robot the act of pouring through an Active Learning framework, where the robot asked questions related to the task and the human provided demonstrations through a haptic device.

There are three main types of queries that the robot can use: label queries, demonstration queries and feature queries. Label queries involve executing a motion and asking the human whether it was correct or not. Demonstration queries involve requesting a type of motion, which the human then demonstrates. One way to request demonstration queries is through *Active Class Selection*, which involves requesting an instance of a particular class [132]. Active Class Selection (ACS) bears some resemblance to Active Learning (AL) in that both involve collecting training data iteratively, based on some criteria. However, they are fundamentally different in that ACS selects classes for which new instances will be created, while AL directly selects instances to label.

Another technique to transfer knowledge to a robot is Interactive Reinforcement Learning (IRL). IRL settings require the human teacher to provide feedback during training, which is used to speed up the training of the RL algorithm and generate an optimal policy. For example, Koert et al. [110] conducted an experiment in which humans could provide advice to teach a Reinforcement Learning agent to combine skills for sequential robotic tasks.

When it comes to designing robots which learn from demonstration, Chernova et al. [39] provided some guidelines which could be helpful to design adaptive learning systems. Among these guidelines,

we explore some of these aspects in this thesis. For example, scaffolding, i.e. organizing skills and building on simpler skills, can be more efficient for learning. However, scaffolding is not straightforward, since it first requires a ranking of tasks to be made if the task difficulty is not clear. Scaffolding without ranking thus requires an exploration of tasks and their performances before scheduling the most appropriate tasks. The second aspect to be considered is transparency, i.e. the system should be able to maintain an accurate mental model of the learner's knowledge. This is important to select suitable interventions. Here the learner is a robot, but this also holds true for humans [44]. As mentioned earlier, obtaining an accurate student model is a difficult endeavor. Another aspect to consider when designing the learning system is whether to acquire training data in batch or online. Batch learning uses the whole data to train a model periodically. Online learning trains a model incrementally, with mini-batches of the data. This affects the interaction with the system. For example, batch learning is a good option for image classification, where data patterns remain constant. Online learning is more adapted to cater for changes in patterns over time, known as concept drifts.

We have seen that humans have acted as oracles and demonstrators to teach robots. The reverse, i.e., the use of robots to teach humans has been investigated in rehabilitation settings [88, 137, 66, 131] but is less common in data-driven applications. An example is the design of a robot to teach fine motor skills using Imitation Learning. [142]. However, the direct impact of this work cannot be measured since they used simulations, which do not fully encompass the complexities of real-world teaching scenarios.

We now look at the different roles that humans can play when interacting with a machine learning system.

2.3.2 Human-Machine Co-learning

Co-learning can be useful to improve both the human's skills and machine learning. Co-learning is the simultaneous learning of human and machine. In this framework, the human learns to perform a task, which also involves a learning system. Both parties simultaneously adapt during the task. Co-learning has been studied in the context of improving human-AI team interactions, to build mutual understanding and adapt mental models [99, 23]. The idea behind Co-learning in human-AI teams is that human and machine should exploit their complementary strengths to benefit each other. In such scenarios, sharing mental models, which can include the human's emotional state, allows both parties to effectively communicate their intentions and actions [23].

In the field of body-machine interfaces, the term Co-adaptation is used to refer to the mutual evolution of human and machine to maximize performance and usability. In particular, Co-adaptation has been explored in the context of prosthesis control and makes it possible for machines to adapt according to human skill level or style [195]. For example, Co-adaptative mechanisms for body-machine interfaces have sought to provide consistent and stable control strategies by adjusting the speed of adaptation of the algorithm to match the human's progress [91] or optimizing the machine's actions to match the user's actions [53, 195]. Finally, in the context of learning motor skills, for example teleoperation, Co-adaptation frameworks have been devised to assist humans based on skill-level [77].

2.3.3 Human and Machine Initiative in Human-ML interactions

While Machine Learning has great potential to design novel movement interactions, using standard Machine Learning techniques involves challenges which can halt their use. Learning movement with the help of

Machine Learning systems implies that the system should learn from few data provided by humans. Training should be relatively short to accommodate humans' limited attention and physical abilities. To increase user adoption of the system, movement interaction should also be designed to balance control between the user and the machine.

Many machine learning models depend on data prepared by humans, but the interaction goes beyond data annotation. Some systems allow for ongoing interaction between humans and machines through a process called "Human in the Loop" (HITL). This process may involve varying degrees of human and machine initiative in selecting or crafting training instances. We describe the main HITL techniques below, ranging from minimal control for humans through Active Learning to more human initiative, through Interactive Machine Learning and Interactive Machine Teaching.

Active Learning

Active Learning (AL) has been used to enhance performance of a machine learning model with a limited amount of training data. AL is a paradigm which assumes the availability of unlabeled instances, which a human will annotate. The instances to be annotated are queried by a ML algorithm - the initiative comes from the learning algorithm. The human is an annotator and does not correct the model's output. The machine learner selects training instances based on specific criteria, such as uncertainty or diversity [184]. Given a budget for labeling samples, AL can improve the accuracy compared to choosing samples randomly.

Research in the context of human-robot interactions investigated how to query the human to optimize learning or how to balance queries and human initiative. Cakmak et al. studied how to teach robots through different types of queries issued by the machine learner e.g.,

selecting examples to demonstrate from a certain class vs labeling an example from a certain class [32]. They also studied how sharing initiative between the human and the machine learner impacts the interaction in terms of preferences and learning outcomes [30]. The main finding is that human-controlled Active Learning — where humans decide when to receive queries from the system, was the most preferred interaction method when training a robot to understand complex concepts. The task involved recognizing objects, such as *house* or *ice-cream*, through conjunctions of attributes such as color and shape of paper cutouts. This strategy maintained user engagement while providing some degree of control.

Interactive Machine Learning

Contrary to Active Learning, where the machine learning algorithm takes the initiative, Interactive Machine Learning (IML) is a field of research where the human selects or crafts data in each iteration of the learning loop to update the machine-learning model. IML is the result of joint research in HCI and ML, which aims to incorporate ML workflows in user practices [172]. It allows both human and machine to continuously learn in a tight loop and is a way to achieve Co-learning.

The aim of IML is to involve users in the model building process by enabling them to iteratively tune training parameters, inspect model outputs and provide feedback [63, 7]. IML is usually described in the context of Supervised Learning, but can also involve other Machine Learning techniques. IML systems typically make use of algorithms which do not require large amounts of data or long training times [67]. The process of building Machine Learning models this way can be very fast, enabling rapid iterations and adjustments to the system's behavior in real time.

Interactive Machine Learning has been used in various domains,

including music [68], health [201, 98], and education [209, 222], to alleviate standard Machine Learning problems. In the movement domain, IML has been used to design movement interactions by allowing users to take actions through movement [81]. For example, Fiebrink et al. [68] enabled users to control a given input (sensor glove) to produce sound. The user created a small number of training examples of controller-sound mappings on the fly, to construct a training set. The learning algorithm learned the mappings in a short time-span (a few seconds) and the user could test the system using the new mapping or keep adding new mappings. This enabled the user to interact with the learning process of the Machine Learning algorithm and shape the learning outcome through rapid exploration of controller-sound mappings.

Fiebrink et al. [69] highlighted that users were non-experts in Machine Learning and they came up with their own ways to assess the system based on their needs. For example, users can ask what types of gestures can cause misclassifications instead of reasoning in terms of accuracy. Thus, studying user interaction with IML systems can provide new insights on users' preferences and processes to design or assess these systems. Other uses of IML techniques for designing movement interaction include enabling users to train machine learning models on real-time gesture demonstrations [95] or to interact with virtual characters through movement [82].

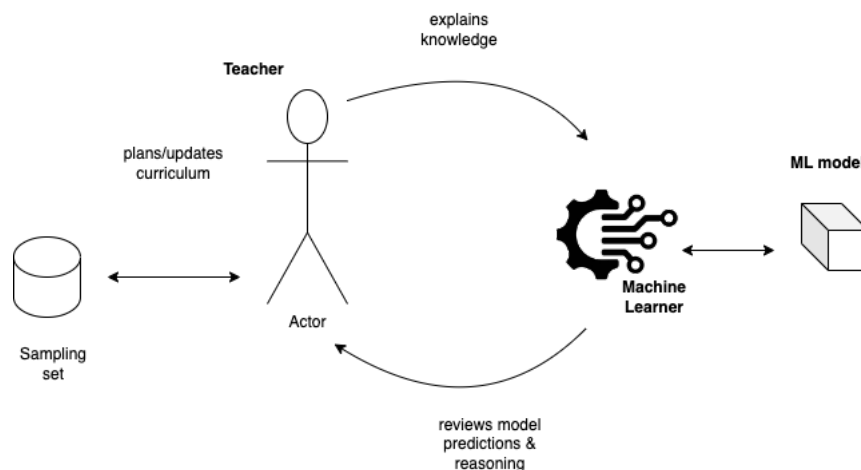
Interactive Machine Teaching

Interactive Machine Teaching (IMT) is a subset of IML that focuses on the teaching capabilities of the human. This research domain considers humans as machine teachers who possess domain knowledge and can provide feedback to steer the Machine Learning model during training. The human teacher plans the curriculum and is responsible for conveying knowledge to the learner. Any updates to the model are reviewed

by the teacher. The teacher may update the curriculum based on feedback from the machine learner. This requires building a good mental model of the machine learner. Figure 2.9 shows the actions taken by the teacher in what is called the IMT loop.

Studies in IMT investigated human-machine interactions during teaching. For example, Cakmak et al. studied teaching strategies which result in near-optimal teaching [31] or how teaching guidance affects the intuitiveness of the teaching task, the machine learning accuracy and the teaching time [33].

Fig. 2.9: IMT loop. The human teacher plans the curriculum, explains knowledge and reviews the machine learner’s state and model’s predictions. Adapted from [165].



When teaching machines, humans are also impacted since the process can shape the perception and reasoning of the human. They build representations of how the system works, known as mental models of Machine Learning, enabling them to predict the future actions of the system. Understanding people’s perception and expectations of adaptive learning systems can lead to better designs and adoption of these systems. The evolution of the user’s mental models when training Machine Learning systems has been studied in the context of recommendation systems, [119], where it was shown that training users to understand the system’s reasoning helped them build a better system,

fostering successful human-AI partnerships [16, 90, 107].

2.4 Summary

In this chapter, we discussed challenges of designing computational tools and learning interventions for motor skill learning. They concern difficulties in technical implementations as well as in designing the interaction with the learner.

The vast literature on Motor Learning highlights which principles can be used to design practice and the multiple factors which influence learning, such as skill level and motivation. This makes designing interventions for each learner difficult.

The algorithms used should adapt to an individual in real-time, preferably without requiring much historical data. While intelligent tutoring systems have been vastly studied, they remain scarce for the Motor Learning domain, since accounting for physiological processes adds another layer of complexity. In particular, assessing the learner's movement and skill level to adapt learning tasks is not straightforward.

Studying Motor Learning principles may help design approaches which speed up or improve motor skill acquisition for a specific learner. In addition, to achieve this goal using computational approaches, we study Interactive Machine Learning in the context of designing movement tasks. Letting users interact with machine learning systems creates new challenges, such as the need to enhance the user's mental model, i.e. their ability to accurately predict the system's behavior, ensuring that their expectations align with the system's actual functionality. This can be especially important to improve the performance of these systems and the chances that users will successfully adopt them.

In the next chapter, we present a study which investigates how curricula can be designed automatically for motor skill acquisition.

Interactive Curriculum-based Learning to structure Motor Learning

In this chapter, we study how theories and principles of learning can be leveraged to adapt practice to the learner through computational learning of a curriculum. This is a first attempt to study *Co-learning*, where both the human learner and the system learn jointly through interaction.

3.1 Introduction

Motor learning is a set of mechanisms through which one is able to perform movements faster, better, and more accurately [59]. When learning any motor skill, whether it is riding a bike, playing a musical instrument, or perfecting a tennis serve, practice is essential for skill development. Practice involves repeating a movement or skill multiple times. Repetition enables the brain to encode and solidify the neural pathways linked to the intended action, known as muscle memory. Beyond repetition, deliberate practice, which involves focused and purposeful efforts to improve performance, is known to enhance Motor Learning and skill acquisition. Nonetheless, the way practice should be structured, i.e. setting goals tailored to the needs and skill level of each learner, remains unclear [62].

In this research, the general problem that we attempt to address is how to structure practice in real-time, i.e. select tasks for a learner with the goal of improving or speeding up learning. Other factors, such as

variability in practice and the environment (e.g. practicing indoors or outdoors), can affect learning. Varying practice tasks has been shown to improve long term performance, also known as retention [180]. Much research has been conducted to understand the effects of varying the task during practice on motor skill acquisition. The Contextual Interference (CI) hypothesis predicts the effects of varying the task on performance and learning [186]. According to the CI hypothesis, inducing variability in task order in ways that create interference (random practice) can unintuitively facilitate learning and transfer skills [135] compared to practicing the same task repeatedly before switching to another task (blocked practice). Thus, while blocked practice yields better performance during or immediately after practice, random practice yields better performance at retention tests.

This theory has been tested in implicit learning contexts [212], applied to sports, such as executing a volleyball serve [198], practicing music (the left-hand interval leap on the piano) [15] and learning piano sequences following a tempo change during practice [34]. However, randomly varying motor tasks induces high levels of CI, altering the difficulty of the tasks without considering the skill level of the learner. Moreover, some research has demonstrated the negated effects of random practice in certain conditions - when the motor skill is complex [26, 8] and when the skill level is poor [93]. Thus, the conditions under which CI is beneficial to learning are not obvious. In this chapter, we focus on how to select the next task to practice, based on the interaction between task difficulty and the learner's skill level.

Our objectives in this work are twofold: (1) develop an approach to select tasks which are adapted to skill level and (2) propose tasks interactively and incrementally, based on previous performance. To this effect, we conducted a study which explores an approach we call *Curriculum-based learning*. Our goal is to automatically create curricula by letting the algorithm make a sequence of decisions.

We evaluate the benefits of such an approach on learners' acquisition and retention performance. In particular, our research aims to answer the following questions: (i) How can we design algorithms which adapt to the learners' skill level?

(ii) How can adaptive scheduling help a learner develop motor skills?

Previous work in adaptive learning has shown that proposing tasks which provide high learning progress can improve performance [44]. Furthermore, previous research in Motor Learning [41, 203] suggest that measuring the skill level of the learner to propose tasks may improve performance compared to a random practice. We hypothesized that by selecting tasks which provide high progress rates to the learner, curriculum-based learning would help learners achieve better performance than a random practice when tested immediately after training and that it could have better or comparable performance at retention. Then, since curriculum-based learning considers the performance of learners over time, we conjectured that it could outperform other state-of-the-art adaptive practices which only consider performances from a previous practice session to schedule tasks.

This chapter is structured as follows: section 3.2 reports previous work on adaptive learning and curriculum-based learning. Section 3.3 presents the data collection process of the study. Then we report the results in section 3.5. We discuss these results in the remaining section.

3.2 Related work

To motivate the lines of inquiry presented in the next section, we first highlight findings from the current literature on learner-adaptive approaches for structuring motor learning sessions.

3.2.1 Learner-Adaptive approaches

Theoretical research in Motor Learning has investigated the role of task order on motor skill acquisition. For example, one common finding is that increasing the amount of task switching leads to better learning. At the same time, models have been developed to explain and predict the relationship between task difficulty, skill level and performance. Recent research on adaptive learning has leveraged these results to design practice schedules.

Adjusting the level of task difficulty appears to be a crucial factor to meet the learner’s requirements during practice [64, 6, 214]. As underlined by many researchers [149, 42, 139], learners should face optimal levels of difficulty or challenge to enhance retention of skills. In particular, many adaptive algorithms follow the recommendations of the challenge point framework [87]. According to this framework, the optimal challenge is expected to evolve throughout the learning process, as learners become more proficient at processing information. Consequently, this framework suggests that the drawbacks associated with random practice i.e, decreased skill acquisition rate, can be overcome by tailoring practice schedules to the learner.

Learner-adaptive algorithms leverage data and feedback from the learner to tailor educational activities and interactions, thus optimizing the learning process. These algorithms use metrics such as performance scores or errors to assess learning. For example, the *win-switch, lose-repeat* paradigm is a performance adaptive schedule where the learner switches tasks based on their performance [189]. When a learner in this schedule achieves success, they switch to a different task. On the other hand, a failure results in repetition of the task. The results showed that the win-shift-lose-stay strategy was comparable to random and blocked practice in terms of acquisition and retention in a key-press timing task.

Another study introduced an algorithm capable of assessing the

difficulty of tasks by analyzing the average performance errors made by learners in a preceding training session. In the work of Choi et al. [42], the number of practice trials per task was adjusted accordingly, assigning more trials to tasks exhibiting lower performance in a previous session. Thus, scheduling was based on heuristics and was determined after performance on a retention test was available. This study found that adjusting the number of trials based on previous retention data, results in superior learning compared to random practice. In particular, the number of trials for a task i is computed as follows:

$$t_i = \min(\max(n \times e_i, n \times a), n \times b)$$

where n is the total number of trials for all tasks, e_i is the normalized performance error (between 0 et 1) for task i , and a and b are the maximum and minimum number of trials per task. The trials were then allocated randomly across blocks to create a sequence of tasks with the least number of repetitions.

In a more recent study, personalized challenge points were computed to adapt practice of a shape pairing task [203]. The challenge points corresponded to the mean reaction time values in each phase of motor learning (cognitive, associative and autonomous [71]) for an individual and were extracted in a prior study. These challenge points were then used to adapt task difficulty in a computer-controlled schedule. In particular, three difficulty levels were created, based on the challenge points extracted during each motor learning phase, in particular a high, medium and low difficulty. They hypothesized that practicing with a high difficulty condition (as expected during the cognitive stage) would provide the best retention results. The challenge points were used as a threshold to switch to a new sequence. The authors found that the high difficulty condition, which also results in more switching, resulted in significantly faster reaction times than the low difficulty condition. They concluded that adaptive practice, when coupled with high levels of contextual interference improves motor learning compared to low

levels of contextual interference, and does not deteriorate acquisition performance.

3.2.2 Generating learning curricula

Research in cognitive science has investigated the interest of using a curriculum-based learning approach to structure practice sessions. Curriculum-based learning involves organizing the learning process based on the learner's skills, e.g. by proposing simple tasks before introducing more complex ones. Generating a sequence of tasks which will maximize a humans' performance has been explored in Intelligent Tutoring Systems. To select pedagogical actions based on unknown learning gains some works have framed the problem either as Multi-Armed Bandits (MAB) [44, 182] or as Reinforcement Learning [100, 163, 18]. Multi-Armed Bandit problems uses a simple Reinforcement Learning setting. Only one state of the environment is available. MABs are commonly used in decision-making processes where the rewards of competing choices are not known in advance. They allow learning task-specific reward distributions in a discrete task space. No domain knowledge of the problem is required to use MABs and training time can be fast compared to approaches based on Markov Decision Processes which train on data from student populations [163]. This makes it suitable for interactive *Pedagogical Action Selection* (PAS) scenarios.

One notable work in automatic curriculum-based learning involves the implementation of an intelligent tutoring system to teach kids how to count money [44]. The algorithm in this work was inspired from a pedagogical theory called the zone of proximal development (ZPD). It recommends tasks which the learner can do when provided with guidance. The algorithm computes learning gains by assessing learning progress on a given task. The goal was to propose an activity currently providing high learning progress. A task which is already mastered or not possible to solve results in a low learning progress, and thus has

a low probability of being selected. The Multi-Armed Bandit strategy used was Exp4 [13], which accounts for the non-stationarity of learning. This means that the reward distribution changes over time, since the learning gains of a task change over time.

3.3 Method

In this study, we investigate the potential benefits of using a curriculum-based learning approach to create variable, but learner-adapted practice.

We conducted a between-subject experiment which lasted two days, where participants had to execute a visuo-motor task (originally designed by Shmuleof et al. [187]). It involved performing wrist movements to move a cursor in a channel.

All experimental procedures were approved by the Ethical Research Committee of Sorbonne university. All participants gave informed consent prior to participating in the study. The experiment was performed in accordance with relevant guidelines and regulations.

3.3.1 Task

The chosen motor task involved performing wrist movements with a cursor while keeping the projected 2D trajectory of the cursor inside a channel of a certain width, which appeared on screen. Figure 3.1 depicts the experimental task. Wrist movements controlled a cursor visualized on a screen placed in front of the participant. At the start of each trial, the participant placed the cursor inside the left circle of the arc-channel (Figure 3.1). Once inside the small circle, an audio as well as a visual signal (the circle turns green) indicated to the participant that they could start to perform the movement. The participant drove

the cursor inside the right circle through a wrist movement, and there was no visual feedback on the trajectory prior to reaching the right circle. Once the right circle is reached, the participant received visual feedback on the quality of the trajectory: the trace of the trajectory was black if it was inside the channel and red otherwise. Performance scores were not displayed during the experiment. Movement time, designated as MT in this paper, was constant; the start and end times of the movement were indicated by an audio signal. To change the difficulty of the task, we varied the channel width (Figure 3.2), while the length of the channel remained constant. There is a theoretical foundation for this task, called the Steering law, discovered by HCI researchers Johnny Accot and Shumin Zhai [3]. This law is a corollary of Fitts's Law and used in the particular case of steering tasks. It predicts the instantaneous speed for navigating a channel and the total time to complete the task. The Steering Law has been used to model the time taken to complete tasks, such as how to navigate hierarchies of menus on a desktop applications or manipulations in Virtual Reality [219].

The Steering Law is expressed as:

$$T = a + b \frac{L}{W}$$

where T is the time taken to navigate the channel, L is the length of the channel, W is the width of the channel and a and b are empirically determined constants.

3.3.2 Performance metrics

- **Accuracy** In the Motor Learning literature, movement execution is usually assessed through two distinct variables: speed - movement time (MT) and accuracy [187]. Skill acquisition is usually characterized as an increase in accuracy and/or smaller movement

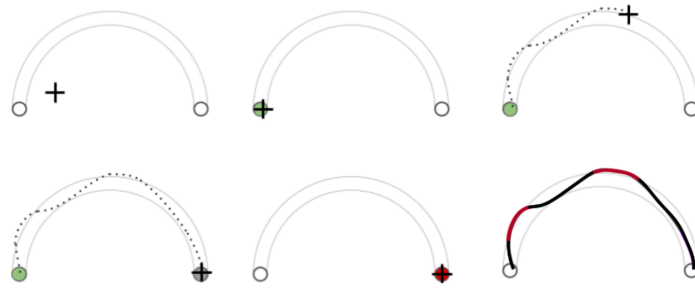


Fig. 3.1: The steps involved in a trial of the experiment. After the leftmost circle turned green, the participant could start tracing the trajectory using the cursor. The participant’s goal was to try to keep the trajectory within the channel and stop in the rightmost circle. The visual feedback of the trajectory was represented by a red trace if the trajectory was outside the channel and black otherwise.

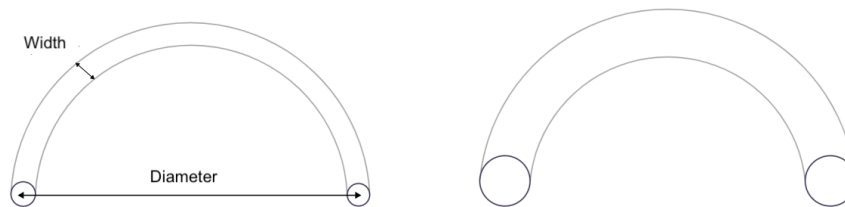


Fig. 3.2: Two examples of the task seen during training. The width of the channel was modulated to change the difficulty.

time. We defined the measure of accuracy of the movement as the proportion of trajectories which were within the channel (called the In-Channel fraction (ICF)), bounded between zero and one.

- **Movement Smoothness** We evaluated the movement jerk as a secondary metric. This metric has been used to evaluate motor learning before [187, 34]. According to the minimum-jerk model hypothesis [72], the motor system aims for maximum smoothness of end point movements. The jerk, defined as the quantity of acceleration variation, is a kinematic parameter used to assess the smoothness of movement [170]. It should be minimal when

a motor skill is acquired. Following this model, we expect the movement smoothness to increase after training.

3.3.3 Participants

We recruited 36 participants, among which 21 identified as male, 14 as female and 1 as a non-binary. We counted 3 left-handed and 33 right-handed participants. The participants were aged between 18–24. They reported not having any motor or cognitive disabilities. They were recruited either on the campus of Sorbonne University or through a mailing list. Prior to participation, the participants signed a consent form and could request to stop the experiment any time.

3.3.4 Apparatus and setup

Figure 3.3 illustrates the experimental setup. The participants were seated at a table equipped with a motion capture system and a screen. Participants placed their non-dominant hand through a splint which was adapted to the size of their wrist for comfort. The splint was used to limit the movements of the forearm to supination, so that the x and y coordinates on the screen were mapped to wrist flexion–extension and radial–ulnar deviation respectively. The participants were also equipped with a cursor in the form of a marker pen, on which was placed a reflective marker. With the marker in the hand, the participant had to trace a path on screen while trying to maintain the path inside the channel. The participant’s movement was captured by an infrared camera (Optitrack v120) and was drawn on screen to provide visual feedback after each trial. Finally, an audio signal indicated that the allocated movement time was over. We implemented the application using the Marcelle library [74], a modular open source toolkit for programming interactive machine learning.



Fig. 3.3: Setup and apparatus used in the study. The participant’s forearm was placed in a splint. The participant traced a path using a marker, which was captured by an infrared camera. The marker controlled a cursor displayed on screen.

3.3.5 Conditions

In this section, we present the three scheduling conditions tested in this study. In the next sections, these conditions will be referred to as **CONDITION**, to connote the type of training.

Curriculum-based Learning (CL) This condition implements the scheduling algorithm described below.

Given 7 tasks (of various difficulty levels), the problem consists of selecting a task in real-time, with a suitable level of difficulty for the learner given his/her learning progress. We implemented a Multi-Armed Bandit (with $K = 7$ arms) to both explore tasks and select tasks which are currently providing the best learning progress. We computed the reward as the absolute difference between the performance score of the previous and current (consecutive) blocks of the same task. Hence, the reward is a measure of the learning progress of the learner on each task. It is computed in the same way as Clement et al. [44] except that the binary variable to denote success or failure on a task is replaced by the performance *Perf* on that task. In particular, the measure of

performance used to compute the reward is the In-Channel fraction (ICF).

Using a *SoftMax* strategy, we favor the selection of tasks currently providing high learning progress. The steps for selecting one task are described below. In particular, in step 3, a minimum of $2 \times d$ trials of all tasks were completed by learners before the weight for that task was first updated. The update in step 4 tracks the estimated reward of the scheduled task. The parameters β and η balance the importance given to the previous estimate and the actual reward (learning progress) obtained for the scheduled task. After a pilot test, we found that an exploration parameter value $\gamma = 2$ provided suitable probability distributions. The values of β and η were set to 0.5, to weigh estimated rewards and actual rewards equally. The weights of the Softmax function are set to 0.1 for all actions, to ensure small updates of the estimated rewards. Formally, we can write the algorithm as follows, where t is the current task being considered, n is the number of trials completed, K is the number of tasks, \mathbf{w}_t is the estimated reward for each task and γ, β, η are the weights.

- *Step 1.* The vector \mathbf{w}_t is initialized.
- *Step 2.* The probability distribution of estimated rewards for task t , is computed as follows :

$$P(t) = \frac{\exp(\mathbf{w}_t^\gamma)}{\sum_1^K \exp(\mathbf{w}_t^\gamma)}$$

- *Step 3.* Select task t proportionally to $P(t)$
- *Step 5.* The reward r is the absolute difference between the last d trials and the previous d trials of the same task. $Perf_i$ is the performance on a task at time i .

$$r = \sum_{i=n-d}^n \frac{Perf_i}{d} - \sum_{i=n-2d}^{n-d} \frac{Perf_i}{d}$$

- *Step 6.* The vector \mathbf{w}_t is updated:

$$\mathbf{w}_t = \beta \mathbf{w}_t + \eta r$$

- Go back to step 2

Error adaptation (EA) This condition is an adapted version of the algorithm [42] described in section 3.2.1, which schedules tasks with the worst performances by adapting the number of trials. The algorithm does not consider how learner performances evolve during practice.

In the original protocol, the tasks were scheduled by estimating performance based on a long-term retention test as well as a more recent test preceding practice. Since we do not have retention data from previous sessions, we estimated performance in the first few trials during practice. Thus, we determined the number of practice trials after the pre-test, according to the performance error (Error = 1 - performance). To avoid allocating too many trials to one task, a minimum and maximum proportion of trials was fixed. We adapted these limits to the number of tasks in our experiment by multiplying the proposed proportions of Choi et al.[42] by a factor of 4/7, where 4 is the number of tasks in Choi et al.’s experiment. Hence, we came up with these numbers: minimum proportion of trials = 7.15% and maximum number of trials = 36.3%. The number of trials was adjusted according to the performance error while satisfying the above proportions:

$$N_i = \min(\max(N \times E_i, N \times 0.0715), N \times 0.363)$$

where N_i is the number of trials for the task i , and N is the total number of trials for all tasks, E_i is the normalized performance error for the task i .

Random This condition is a baseline strategy commonly used in the literature [135] to illustrate the advantages of contextual interference for scheduling tasks. All blocks (each block consisting of 4 trials each) were pseudorandomly shuffled for each participant.

3.3.6 Procedure

The participants took part in two separate sessions on two consecutive days: *training* (day 1) and *retention-transfer* (day 2). The two sessions were separated by 24 hours. We adopted a between-subject design with three conditions. We assigned the participants randomly to one of the three condition, so that there were 3 groups of 12 participants.

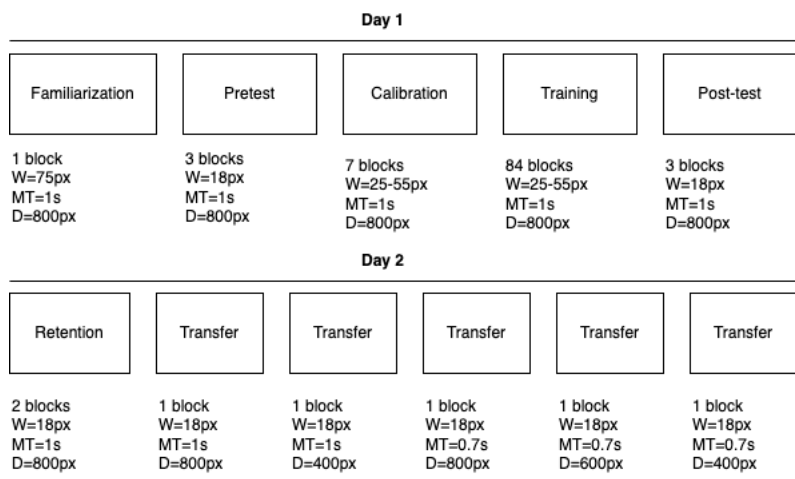
The first session (day 1) lasted 45 minutes on average and consisted of 5 phases: familiarization, pre-test, calibration, training and post-test. All blocks of the first session had 4 trials. The second session lasted 15 minutes on average and had 2 phases: retention tests and transfer tests. All the blocks of day 2 had 12 trials. Figure 3.4 illustrates the procedure. We describe the different phases below.

- **Familiarization:** This single block task was designed to help participants get familiar with the task. It involved tracing a trajectory in a channel which was 75 pixels wide and had a diameter of 800 pixels, within 1 second (MT=1sec).
- **Pre-test:** A pre-test measured the baseline performance of participants before training. It comprised 3 blocks of 4 trials and participants had to trace a trajectory in a channel which was 18 pixels wide and had a diameter of 800 pixels, MT=1sec.
- **Calibration** This phase had 7 blocks and was included to ensure that participants trained on all the 7 widths of the channel, irrespective of the scheduling algorithm. This was necessary for the

Error adaptation condition, where the tasks to be scheduled depends on the performance on each task during the pre-test phase.

- **Training** The training phase consisted of 84 blocks of 4 trials each. The arc channels had the following widths: 25, 30, 35, 40, 45, 50 and 55 pixels. The length (diameter) of the channel was fixed to 800 pixels during this phase, and $MT = 1\text{sec}$. The practice schedule depended on the condition assigned to the participant.
- **Post-test** The post-test consisted of 3 blocks of the same task seen during the pre-test. The goal of this phase was to verify the effect of each condition on performance.
- **Retention** Retention tests consisted of 2 blocks of 12 trials each, conducted 24 hours after training. The task parameters were the same as those of the pre-test and post-test, i.e. a 18 pixels wide channel with diameter 800 pixels and $MT = 1\text{ sec}$.
- **Transfer** The Structural Learning theory [27] posits that inducing variations randomly during training of a motor task facilitates learning of other motor tasks sharing the same structure as the original. The goal of this phase was to test how variations induced by the training condition affect the generalization of skills to similar tasks. This phase consisted of 5 blocks of 12 trials. We changed the length (diameter) of the channel and the movement time indicated to participants to complete a trial. The width remained constant. Each block is a combination of a unique diameter (D) and movement time (MT) as follows : Block 1 : $D = 600\text{px}$, $MT = 1\text{s}$; Block 2 : $D=400\text{px}$, $MT=1\text{s}$; Block 3 : $D=800\text{px}$, $MT=0.7\text{s}$; Block 4 : $D=600\text{px}$, $MT=0.7\text{s}$; Block 5 : $D=400\text{px}$, $MT=0.7\text{s}$.

Fig. 3.4: Experimental procedure. The first session (day 1) lasted 45 minutes on average and consisted of 5 phases : familiarization, pre-test, calibration, training and post-test. All blocks of day 1 comprised 4 trials. The second session (day 2) lasted 15 minutes and comprised 2 phases: retention and transfer.



3.4 Data Collection and Analysis

In order to analyze the movement data, we chose two metrics: the portion of the trajectory which is inside the channel (*In-Channel Fraction* (ICF)) and the smoothness of the movement *Movement jerk* (Jerk). Participants were told that these two measures were equally important: they were instructed to perform smooth movements and try to remain within the channel for all trials of the experiment.

- **Accuracy analysis (ICF)** The performance measure is the In-Channel fraction (ICF), defined as the proportion of movements in the channel, bounded between 0 and 1. Hence, ICF values close to 0 indicate that the movement was poor, while values close to 1 indicate good performance. Performance error is computed as the complement of the ICF (1-ICF). To compare the effect of practice on trajectory, the block mean and variance were computed (over all trials in a given block) per participant before and after practice. This allows comparison of mean trajectory and trajectory variability at pre-test and post-test.
- **Movement analysis (JERK)** We began by filtering the raw data. We applied a third order Savitzky-Golay filter of degree 3 polynomial, taken from the Scipy signal library ¹ to each of the x and y position data respectively. The jerk was then computed as the sum of the squares of the filtered data along each dimension to obtain a single value.

The datasets used in this study are available on Zenodo ².

¹https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.savgol_filter.html

²<https://doi.org/10.5281/zenodo.7824331>

3.5 Results

In this section, we present results obtained for each phase of the experiment. In order to designate each phase of the experiment, we will use the following terms : *Phase*, which was either Pre-test, Post-test, Retention or Transfer-x, where x is between 1 and 5 to designate different channel diameter and movement time. The specificities of each task are listed in Table 3.1.

Phase	Movement Time	Channel Diameter
Pre-test	1.0 s	800px
Post-test	1.0 s	800px
Retention	1.0 s	800px
Transfer-1	1.0 s	600px
Transfer-2	1.0 s	400px
Transfer-3	0.7 s	800px
Transfer-4	0.7 s	600px
Transfer-5	0.7 s	400px

Table 3.1: Phases of the experiment and the corresponding task specifications: movement time and channel diameter.

The movement onset and end were indicated by an audio signal. In order to rule out the possibility that larger movement times yielded better performance, we began by analyzing whether movement time was comparable between participant's performances per phase. We conducted a one-way ANOVA with CONDITION and relative MOVEMENT TIME taken by participants assigned to each condition. There were no significant differences between conditions for the Post-test ($F(2, 105) = 0.190, p = 0.826$), Retention ($F(2, 69) = 0.572, p = 0.567$), or transfer tests (Transfer-1 ($F(2, 33) = 0.084, p = 0.920$), Transfer-2 ($F(2, 33) = 0.340, p = 0.714$), Transfer-3 ($F(2, 33) = 0.475, p = 0.626$), Transfer-4 ($F(2, 33) = 0.034, p = 0.967$), Transfer-5 ($F(2, 33) = 2.165, p = 0.131$)). Thus, the conditions were comparable in terms of time taken to perform the movement.

3.5.1 Assessment of the impact of practice schedule on movement accuracy

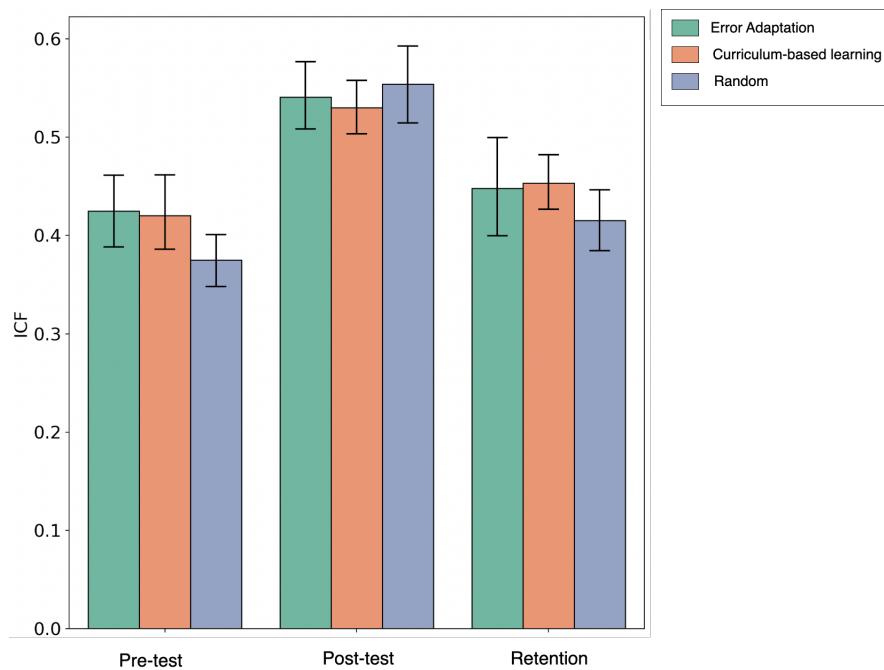
We began by assessing their *In-Channel Fraction* (ICF) performance, i.e. the portion of the executed trajectory that is traced within the channel at pre-test. To analyze whether the initial performance between conditions is comparable, we conducted a two-way ANOVA with practice CONDITION and PHASE (pre-test and post-test) as independent variables and ICF as dependent variable. We found no significant difference in the mean ICF between the three conditions considered in the study ($p=0.60$), but a significant effect of phase (pre-test, post-test) ($F(1, 210) = 83.2, p < 0.0001, \eta^2 = 0.28$) and no interaction ($p = 0.08$). In other words, the type of training does not seem to have an influence on the performance of the participants measured via the ICF. A T-test between the aggregated means for these two phases (pre-test and post-test) shows a significant difference ($p < 0.001$), where the means are $\mu_{ICF} = 0.42$ at pre-test and $\mu_{ICF} = 0.55$ at post-test. Therefore, performance increased between these two phases, confirming a motor learning mechanism in participants.

We then analyzed whether retention performance differs across conditions. An ANOVA with CONDITION as the independent factor and ICF as the dependent variable shows no significant difference. In other words, the type of condition has no influence on ICF performance at retention. If we study the difference in performance between the pre-test, post-test, and retention phases with a one-way ANOVA, we observe that the phase has a significant impact on ICF ($F(1, 105) = 46.2, p < 0.0001, \eta^2 = 0.25$). Tukey's test shows that ICF values are higher at post-test than pre-test ($p < 0.001$) and retention ($p < 0.001$) but there is no difference in ICF between retention and pre-test ($p = 0.16$). , see Figure 3.5.

For the transfer tasks, we analyzed whether performance in terms

of ICF depends on the conditions and the type of transfer. A two-way ANOVA with CONDITION and TRANSFER (Transfer tasks 1-5) as factors and ICF as the dependent variable shows a significant effect of the type of TRANSFER on ICF ($F(1, 105) = 14.9, p < 0.0001, \eta^2 = 0.24$) but not the CONDITION ($p = 0.07$). Tukey's test shows that ICF does not significantly vary when the movement time decreases from 1.0 to 0.7, but significantly varies between transfer tasks where the diameter changes from 800px to 400px ($p < 0.001$ for each pairwise comparison) and from 800px to 600px ($p < 0.01$ for each pairwise comparison), but does not vary when diameter changes from 600px to 400px.

Fig. 3.5: ICF at pre-test, post-test and retention. The error bars show the confidence intervals.



3.5.2 Assessment of the impact of practice schedule on movement smoothness

We also evaluated the movement smoothness by computing the jerk; the third derivative of the movement, integrated along the trajectory [187,

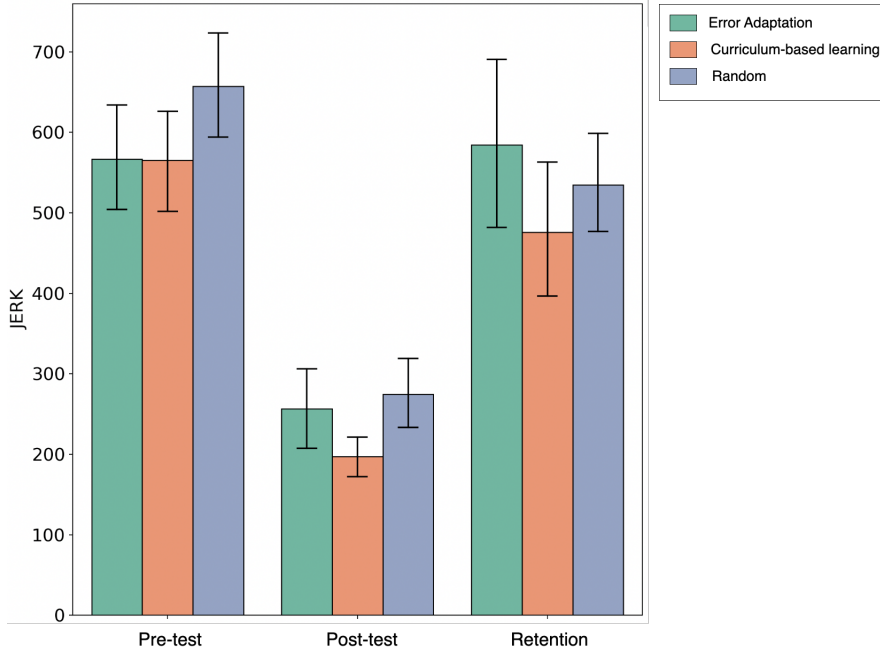
72]. A two-way ANOVA with CONDITION and PHASE (pre-test, post-test) as independent variable and JERK as dependent variable shows an effect of condition ($F(2, 105) = 4.60$, $p = 0.01$, $\eta^2 = 0.04$) and phase ($F(1, 105) = 226.7$, $p < 0.0001$, $\eta^2 = 0.52$) and no interaction ($p = 0.42$). A post-hoc analysis with Tukey's test (with 95% confidence level) at pre-test shows that there is no significant difference in mean movement jerk between practice conditions. A similar test performed at post-test shows that the mean JERK for curriculum-based learning is significantly lower than the random condition ($p = 0.03$). On the other hand, there is no significant difference between the random and error-adaptation condition ($p = 0.71$).

In the retention test, the task parameters were the same as those of the pre-test and post-test (i.e. a channel of width 18 pixels, diameter 800 pixels, and movement time 1s). A similar analysis taking the JERK of the movement as the dependent variable shows no significant difference between the conditions on the value of the average JERK at retention ($p = 0.24$). Moreover, if we compare the average JERK values of the pre-test, post-test and retention phases using a one-way ANOVA, we observe that phase has a significant effect on the JERK value ($F(1, 105) = 108.1$, $p < 0.0001$, $\eta^2 = 0.44$) (see Figure 3.6). A Tukey's test shows that the JERK value is significantly lower at post-test than pre-test ($p < 0.001$) and retention ($p < 0.001$). The JERK is also smaller at retention than at pre-test ($p = 0.037$).

In the transfer tests, the diameter of the channel and movement times were modulated while the channel width remained constant. In particular, each transfer test was a combination of a unique diameter (D) and movement time (MT) as follows: (D=600px, MT=1s), (D=400px, MT=1s), (D=800px, MT=0.7s), (D=600px, MT=0.7s), (D=400px, MT=0.7s).

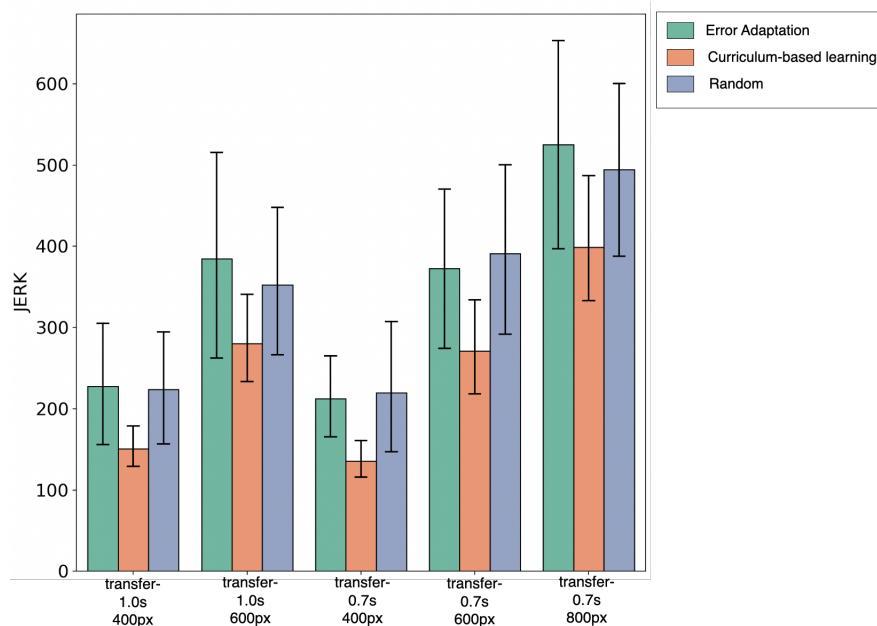
For the transfer tasks, a two-way ANOVA with CONDITION and PHASE (Transfer tasks 1-5) as factors and JERK as the dependent

Fig. 3.6: JERK at pre-test, post-test and retention. The error bars show the confidence intervals.



variable shows that these two factors also have a significant impact on the Jerk ($F(1,105) = 28.7, p < 0.0001, \eta^2 = 0.38$ for PHASE, $F(1,105) = 7.1, p < 0.01, \eta^2 = 0.06$ for CONDITION) and no interaction ($p = 0.99$). A post-hoc analysis using Tukey's test shows that there is no difference in terms of movement smoothness between the random condition and error adaptation condition ($p = 0.89$) but movement smoothness is significantly lower for curriculum-based learning condition ($p = 0.014$ for the comparative test with the error-adaptation condition and $p = 0.047$ with the random condition). In addition, movement smoothness also significantly varies when the diameter varies ($p < 0.01$ for changes between 800px to 600px or 400px and $p < 0.05$ for changes between 600px to 400px, independently of movement time). Thus, we obtain smoother movements for curriculum-based learning than the random condition and the error-adaptation condition at transfer and a decrease in movement smoothness for longer trajectories. These results are shown in Figure 3.7.

Fig. 3.7: JERK performance at transfer. The error bars show the confidence intervals.



Finally, in Figure 3.7 we observe a difference in jerk variance between conditions for the test phases. Thus, we plot the standard deviation of JERK performance across participants for each condition. Specifically, we compute standard deviations of trials for each condition and phase (post-test, retention and transfer). A one-way ANOVA with CONDITION as the independent variable and STANDARD DEVIATION as the dependent variable shows that the condition has a significant impact on the standard deviation of the JERK ($F(2, 18) = 4.97, p < 0.019$). Tukey's post-hoc test shows that the curriculum-based learning condition leads to a lower JERK standard deviation than the error adaptation condition ($p = 0.029$) and, and the random condition ($p = 0.035$) see Figure 3.8. Thus, curriculum-based learning has the smallest jerk variability ($M = 121.22, SD = 49.55$) compared to the error-adaptation ($M = 216.34, SD = 82.79$) and random conditions ($M = 202.91, SD = 43.46$).

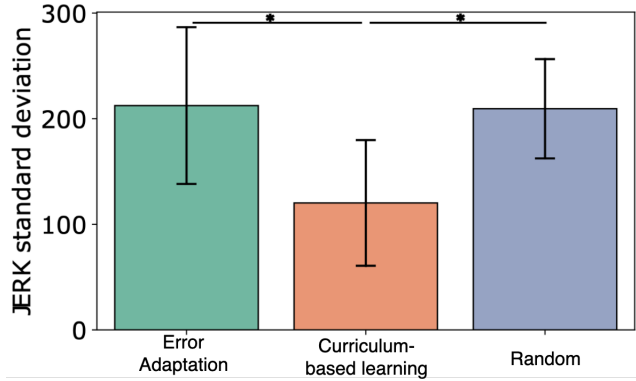


Fig. 3.8: Variability of the JERK for each practice condition. The error bars show the standard deviation of the JERK standard deviation.

3.5.3 Investigating learning schedules and rates

To study the task schedules for each condition on learning, we counted the number of blocks of each width (25px to 55px) allocated in the two conditions: error adaptation and curriculum-based learning (the random condition leading, by design, to an equal number of task trials per width). Figure 3.9 depicts the results, with the count of the number of blocks on the y-axis and the task width on the x-axis. We analyzed whether the number of task blocks differed between width for each condition. We conducted a two-way ANOVA with CHANNEL WIDTH and CONDITION as independent variable and COUNT as dependent variable. We found a significant effect of width on count ($F(1, 164) = 27.6, p < 0.001, \eta^2 = 0.14$) and a significant interaction between width and condition $F(1, 164) = 29.1, p < 0.001, \eta^2 = 0.15$. Therefore, we applied pairwise t-test between condition for each width (with Bonferroni correction) and found that there were significantly more blocks with width 25px in the EA condition compared to CL condition ($p = 0.0013$) and there were significantly more blocks with width 40px in curriculum-based learning compared to the error-adaptation condition ($p = 0.0019$). This means that on average, compared to

the participants assigned to the error-adaptation condition, curriculum-based learning participants practiced a larger number of low and intermediate difficulty tasks. However, a similar analysis at the start of practice (first 10 blocks) shows no difference between the two conditions either in terms of CHANNEL WIDTH ($p = 0.39$) or CONDITION ($p = 0.94$).

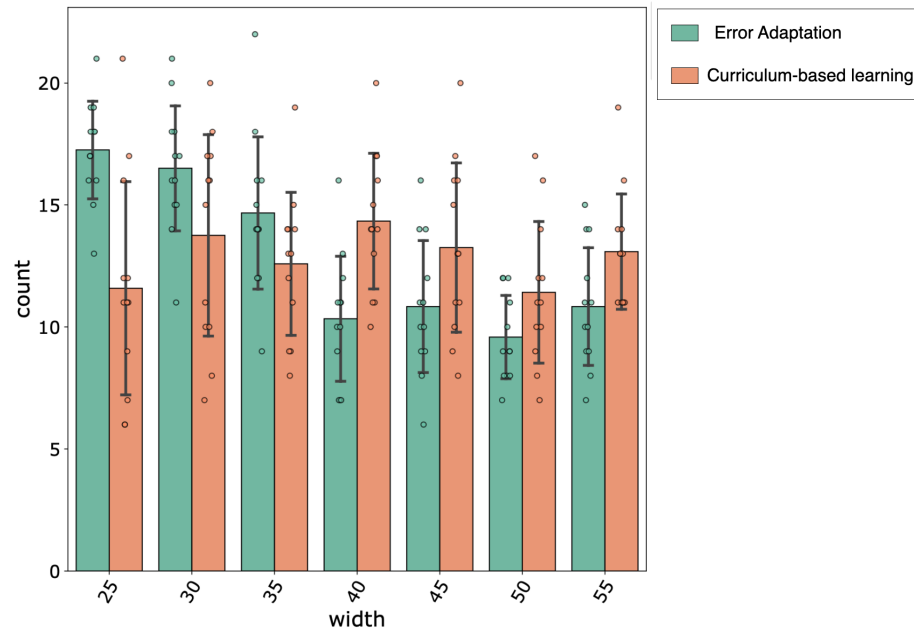


Fig. 3.9: Count of tasks during practice for curriculum-based learning and error-adaptation conditions. The error bars show the standard deviation of task count.

To investigate how movement smoothness evolved during training, we computed JERK over the training blocks (blocks 4 - 94). Figure 3.10 shows the average movement jerk over training blocks. Performing an ANOVA yields a significant difference between conditions ($p < 0.001$) in the final 10 training blocks. Tukey's post-hoc tests show that curriculum-based learning has lower JERK values over the last 10 blocks of training compared to the error adaptation ($p = 0.013$) or random condition ($p < 0.0001$).

To investigate the level of contextual interference for each condition, we computed the number of task switches for each participant of each

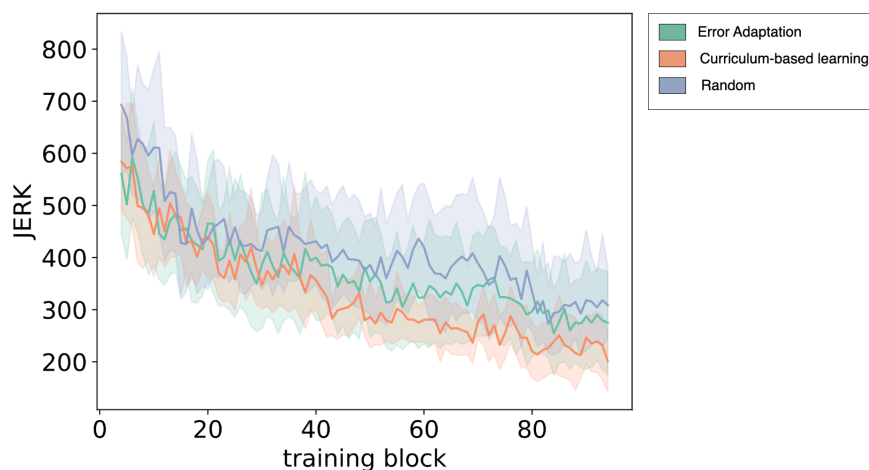


Fig. 3.10: Average JERK over training blocks. The error bars show the standard deviation of the JERK.

condition. An ANOVA with `CONDITION` and `NUMBER OF SWITCHES` shows a significant influence of `CONDITION`. A post-hoc analysis using Tukey’s test shows that the curriculum-based learning condition has a lower number of switches than the random condition ($p < 0.01$) as well as the error adaptation condition ($p < 0.01$). There were no significant differences between the other two conditions.

We also inspected the learning rates for each condition. To measure the learning rate of each task during practice, we performed a linear regression of the log-transformed ICF and Jerk values. An ANOVA with `CONDITION` as factor and `ICF LEARNING RATE` as the dependent variable shows no significant difference. Thus, neither the type of task nor the practice condition had an impact on the rate of learning when measured in terms of ICF. We then conducted a similar test with `JERK LEARNING RATE` as the dependent variable and it shows that there is a significant impact of `CONDITION` ($F(2, 231) = 6.55, p = 0.0017, \eta^2 = 0.05$). A post-hoc analysis using Tukey’s test shows that learning rates for curriculum-based learning is significantly higher than both the random condition ($p = 0.003$) and the error adaptation condition ($p = 0.009$). Figure 3.11 reports the mean learning rates per condition together with their confidence intervals.

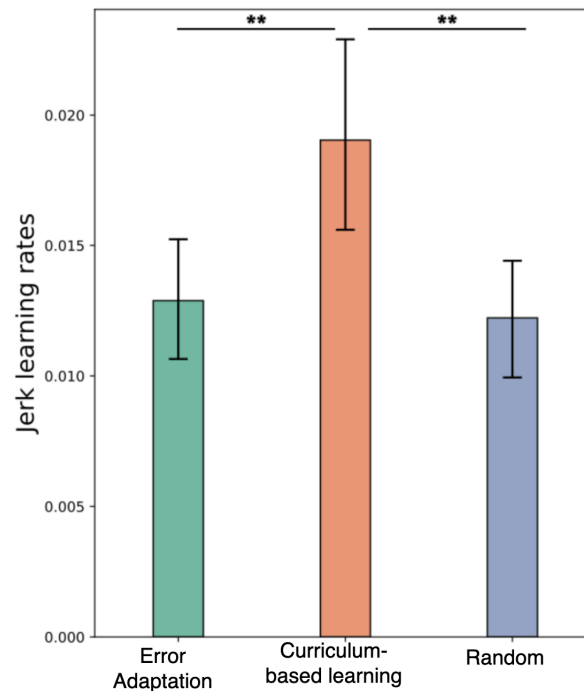


Fig. 3.11: Learning rates for the JERK across conditions. The error bars show the standard deviation of JERK learning rate.

3.6 Summary

The main aim of the present study was to investigate the effects of adapting the task difficulty based on a strategy which adapts the learning schedule in real-time using machine learning techniques. We compared three strategies, as follows (i) error adaptation, which scheduled a larger number of tasks with the worst performances and (ii) curriculum-based learning, which scheduled tasks currently providing a larger increase in movement accuracy and (iii) random practice. Our results show that the adaptive practice conditions yield comparable performances to the random practice in terms of movement accuracy

when evaluated immediately after practice and when tested for transfer tasks. On the other hand, participants assigned to the curriculum-based learning condition demonstrated smoother movements immediately after practice and when tested for generalization, than those assigned to the random condition. Finally, we did not find any difference between conditions when tested on day 2, for retention.

3.7 Discussion

In this section, we discuss the results reported earlier in terms of acquisition performance, retention and transfer performance. We also discuss the limitations of this study.

3.7.1 Impact of practice schedule on acquisition performance

The lower JERK performance of the adaptive conditions compared to the random condition suggests that adaptation of the difficulty based on skill level could be an important factor for decreasing movement effort and improving movement efficiency. In general, these results are in line with findings of other studies on learner-adaptive practice [42, 189], i.e. performance is better when practice is adapted to the learner than when tasks are scheduled randomly.

Executing smoother movements after practice can be seen as a result of trajectory optimization, which leads to skill acquisition [161, 187]. This definition of skill acquisition also suggests that smoother movements are a result of reduced effort to perform the movement. A lower jerk value suggests that participants assigned to the curriculum-based learning condition were closer to reaching a proficient skill level than participants assigned to the random condition.

While the adaptive schedules were created based on the movement accuracy metric (ICF), we found differences between conditions only when we assessed the movement smoothness (JERK). One interpretation is that because participants assigned to the Curriculum-based learning condition were provided with tasks of larger widths on average, this could have made tracing smoother paths easier. To better understand the implications of these results, future work should investigate the movement smoothness as a metric for motor learning. In particular, it would be interesting to investigate what strategy participants used to improve movement smoothness, e.g. did they learn to trace the arc shape and then increase the smoothness or the other way round?

3.7.2 Impact of practice schedule on retention and transfer

Results for retention, on day 2, showed that the type of practice did not have an effect on either the ICF or the JERK. Our interpretation is that this effect could be due to our choice of test task, which was more complex than those presented during the practice phase. Retention tests in other studies usually involve tasks which have already been practiced. However, in this study, the adaptive conditions scheduled some tasks more than others. Testing a task which has been practiced would mean that some participants would have practiced this task more often than others. A longer delay between training and testing could resolve this problem.

In addition, benefits of adaptive practice compared to random practice in terms of retention have not been observed in this study. However, since the advantages of random practice are less unanimous in applied tasks [26, 8], this calls for more investigations on adaptive learning in these settings.

We tested transfer capabilities on the next day by modulating either the diameter of the channel or the movement time, or both. While differences between conditions were not observed in terms of movement accuracy, there were differences in movement smoothness. In particular, curriculum-based learning outperformed the other conditions in terms of movement smoothness. There were no differences between the other two conditions. According to the Structural Learning theory [28], inducing variations randomly during training of a motor task facilitates learning of other motor tasks sharing the same structure as the original [27]. Our results suggest that an adaptive strategy could also have the potential to improve the transfer capabilities of learners.

3.7.3 Learning schedules and usage implications

The results showed that with curriculum-based learning, participants learned to increase the movement smoothness faster than the other participants. Past research in the cognitive domain [44] showed that skill acquisition was faster when the learning progress was optimized. Our findings suggest that this effect could extend to a motor learning context.

Remarkably, the JERK standard deviation for participants assigned to the curriculum-based learning condition was significantly lower than the error adaptation and random condition. This suggests that curriculum-based learning leads to more consistent or homogeneous performances across participants in terms of movement smoothness.

We also found that on average, participants assigned to the error adaptation condition trained on tasks of higher difficulty than the curriculum-based learning condition and switched exercises more often (higher CI). However, curriculum-based learning yielded comparable

performances (ICF at post-test, retention, transfer) or better performances (JERK at post-test, transfer) than the error-adaptation approach. If practicing tasks of lower difficulty level do not penalize motor learning, this type of practice could also be more motivating to learners, making curriculum-based learning an attractive strategy for customizing learning tasks in interactive motor learning systems.

3.7.4 Modeling performance

In this study, the movement data was rather noisy and participant variability was high. This could have contributed to the lack of clear differences between conditions at post-test and retention. One way of improving the analysis is to model the movement accuracy or movement smoothness. Given our experimental data, we can deduce a relationship between accuracy and the width and length of the channel. This would allow us to compute accuracy values using the model and reduce the noise in the data. From the Steering law, the time taken to trace a path in a channel of width w and diameter D is expressed as:

$$T = a + b \frac{D}{W}$$

. Given this relationship, we can indirectly relate the accuracy to the Steering Law parameters. A wider channel (larger W) increases the probability of staying within the channel, while a longer channel (larger L) makes it harder to maintain precision. The accuracy is thus proportional to the width of the channel and inversely proportional to the diameter:

$$ICF \propto \frac{W}{D}$$

We can thus model the accuracy based on the Steering Law as follows. $ICF = m \frac{W}{D} + c$ where m and c are parameters which must

be determined based using the actual ICF values obtained during the experiment. For example, they can be fitted using linear regression. The model can then be validated or modified based on the model fit.

3.7.5 Limitations

We used an adaptive algorithm to schedule tasks among a set of 7 tasks. Clement et al. [44] reported benefits of a curriculum approach based on MAB with a large number of cognitive tasks, 100 in their case. We speculate that more benefits of curriculum-based learning may be seen with a larger number of tasks, e.g., continuous changes in width (this would require a different choice of algorithm than what we used). Having a larger number of tasks means that the random strategy has higher chances of picking inappropriate tasks (too easy or too hard). Indeed, Clement et al. did not compare their curriculum approach to a random strategy because frequent task switching could be disturbing for learners. Thus, the number of tasks considered could be a factor in the success of the curriculum-based learning approach.

3.8 Conclusion

Our results suggest that Curriculum-based learning could be promising to increase movement smoothness as well as to take into account inter-individual differences to standardize performances. Nonetheless, this effect was not seen at retention. In addition, there was no clear distinction between the three strategies regarding the movement accuracy. Our data were also noisy and there was high variability among participants. Thus, recommendations on the use of a specific adaptive algorithm for real-world problems may not be easy to infer.

This first study thus served as a proof of concept, where we used

theoretical grounding in Motor Learning to design a Co-learning experiment. In the next chapter, we change gears and explore a different algorithm and use-case, to look at the human/machine agency and learning strategies in Co-learning.

Using Interactive Machine Learning to design adaptive systems for prosthesis control

In the previous chapter, we explored an approach to schedule practice tasks in real-time for individuals learning to perform a visuo-motor task. To extract more concrete insights on adaptive algorithms for motor learning, this chapter explores a more realistic motor task, which involves a human learning to control a prosthesis. We focus both on improving performance and the user interaction.

4.1 Introduction

In recent years, advances in body-machine interactions has led to improvements in myoelectric control strategies. In particular, using Machine Learning (ML) for prosthesis control is considered to be intuitive. Most commercial prosthesis systems make use of a technique called direct control (DC). It works by using the amplitude of EMG signals from one muscle to control one movement. Thus, a pair of antagonist muscles is required to control one degree of freedom e.g open and close the hand. Co-contraction, e.g., simultaneous flexion and extension is required to switch hand grasp. This can induce a cognitive burden as the number of hand grasp increases [54]. ML-based control allows more degrees of freedom and has the potential to control a greater set of gestures compared to existing control strategies such as direct control. ML-based prostheses work by attempting to extract the user's intent to control a prosthesis, using multiple electromyography (EMG) signals and classifying those signals into output gestures of the prosthesis ,i.e.,

a finite number of movements.

One challenge of ML-based prosthesis control is robustness, classification accuracy remains low in ecological settings. This lack of robustness is mainly caused by concept drift, which makes the model initially trained on to become irrelevant for usage since the old samples are likely to be outdated. This can happen for several reasons, e.g., due to physiological factors (muscle fatigue and changes in skin conditions) or external factors, such as electrode shifts when removing and wearing the device again. In addition, EMG signals vary over time and are likely to be different between training and time of use.

Some studies [153, 37, 220, 206] suggested that using training data collected over a long time can enhance recognition accuracy. Others have studied how using ML-based prostheses over a long time can improve control [92] or how improving the sample efficiency during training can enhance accuracy [194]. Equally important to make prosthesis control more reliable, is the human's ability to adapt and learn [160, 141].

In this chapter, we investigate the question of how to organize training examples on the fly by using different strategies to train the machine learning algorithm. We study how these strategies affect the system's recognition accuracy and the user's understanding of the system's behaviour. To do so, we take a complementary view of a human teaching a machine to classify gestures through continuous interaction.

In particular, the study aims to answer the following research questions: How does the teaching strategy affect **recognition accuracy** and **user's understanding** of an ML-based prosthesis when the training strategy is either *random*, *directed by the user*, or *directed by the system* according to an optimization criterion? Our hypotheses are as follows:

- Allowing the user to take an active role (“teacher”) by structuring their training session can help them test and improve their understanding of the system. This assumption is guided by (a) the learning by design (LBD) approach [111], which argues that being engaged in the process of design enhances skill acquisition, and (b) the interactive machine teaching approach [165], suggesting that users engaged in the role of a machine “teacher”, rather than annotator, develop investigative and self-reflecting behaviors [172]. We call this a *teacher-led* approach.
- Guiding users to select examples that maximize a given metric (the separability of the gesture, might lead to better model accuracy. This assumption is led by the fact that in the context of prosthesis control, increasing the separability of EMG patterns in the feature space of the classifier is conceptually linked to higher accuracy [141]. Since the machine learner queries the human teacher, we call it a *learner-led* approach.

This chapter is structured as follows: section 4.2 presents previous work on supervised learning for prosthesis control, reports on machine teaching methods to improve training efficiency and performance and on mental model evaluation techniques. Section 4.3 then presents the study, followed by a discussion of the implications of this work.

4.2 Related work

Given a movement goal, there are many ways for a human to reach that goal. Humans have inherent variability in their motor control systems. Even when attempting to repeat the same movement, subtle differences in muscle activation, joint angles, and force application can occur. One of the requirements of pattern recognition is to produce consistent movements, i.e. repeat movements with little variability [160].

For this reason, it is often necessary to retrain gestures to improve recognition accuracy. However, the underlying mechanisms of the machine learning algorithm used for pattern recognition are not intuitive to users. Without proper training, it may be difficult for users to know how to retrain their prostheses. Aligning the user’s understanding of the ML algorithm with their actions has the potential to overcome these limitations.

In the next sections, we discuss how these challenges have been addressed in recent research. We start by presenting research on supervised learning to control upper limb prostheses, with a focus on user training approaches to improve performance. We then present the literature on interactive machine learning, which has been used to convey concepts to a machine. Lastly, we report findings on how past research have probed users’ comprehension of machine learning models, also known as mental models.

4.2.1 Pattern Recognition for Upper-Limb Myoelectric control

Myoelectric prostheses work by leveraging the electrical signals generated by muscles to power the movement of these devices. Electromyography (EMG) involves recording these electrical signals. EMG recording can be invasive (needles are inserted under the skin, close to relevant muscles) or non-invasive, such as surface EMG (acquisition of signals using electrodes placed on the skin), depending on availability of useful muscle sites in amputees. Surface EMG signals are most commonly used to acquire data in experiments. These signals are processed to extract features in the time or frequency domain, which are then used by the machine learning algorithm.

Many EMG features and different ways of extracting them have been investigated, including time-domain [217, 17], autoregressive [60,

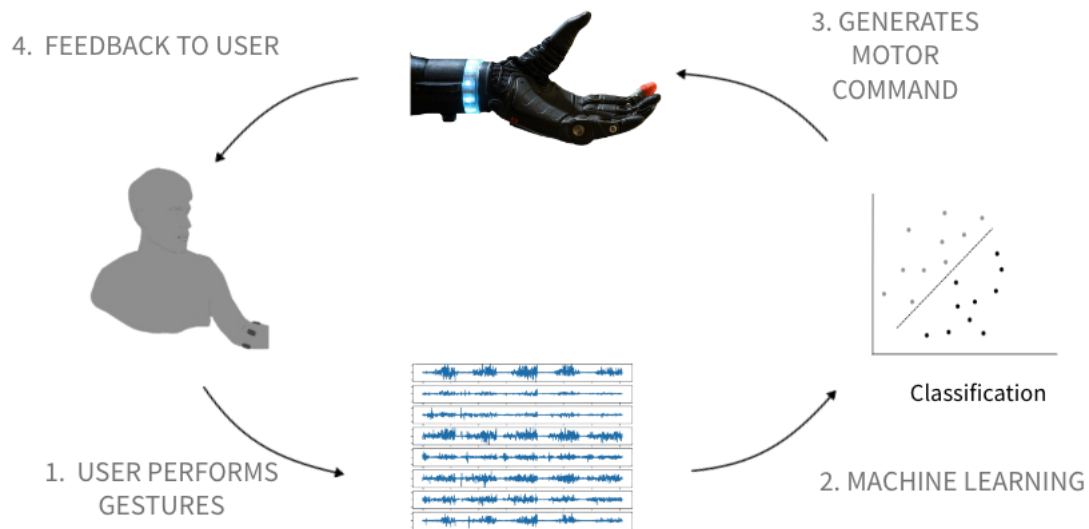
151] and time-frequency methods [61, 144]. Using the features, the goal of machine learning is to minimize the penalty for bad prediction while learning from input data. The machine learning algorithm can be used for classification or regression. Model training can be offline - prerecorded signals are used for learning or online - learning is real time. Offline training can be less cumbersome to the user, since signals are recorded prior to usage, but online learning has the advantage of being more ecological and accurate. In offline learning, the resulting model is evaluated on data generated by the user, after a previous training session. In online learning, the model can be tested on the fly, if it is trained in an incremental way. Researchers have thoroughly investigated and compared all types of classifiers for myoelectric control [218, 177]. Feedback is usually provided to the user in closed-loop protocols, usually in a visual form, e.g. prosthesis movement. The importance of proper feedback has been demonstrated [160, 65, 141]. Figure 4.1 shows the pipeline for online training.

While the focus of past research was mostly on machine adaptation, more recent research has shown interest in human learning and adaptation and has demonstrated its importance in the effectiveness of myoelectric control. Humans have the capacity to learn from the machine's output and adapt movements or develop new muscle contractions strategies to improve the machine's behaviour.

User Training

One of the reasons that ML-based prostheses have not been employed in commercial systems is that they are not robust, i.e. accuracy remains low in real-life applications. Training the user to adapt movements based on feedback from the machine learning algorithm has been shown to be effective.

Fig. 4.1: Illustration of closed-loop prosthesis control adapted from Igual et al. [101]. First, EMG data is acquired from multiple electrodes placed on upper limb muscles. Second, the data is processed and the extracted features are learned with machine learning (classification or regression). Third, a model is created and updated to predict the prosthesis output. Finally, feedback is provided to the user from the prosthesis or another interface.



The importance of user training in the ecological context of ML-based prosthesis control was highlighted by Powell et al. [159]. In a ten-day experiment, they showed that amputees improved their control performance with the help of visual feedback, which showed the movement of a virtual prosthesis. Subjects were coached by the experimenter to produce more separable and consistent gestures. However, another study with able-bodied subjects [117] showed that subjects can improve with training alone, independently of feedback on how to perform the movement or on performance during training.

Recently, research has shown that biofeedback in the form of visualization of EMG data points in a Linear Discriminant Analysis classifier's (LDA) feature space can improve user training [65, 141]. De Montivalet et al. [141] showed that allowing users to explore new ways of performing a movement using continuous visual feedback of the mean EMG data for each class improved the accuracy of the retrained class

without affecting overall accuracy. They used three metrics to compare two different feedback methods; classification scores, separability index (a measure of overlap of class clusters), and plots showing variations in muscle contraction strategies before and after training. When compared to using predicted labels of the classifier as feedback, the biofeedback yielded a larger variation in classification performance after training, fewer false positives of the retrained class and more variation in the contraction strategies. Human feedback has also been exploited to facilitate online learning. Pilarski et al. [154] proposed a reinforcement learning approach which leveraged binary reward signals to train and adapt a myoelectric controller. However, data was collected for only one participant and the number of movements was limited to two.

As mentioned before, compared to online training, offline model training can be suboptimal; users only get a chance to test the classifier at the testing phase (after a data collection phase to train the gesture classifier) and can only make adjustments to the classifier in the next training phase. This restrains human learning [29] and limits the user's capacity to adapt. Other research has employed online learning e.g. incremental training to explore different feedback [65] or serious games to adapt muscle contractions and create more separable EMG patterns [118].

Since training alone has the power to improve EMG patterns [117], it remains to be seen whether other training approaches can facilitate implicit learning and lead to further improvements. Only a few studies [207, 25] explored the effects of training curricula in a prosthesis context. These studies applied principles derived from motor learning research [186, 123, 162] to determine effective training methods. For example, Bouwsema et al. [25] studied the order of practice tasks (based on functional uses of prosthesis) and their effect on movement time (time to start movement and time to perform task) with a myoelectric simulator. Their findings suggest that performance in daily life is independent of training structure, but a blocked practice leads

to faster learning than a random practice. However, this remains to be explored for ML-based prostheses, where interaction with a machine learner provides an opportunity to explore different ways of teaching it.

In prosthesis control, both the user and the machine should adapt to address performance decline over time [178]. A few works have explored co-adaptation, the mutual adaptation of human and machine. Hahne et al. [91] investigated co-adaptation for regression-based myoelectric control with able-bodied and limb deficient participants. The user is fitted with EMG electrodes, with the goal of controlling a cursor on a screen. The regression model predicted the position of the cursor on the screen. The user (and the machine) learns to follow a target on a screen. They compared a baseline condition where users learnt the task without any machine adaptation, against conditions where the user adapted to different learning speeds of the machine learning algorithm. Compared to the baseline condition, the co-adaptive approach with appropriate adaptation rates produced better results. Other works leveraged models of human learning to simulate various co-adaptation levels [47, 53].

4.2.2 Guiding humans to teach machines

Research in interactive machine learning (IML) and human-robot interaction (HRI) investigated how guidance can help human teachers convey concepts to a machine learner. Teaching guidance mainly takes two forms: *delegation of initiative* and *instructional teaching*. The first approach: Delegation of initiative mainly explored Active Learning (AL), a strategy where the machine learner can query examples based on specific criteria e.g. informativeness or diversity [184]. An example is the work of Cakmak et al. [30], who investigated how humans teach a robot in a finite concept space. Their study compared self-directed teaching

(supervised learning with no queries from the machine) to three active learning variants: full AL, mixed-initiative AL (queries are made when certain conditions are met) or human-controlled AL (queries are only made when requested by the human teacher). They found that active learning conditions, including human-controlled AL, resulted in significantly higher F1 scores than self-directed teaching.

Instructional teaching guidance was explored by the same author, Cakmak et al. [33], across more complex and realistic tasks, including binary classification of drawings. Participants were primed with different teaching heuristics, e.g. an efficient teaching strategy must sample examples close to the decision boundary. They found that instructional guidance influenced human teaching to be more beneficial for the machine learner’s accuracy. Without guidance, participants had a tendency to provide typical rather than borderline examples (a negative example which is close to being positive or vice versa). In addition, they found that participants were more successful at providing positive rather than negative examples.

4.2.3 Humans’ mental models in interactive ML

The research literature involving a human teacher and a machine learner focuses primarily on model performance. However, an essential aspect in ML-based myoelectric control is users’ comprehension of the model, also referred to as the user’s mental model.

Mental models about a machine learner can be *functional*- the comprehension of the model’s learning or final behavior or *structural*- the understanding of the machine learner’s underlying mechanisms (e.g., neural network, k-NN, etc.). In our case, we are interested in assessing participants’ *functional* mental model, since the comprehension of the learner’s behavior, its strengths and weaknesses can help users adapt their muscular contractions and avoid errors in real-life scenarios.

Probing and evaluating users' mental model of a system is challenging [20]. The approaches employed to assess users' mental model of a ML system in the interactive ML literature often triangulate quantitative (objective understanding) and qualitative (self-reported understanding), including: assessments of users' ability to predict the system's predictions [174, 38], verbalization analysis from interviews [174, 120], think-aloud protocols [174, 173], or written responses to open-ended questions as well as analysis of responses from close-ended questions during post-hoc surveys [30, 119, 120, 115, 94].

Several studies have designed variants of tasks which assessed the user's ability to predict system output. Users' ability to accurately and consistently anticipate system outputs suggests that their mental models are well aligned with how the system works. Conversely, inconsistencies between expectations and actual system behavior suggest a limited understanding on the part of the user. Sanchez et al. [174] sampled input data to be shown to participants, who had to guess if their model would correctly or incorrectly recognize the selected input. They also introduced an exploration phase after the teaching session for participants to familiarize with the final model's behavior. Cheng et al. [38] introduced variants of tests that assess participants' predictive ability concerning the model. These variants, called *unnamed attributes*, *alternative prediction*, and *decision prediction*, are based on attributes that the user considers as having an impact on the algorithm's output and whether they can predict the output. Querying positive and negative samples for participants to predict or asking them to identify attributes as in Cheng et al. [38], are not feasible in the context of myoelectric prosthesis control; showing a muscular contraction pattern would not be evocative to the user.

On the influence of the machine learner's performance on users' comprehension, Hedlund et al. [94] found that the machine learner's (a reinforcement algorithm) performance can affect a teacher's mental model about the learner e.g., its capacity and reliability and their own

teaching capacity. Sanchez et al. [174] investigated how people use and understand two types of uncertainty feedback while teaching an image classifier. Both types of uncertainty feedback yielded similar predictive accuracy, but they found a strong correlation between users' predictive accuracy (e.g., objective understanding) and the machine learner's final accuracy.

On the influence of the training curriculum on users' comprehension, Cakmak et al. [30] conducted subjective ratings from a post-hoc survey, which revealed that people had a better mental model of the system's performance in the 3 active learning (AL) conditions rather than self-directed teaching. On the other hand, participants, reported less engagement in the full AL condition. Using a think-aloud protocol, Sanchez et al. [173] explored humans' understanding when incrementally teaching a deep neural network to recognize sketches. Their results underscore the importance of the training sequence, both for classifier performance and user understanding of the model behavior. In particular, curating examples which are imbalanced across classes at the beginning of the teaching was detrimental to learners' performances and users' comprehension. Researchers [30, 173, 204] converge on the usefulness of guidance prior or early in the teaching phase. Letting users interact with data triggers investigative behaviors [173] but requires engagement and time [38], suggesting a trade-off between efficiency and understanding.

In the present study, we combine methods to assess users' functional mental model to investigate both objective (users' predictive abilities) and self-reported understanding (think-aloud protocol and survey).

4.3 Method

We want to evaluate users' ability to build accurate classification models based on different ways of teaching the machine learning model to recognize gestures, and to investigate to what extent they foster the development of accurate mental models of the classifiers.

To allow users to convey movement concepts to a machine by generating movement data, we use Interactive Machine Teaching techniques. Research in Interactive Machine Teaching (IMT) focuses on improving human's teaching capabilities when interacting with a machine learner. Previous research in IMT has shown that people adapt their teaching strategy as they develop a mental model of how the machine learns[196]. A better mental model of the learner has in turn been linked to better behaviour [119]. Thus, allowing the human to develop intuitions and investigative behaviors by teaching can lead to better human mental models and more robust machine learning models.

To answer our research questions, we compare three model-training conditions under which participants incrementally train the gesture classifier: (1) Random-Condition (RC), which cued gesture classes randomly; (2) Teacher-led Condition (TLC), in which the user could choose the gesture classes for which to give examples; and (3) Learner-led Condition (LLC), which cued gesture classes based on their separability in the feature space.

To assess the effects of the training condition on participants' functional mental models, we combined objective and self-reported insights. In this section, we provide the details of the experimental protocol.

4.3.1 Participants

51 people participated in this study (25 males, 25 females, and 1 non-binary, aged between 18 and 36, $M = 24.8$, $SD = 4.2$). We recruited able-bodied participants to ensure comparable prior knowledge and sensorimotor expertise with myoelectric control technology. They were required to have no neurological or upper-extremity musculoskeletal problems that might influence performance. They received 15 euros as compensation. Participants' experience in Machine Learning and Robotics in Healthcare varied from novice (no knowledge) to advanced (experienced in Machine Learning / Robotics in Healthcare) (see table 4.1). The University's Ethical Research Committee approved all experimental procedures.

	Knowledge in Healthcare Robotics	Knowledge in Machine Learning
(Expert)	0	0
	1	3
↓	3	7
	14	12
(No knowledge)	33	29

Table 4.1: Number of participants having knowledge in (1) Robotics and (2) Machine Learning. Ratings were provided on a likert scale of 0 (expert) to 5 (no knowledge).

4.3.2 Task

We asked participants to teach the machine learning model to create the best possible recognition system for the following 8 gestures: (1) Palm Down, (2) Palm Up (3) Close Hand (4) Open Hand, (5) Close Pinch, (6) Open Pinch, (7) Rest Hand, (8) Point Index. These eight gestures are depicted as pictograms in Figure 4.2 and were specifically chosen because they are common actions performed by upper-limb amputated users fitted with current commercial myoelectric prostheses. They define the typical gesture set used in studies in rehabilitation engineering

focusing on myoelectric prostheses [141].

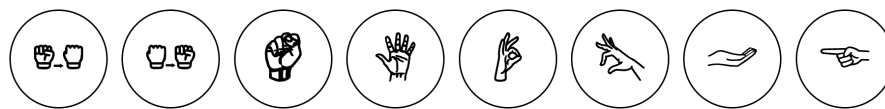


Fig. 4.2: The ML algorithm had to learn a set of gestures from examples provided by participants. We considered 8 gestures, from left to right: Palm Down, Palm Up, Close Hand, Open Hand, Close Pinch, Open Pinch, Rest Hand, and Point Index.

Training the best gesture recognition system implies that participants must consistently produce precise muscle contractions for the eight gesture categories, ensuring that the resulting model achieves optimal recognition. We implement an incremental training protocol, where the model is retrained for each new example demonstrated by participants.

As further detailed below, the interface shows gesture icons that indicate to the participants which gesture to perform at each trial. The icon represents the gesture class used as a ground truth label (see Figure 4.2).

4.3.3 Apparatus and Setup

The experiment consists of four components: a muscle contraction sensor, a web-based interface, a Python-based software module, and a prosthetic arm. Figure 4.3 illustrates the setup with the various components we explain in this section. The surface myoelectric activity of the forearm is measured with a dedicated device, a Myo armband from Thalmic Labs. The Myo armband comprises 8 channels to record electro-physiological signals with an 8-bit resolution. No specific skin preparation was used before placing the armband on the participant's forearm, approximately 5 centimeters from the elbow joint.

EMG data are sent to the Python-based software module. Features

are extracted from the Root Mean Square (RMS) of the raw EMG signal. It was computed from the surface EMG (sEMG) over a 128-ms sliding window, with a 32-ms overlap between successive windows. The dataset is available on Zenodo ¹. Among the wide variety of features that have been investigated in the literature, RMS features are known to be the most efficient and robust processing for classification of sEMG with LDA [153]. In addition, they are standard features in the literature on myoelectric prostheses, allowing the community to compare our results with other research such as Roche et al. [167] or De Montalivet et al. [141]. However, since we use a different protocol to these works, we do not make direct comparisons to them. We recorded about 2 seconds of data and averaged the features to obtain a vector of 8 RMS values for the 8 channels of the Myo Armband. For classification, we used a Linear Discriminant Analysis (LDA) classifier (taken from the Scikit-learn python library ²). We chose the LDA since it is the most used algorithm in to classify EMG signals [215, 141]. The Python-based software module sends classification predictions to the web-based interface through a web socket. The Python-based software module also sends the classification prediction to the prosthetic arm through WiFi to provide feedback on model performance to the participant.

The web-based interface was created using the Marcelle toolkit³, a modular open-source toolkit for programming interactive machine learning applications. The interface shows the icons described above, and a capture button used by participants to record muscle contraction associated with gesture classes. Participants are told to hold the gesture and click on the 'Capture' button, which records EMG data for approximately 2 seconds.

To provide motion feedback, a TASKA, NZ prosthetic hand ⁴ along with a conventional electric wrist rotator is used. The prosthetic hand

¹<https://doi.org/10.5281/zenodo.10528482>

²https://scikit-learn.org/stable/modules/generated/sklearn.discriminant_analysis.LinearDiscriminantAnalysis.html

³<https://marcelle.dev> [74]

⁴<https://www.taskaprosthetics.com/>

was programmed to enact the 8 gesture classes. This motion feedback is not essential in this scenario, and could be replaced by feedback on the interface. However, it creates a more ecological scenario; an amputee would normally test an actual prosthetic arm.

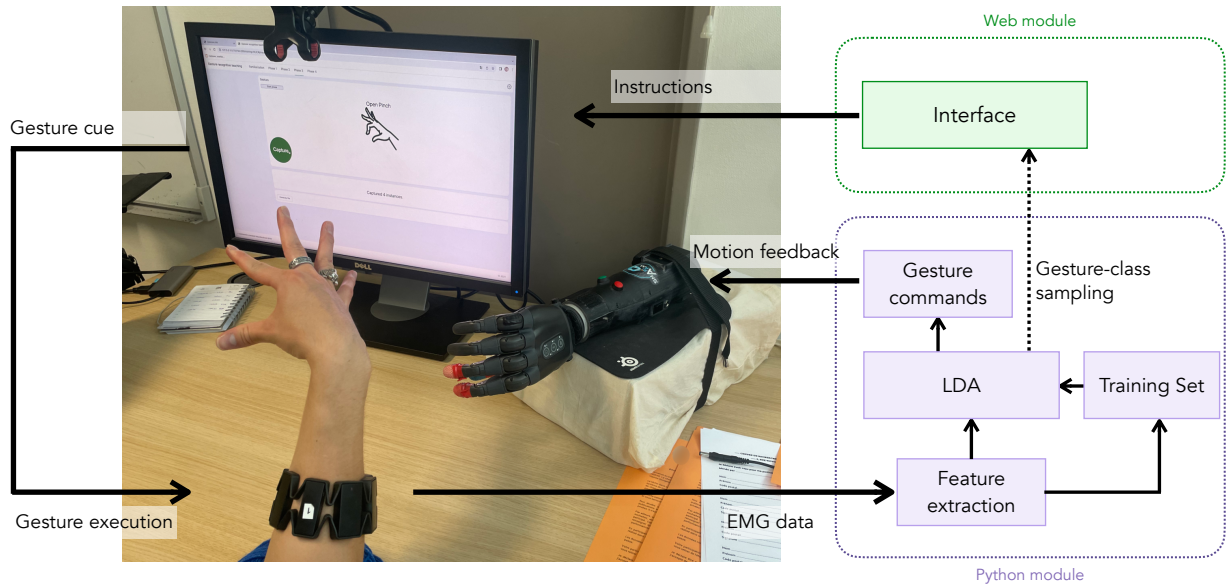


Fig. 4.3: The participant wears the Myo armband on the forearm and performs a gesture. A screen in front of the participant displays the interface for capturing data. The interface for the random condition (RC) is shown here. The interfaces for the other conditions can be found in the appendix (see Section .2). On the left, a prosthetic forearm (composed of a wrist rotator and a prosthetic hand) provides feedback during the training phase.

The training pipeline is as follows: a gesture class is selected (by the system or the participant, depending on the condition), and the participant provides an example of that gesture class through muscle contractions. After data windowing, the RMS is computed from the acquired EMG data. RMS features are used for classification with LDA. The predicted class is sent to the prosthetic hand to trigger the appropriate motor command.

4.3.4 Conditions and experimental design

We used a between-participant experimental design, where we compared three conditions, each with different ways of selecting gestures for training.

- **random condition (RC)**: at each trial during training, the system queries a gesture to be executed by the participant. This gesture is picked pseudo-randomly by shuffling the set of 8 gesture classes. Consequently, the number of gestures executed by a participant is balanced among gesture classes. There is no consecutive repetition of a gesture class, i.e., gesture classes always change from one trial to another.
- **teacher-led condition (TLC)**: at each trial during training, the participant selects the gesture class for which they wish to produce an example. The number of gestures per class executed by a participant depends on the sequence created, which can lead to an imbalanced dataset across classes. Participants (i.e. teachers) can also choose to provide several consecutive examples for a gesture class.
- **learner-led condition (LLC)**: the system (i.e. the learner) sorts gesture classes based on a separability index and queries the least separable gesture class at each trial during training. We compute the gesture class separability index as a ratio of the inter-class variance to the intra-class variance computed on the captured data (EMG features; see more details below). The intra-class variance for a class c is computed as the mean-variance of EMG data within c . The inter-class variance is computed as the mean of the variance of EMG data from class c and every other class c' different from c . A pilot study showed that, in practice, this strategy can create a highly imbalanced dataset depending on the initial data points. Therefore, to mitigate the curation

of imbalanced training datasets, the gesture separability index is weighted by the inverse number of instances for this gesture. This is depicted by the following algorithm 1 .

Algorithm 1: Gesture Class Separability Index

Input: A training dataset: $(X_{\text{train}}, y_{\text{train}})$

Output: Per-class separability index: SI

for class c **do**

$$SI(c) \leftarrow \frac{Var_{\text{inter-class}}(c)}{Var_{\text{intra-class}}(c)} ;$$

$$SI(c) \leftarrow SI(c) * \frac{n_c}{\sum_{i=1}^m n_m} ;$$

end

where m is the number of classes,

n is the number of samples per class,

$$Var_{c_i, c_j} = \frac{1}{n_{c_i} + n_{c_j}} \sum_{x \in c_i \cap c_j} (x - \mu^{c_i \cap c_j})^2,$$

$$Var_{\text{inter-class}}(c) = \sum_{j=1, j \neq i}^c Var_{c_i, c_j}, \text{ and}$$

$$Var_{\text{intra-class}}(c) = \frac{1}{n_c} \sum_{i=1}^{n_c} (x_i^c - \mu^c)^2$$

Two of the conditions, namely teacher-led and learner-led, can create training datasets which are not balanced. A common assumption in supervised machine learning is that training data points are independent and identically distributed (i.i.d) regarding the problem under scrutiny. This assumption is rarely met in simulated or human teaching, as well-explained in [223]. Teaching sets are often non-independent and identically distributed (non-i.i.d.) as they might be designed, for instance, to mitigate the inherent ambiguity between two classes. For this reason, we do not enforce balanced training sets in the teacher-led and learner-led conditions in our experiment. Strictly forcing an equal number of instances per class, besides the random condition, might undermine a crucial characteristic of teaching: planning and learner adaptivity.

4.3.5 Procedure

We welcomed participants and explained the task, the different phases, and the interface. Participants were fitted with a Myo armband. They were asked to place the elbow of the dominant arm on a ball of wool for comfort and to maintain this position throughout the experiment. To familiarize participants with the gestures, they were shown icons of each gesture and an image showing the corresponding gesture. Participants in all groups performed four phases (the procedure is also depicted in Figure 4.4).

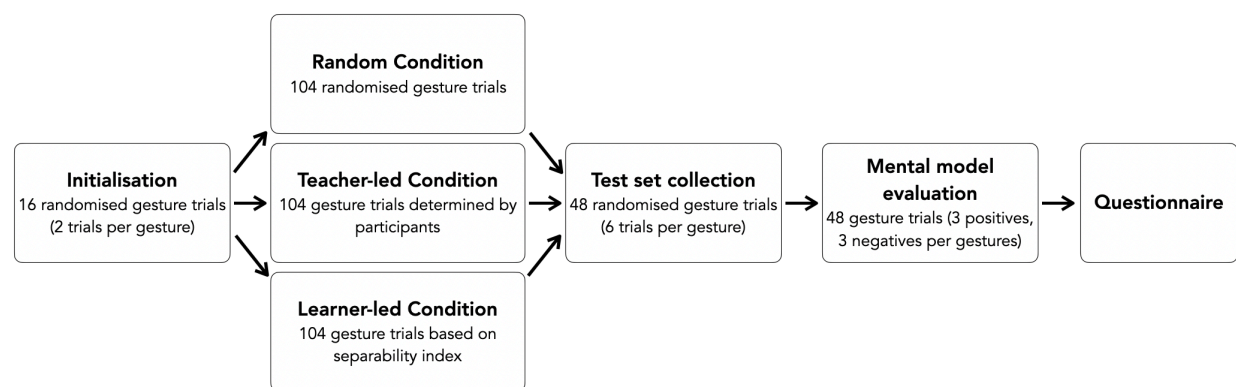


Fig. 4.4: The 5-phase experimental design. It involved a between-subject comparison of three conditions. Participants received feedback only during the training phase.

- (1) **Initialization.** This phase aims to provide an initial dataset to train the gesture classification model before starting the training phase. Participants are asked to record two gesture examples per class (16 trials in total). Each gesture is selected according to a pseudo-random strategy. There is no repetition of gestures.
- (2) **Training.** During the training phase, participants are asked to give an example of a gesture (RC and LLC) or to choose a gesture for which to provide an example (TLC). Participants are briefed about the conditions: in the teacher-led condition (TLC), they are told to choose which gesture they want to train, and in the

random condition (RC), they are told that the gesture classes are proposed in a random order. Finally, in the learner-led condition (LLC), participants are told that the most inconsistent gesture classes are prompted. In the RC and LLC conditions, gestures are presented as icons, and in the TLC condition, participants select gesture classes by clicking on the corresponding button illustrated by the icon. After each example, the classifier is trained on the entire dataset collected until this point, and the participant receives gesture feedback from the prosthetic hand. For instance, if a participant performs the “close hand” gesture, and if the classifier correctly recognizes this example as “close hand”, the prosthetic hand closes. Participants are told to pay attention to the feedback, which could be leveraged to reflect on future gestures. This phase includes 104 trials. The number of trials was decided based on a pilot study, which showed that the learning curve of the classification model plateaued after around 100 trials. In total, the aggregation of the examples from both the initialization and training phases add up to 120 gesture examples in the training set.

- (3) **Post-test.** To assess the model’s final accuracy after training, the participant completes a post-test. This post-test served as a data collection phase, comprising 48 trials to create a test set of 6 trials per gesture class. This phase was similar to the initialization phase in that the gestures were collected randomly and without any feedback.
- (4) **Positives-Negatives.** To assess participants’ mental model of the system, they were asked to complete a task that involved providing gestures while explaining their reasoning. In this task, participants were prompted to give three gesture examples that

would be correctly recognized, called *positives*, and three examples that would incorrectly be recognized, called *negatives*. Asking participants to curate positive examples is a way to understand whether they were aware of the technique that was producing success and could repeat it. Conversely, negative examples can provide insights into participants' awareness of borderline examples.

They were told that they could give different examples or repeat their examples. The examples could be drawn from observation during training or from their own understanding and interpretation. Participants were asked to verbalize (think aloud) their strategies to produce positive and negative examples. Therefore, this phase comprised 48 trials. Each participant, across conditions, experienced the same gesture order. The 3 positives were queried in a row, followed by the 3 negatives.

- (5) **Questionnaire.** Finally, participants were asked to answer a questionnaire where they rated the perceived accuracy of gestures of the trained model. Perceived accuracy is measured on a scale of 0 to 100, where 0 means never correctly recognized and 100 means always correctly recognized.

4.3.6 Data Collection and analysis

We logged each example recorded by participants and the classifier trained by users after each trial to compute the model accuracy along trials. During the 'Positives-Negatives' phase, we collected additional EMG data and participants' verbalizations with audio recordings. Finally, we collected answers to the post-study questionnaire (See Appendix .2 6) to assess the participant's mental model. Using different evaluation methods could help provide a fuller picture of the user's mental model (which is difficult to capture) than we would have been able to get from only questionnaires and subjective responses. Based

on these collected data, we computed the following measures:

Model Accuracy. We compute the model accuracy by selecting a trained model at a given trial, from trial 16 (after initialization) to trial 120 (at the end of training), and use data collected during the post-test phase as test set. The test set is balanced and contains 6 instances of each gesture. Accuracy (Acc_c) is computed per gesture class (from confusion matrices) to take into account the variation between classes when calculating statistics between conditions.

$$Acc_c = \frac{TP_c}{TP_c + FP_c}$$

Gesture separability. To understand how the separability of the EMG data evolves over time, we compute a measure of participants' ability to produce consistent and separable gestures over 3 phases: the start of training (16 gestures), end of training (120 gestures) and the post-test set (48 gestures). In the next section, these 3 phases will be designated as the variable PHASE. Gesture separability is computed similarly to the separability index used in condition LLC: we compute the gesture class separability as a ratio of the inter-class variance to the intra-class variance computed on the captured data. This computation is done pairwise to ensure a comparable metric between the beginning of training (where only 2 instances per class are available) and the end of training.

True Positive and True Negative rates. To quantify differences in participants' understanding of two types of tasks, i.e., their capacity to identify positive and negative examples of gestures, we calculate the true positive rate (TPR), which is the quantity of correctly classified gestures among the set of per-class positives. We then calculate the true negative rate (TNR) for the negative examples, which is the quantity of incorrectly classified gestures in the per-class negative examples. For both rates, high values mean an accurate model for positives and, respectively, a model that handles negatives correctly.

$$TPR = \frac{TP}{TP+FN}$$

$$TNR = \frac{TN}{TN+FP}$$

Participants' perception of class accuracy. We asked participants to complete a post-study questionnaire to assess their ability to keep track of training (see Appendix .2). We compute the correlation between the perceived accuracy for each class and the actual accuracy provided by the model at the end of the training phase, using data collected during the post-test set as test set.

To compare each participant's answers in relation to all the other participants, we transform the raw accuracy values to standard scores (z-score).

4.4 Results

In this section, we present the findings of the user study, starting with the analysis of the performance of the models built by participants, followed by the analysis of the mental models of the participants after having trained their gesture classifiers.

4.4.1 Machine learner's performance

In this section, we analyze the machine learner's performance and the extent to which the created training sets include separable gesture classes according to the training condition.

Model accuracy

We first analyzed whether the initial models built by participants (model comprising the initial 16 trials) are different between conditions, i.e. they result in significantly different accuracy values if tested on the post-test data. The mean accuracies for the initial models are as follows: 30.14 %(RC), 37.62 %(TLC) and 30.27 %(LLC). A Shapiro-Wilk test shows that the per-class accuracy values do not follow a normal distribution ($p < 0.05$). We conduct a non-parametric Kruskal-Wallis test, which shows no significant differences between initial models trained for each condition ($\chi^2 = 3.30, df = 2, p = 0.19$).

We then examined how the accuracy of the models changed based on the training conditions. We assessed model accuracy after each new gesture was demonstrated and added to the training set. Since the model is updated after each new gesture, the number of user trials equals the size of the training set, ranging from 1 to 104. We computed the model accuracy for each trial using post-test data as test set. The average learning curves for each condition and the 95% confidence intervals are shown in Figure 4.5.

We evaluated the final model from the training phase, which is trained on all the examples demonstrated by users, using the post-test data as test set. The mean model accuracies for each training condition are as follows: 70.83% for RC, 65.81% for TLC, and 68.38% for LLC. To verify whether these means are significantly different, we conducted a Kruskal-Wallis test, taking ACCURACY as dependent variable and CONDITION as independent variable. We found no significant differences between training conditions on the per-class model accuracy ($\chi^2 = 0.74, df = 2, p = 0.69$). Therefore, the three conditions lead to equivalent model performance after the training phase.

Even though there were no statistical differences between the mean accuracies of the model at the beginning of training, we observed a

variability between the initial mean values, which could suggest heterogeneity between groups. Therefore, we carried out a complementary analysis in which we considered the average delta accuracy (difference between the final and initial accuracy). Figure 4.6 reports the results. A Kruskal-Wallis test, taking DELTA ACCURACY as dependent variable and CONDITION as independent variable, shows a significant difference between conditions ($\chi^2 = 19.48, df = 2, p < 0.001$). A posthoc analysis with Dunn's test showed that LLC leads to a significantly higher improvement in accuracy compared to RC ($p < 0.05$) and TLC ($p < 0.001$), and there is a borderline difference between RC and TLC ($p = 0.053$). Consequently, although there is no difference between model accuracy created between the conditions, the performance improvement is larger when gestures are queried based on their separability and smaller when users choose the gestures to be trained.

Finally, we measured the learning rate to assess the evolution of skill development during training. We fit a linear regression model to the training set size (i.e., number of trials) and task performance. The logarithm of task performance plotted against the logarithm of the number of trials gives a straight line. To compare learning rates across conditions, we conducted a one-way ANOVA, taking LEARNING RATE as dependent variable and CONDITION as independent variable (a Shapiro-Wilk normality test shows that data are normally distributed ($p = 0.62$)). The ANOVA shows a significant effect of CONDITION ($p < 0.001$). A post-hoc analysis shows that the learning rate is higher for TLC than LLC ($t = -4.655, df = 31.369, p < 0.001$). Furthermore, the learning rate is higher for RC than LLC ($t = 2.3891, df = 30.757, p = 0.023$).

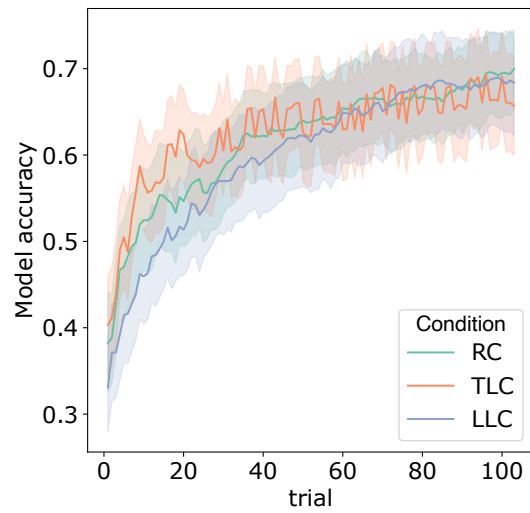
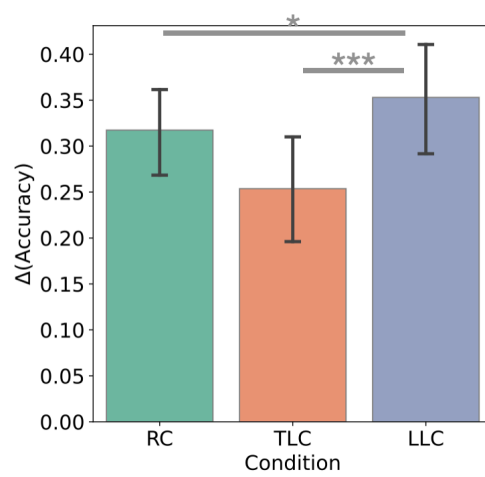
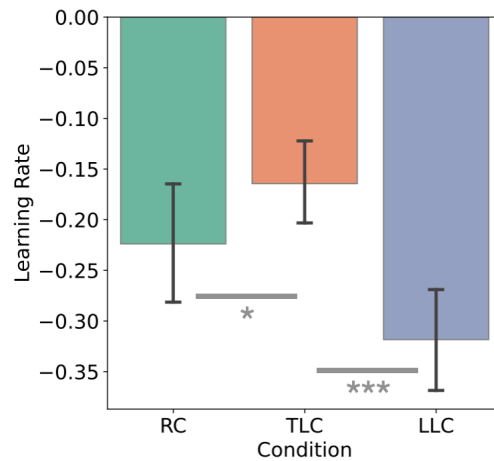
Fig. 4.5: Model accuracy evolution during training.**Fig. 4.6:** The difference in model accuracy between the beginning and the end of the training phase for each condition.

Fig. 4.7: Mean learning rates of model error reduction for each condition.

- **Finding 1.** Performance improvements of the ML-based myoelectric prosthesis are higher when gesture classes are queried to optimize gesture separability than in the random or Teacher-led curriculum.
- **Finding 2.** Performance improvements of the ML-based myoelectric prosthesis are fastest when gesture classes are queried to optimize gesture separability.

Gesture Class Separability

Incrementally training the gesture recognition model led to datasets that may differ across conditions. In this subsection, we analyze these demonstration datasets regarding gesture class separability. High gesture class separability implies concentrated gesture class clusters (low intra-class variance) far from the other (high inter-class variance). This index of gesture class separability is computed similarly to condition LLC (cf Section 4.3.6). Therefore, this measure indicates the consistency of the executed gestures, where more consistent gesture classes will lead to higher separability. Figure 4.8 depicts the mean separability

values per condition at three different phases: at the beginning of the training session (after the first training trial), at the end of the training phase (after the last training trial) and at the post-test phase. First, we performed a Kruskal-Wallis test at each phase, considering *CONDITION* as independent variable and *SEPARABILITY* as dependent variable. We found a significant effect of *CONDITION* only at the end of the training ($\chi^2 = 18.3, df = 2, p < .001$) where gesture class separability is higher for LLC than in the other conditions. We also inspected how the values of separability vary according to the phase. We performed Kruskal-Wallis non-parametric tests with *PHASE* as an independent variable and *SEPARABILITY* as dependent variable, for each *CONDITION*. We found that *PHASE* has a significant effect on *SEPARABILITY* for each condition ($\chi^2 = 13.5, df = 2, p < .01$ for RC, $\chi^2 = 30.2, df = 2, p < .001$ for LLC and $\chi^2 = 19.9, df = 2, p < .001$ for TLC). For each condition, gesture class separability values are higher at the end of training and at the post-test compared to the separability at the beginning of training. In addition, for LLC, separability is higher at the end of the training phase than post-test, as shown by Dunn's test, $p = 0.02$. It shows that overall, the gesture class separability increases, which can be related to the improvement in performing gestures during training, with a higher increase for LLC. However, at post-test, gesture class separability values are comparable across conditions.

- **Finding 3.** The separability of gesture demonstrations increases during training, irrespective of the condition.
- **Finding 4.** Increase of gesture separability is significantly higher when gesture classes are queried to optimize gesture separability than in the Random or Teacher-led condition.

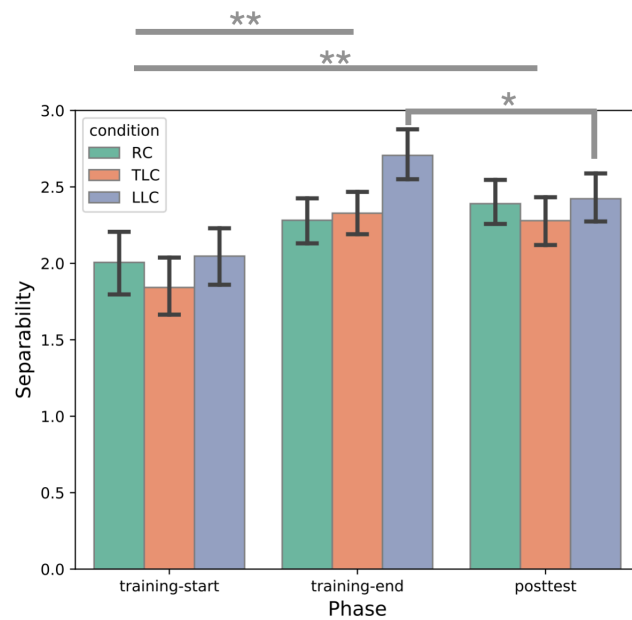


Fig. 4.8: Separability of gestures along different phases: at the start of training (after the first training trial) at the end of training (after the last training trial) and at post-test.

4.4.2 Human teachers' mental model

In this section, we assess the mental models of participants after they built their gesture classifier.

We assessed participants' mental model following two methods. First, we assessed participants' ability to predict where the machine learning model will make correct or incorrect predictions. We present results regarding participants' ability to execute correctly classified (positives) or incorrectly classified (negatives) examples for each gesture class. Second, we assess self-reported understanding through participants' answers to a post-training questionnaire on their perceived accuracy for each gesture class.

Participants' predictive abilities about the model

We want to test participants' ability to produce gestures of each class, which will be correctly recognized by the system (positives), and gestures that will not be correctly recognized (negatives). We evaluate the true positive and true negative rates of examples collected for both types (positive and negative), as well as participants' interpretation of these two types of examples. To compare the rates of true positive and true negative for each class and between conditions, we first conduct a Kruskal-Wallis test with TRUE POSITIVE RATE as dependent variable and CONDITION as independent variable. This yields a significant difference between conditions ($\chi^2 = 7.31, df = 2, p = 0.026$). Pairwise comparisons using Dunn's test show that the mean true positive rate is higher for condition LLC than condition TLC ($z = 2.49, p = 0.039$, see Figure 4.9). There is a borderline effect between RC and TLC ($z = 2.16, p = 0.061$) and no difference between RC and TLC ($z = 0.32, p = 0.75$). A similar test considering TRUE NEGATIVE RATE as dependent variable and CONDITION as independent variable shows no differences between conditions for the negative examples. Finally, a Kruskal-Wallis test considering the type of test (True Positive Rate and True Negative Rate) as independent variable and the rate as dependent variable shows that True Negative Rates are significantly higher than True Positive Rates ($\chi^2 = 25.26, df = 1, p < 0.001$). Overall, participants' understanding of positive examples is worst for condition TLC, while participants' understanding of negative examples does not differ across conditions.

During the think-aloud phase, a number of participants (P4, P8, P19, P20, P41) explained that to create a positive, they exaggerated the gesture. For example, while giving a positive example of the gesture 'Palm Down', P41 said : "*[..]rotate the hand until I hurt myself*". Some participants considered positive examples of gestures to be clear, slow, and precise : "*high up and poised, like this*" [P19], or "*I'm going to*

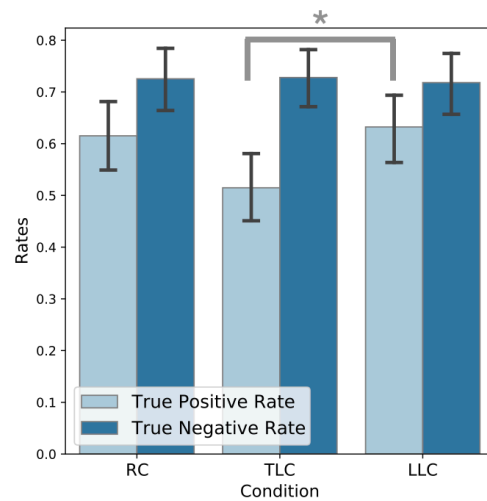


Fig. 4.9: True positive and negative rates from examples provided by participants after training. Participants have a less good mental model of what it means to produce positive examples of gestures when trained under condition TLC.

make a slow, detailed movement” [P4]. On the other hand, negative examples were considered as fast, incomplete, and casual: “*A negative would be a bit of a jerky movement, like this. Maybe it’s too fast for it*” [P19], or “*a lighter rotation*” [P1].

A few participants mentioned that it was difficult to imagine negative examples. P21 pointed out: “*In general, the robot recognizes the ‘Close Hand’ at all times, it’ll be hard to create a negative for that*”. Some participants who encountered errors during training easily identified examples that could confuse the system. While giving a negative example of ‘Close Hand’, P31 said: “*Earlier, it interpreted [Close Hand] as a downward rotational movement. I’m actually going to make a tiny downward movement too*”. Besides recalling training errors, another strategy employed by participants to create negative examples was to combine gestures. For instance, while creating a negative example of ‘Palm Down,’ P23 said: “*It’s a mixture of Close Hand and Palm Down*”, which may have contributed in deceiving the model.

- **Finding 5.** Participants' predictive abilities about the trained model are above random. Surprisingly, participants can better reproduce negative than positive examples.
- **Finding 6.** Participants' ability to reproduce correctly identified examples is significantly lower when the user chooses gesture classes to demonstrate rather than queried to optimize gesture-separability or at random.

Participants' perception of class accuracy

As a second evaluation of mental models, participants were required to answer a questionnaire about their perception of how well the system learned to recognize each gesture. Participants' answers about their perceived accuracy of each gesture class had to be chosen among 11 discrete percentage values ranging from 0 (bad recognition) to 100 (excellent recognition). Since participants' answers depend on their rating style and the scale provided (e.g., a participant's perception of a good recognition can be 80% while another's perception can be 100%), we transform all values to z-scores. This allows us to consider participants' answers relative to each other. Then, we computed a Pearson correlation coefficient to assess the linear relationship between perceived accuracy for each gesture class at the end of training and the actual accuracy computed on the post-test data at the end of training. The results indicate a positive relationship for LLC (Pearson's r score is 0.30, with $p < 0.001$, see Figure 4.11) while there is no significant correlation for the other two conditions TLC and RC (see Figures 4.10 and 4.12). This suggests that condition LLC allowed participants to better keep track of classification errors during training.

Fig. 4.10: Random condition: correlation of z-scores of actual accuracy values (y axis) and the corresponding z-scores of participants' perceived accuracy values (x axis) for each gesture class.

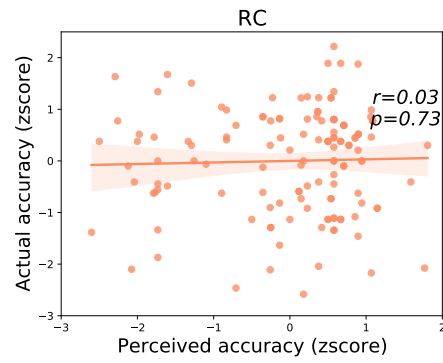


Fig. 4.11: Correlation of actual accuracy values and participants' perceived accuracy values for the Learner-Led condition.

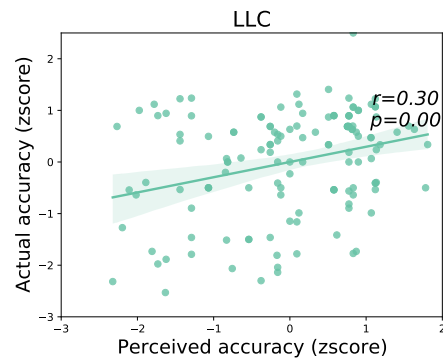
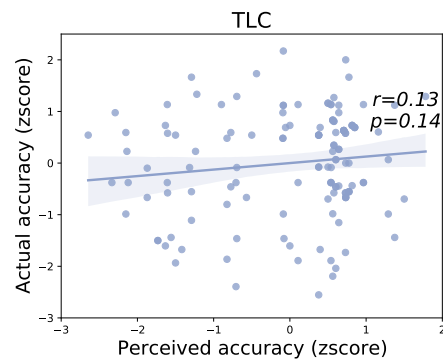


Fig. 4.12: Correlation of actual accuracy values and participants' perceived accuracy values for the Teacher-Led condition.



Finding 7. Participants better perceive the ML-based myoelectric prosthesis accuracy when gesture classes are queried to optimize separability during training than for the Random or Teacher-led conditions.

4.5 Summary

In the presented study, we investigated user-driven teaching strategies for ML-based myoelectric prostheses and their influence on the machine learner's accuracy and the human teacher's mental model. From the machine learner perspective, we found that the model's performance maximally increases when gesture classes are queried to optimize gesture separability, outperforming both random and teacher-led strategies. That said, we also showed that training is faster when users select the gesture class to be demonstrated. The three training strategies similarly led participants to increase the separability of examples across gesture classes, with a greater increase when gesture classes were queried to optimize gesture separability. From the human teacher perspective, participants' ability to predict the model's behaviors was more accurate, particularly in reproducing negative examples over positive ones. Participants' predictive abilities, though, diminish when they are left to select gesture classes during training, a discrepancy that is not observed with negative examples. Lastly, participants' perception of the model accuracy is better when gesture classes are queried to optimize separability during training.

This chapter illustrated the potential of IML techniques to develop strategies which can help users effectively retrain their ML-based prosthesis during daily life activities. In addition, it demonstrates the need for further research in mental model development of humans interacting with a learning system to perform movement tasks.

4.6 Discussion

4.6.1 Influence of training strategy on model accuracy

Several aspects of a training strategy can contribute to its efficiency. We tested whether giving users the choice to select the gesture class to train (teacher-led condition) results in better recognition accuracy than imposing gesture classes to train (random condition and learner-led condition based on a gesture separability index). We found that the teacher-led strategy did not yield better accuracy than the other training strategies. This is in line with findings in the interactive machine teaching literature, where Cakmak et al. [30, 31] showed that self-directed human teaching is rarely optimal, including for tasks where the human teacher generates training data [33]. We found that querying the least separable gesture class led to faster training, accompanied by a larger overall increase in accuracy. Previous research showed that both instructional guidance [33, 31] and sharing initiative with an active learner [30] yield better accuracy than self-directed teaching. The authors also showed that teaching an active learner, even with partial initiative, is faster than self-directed teaching, i.e., active learners converge towards the maximal accuracy with fewer examples. Thus, previous works corroborate our results, despite differences in implementation. Unlike previous work, our study does not employ an active learner that queries labels but rather demonstrations. Such a scenario affords greater human control and engagement than label queries. Thus, our results demonstrate its potential to support ML-based prosthesis control.

Learner-led strategy yielded faster resp. greater performance increase. Looking at the problem solely from the point of view of learner performance, a direct implication would be to use this strategy in practice. Alternatively, Powell et al. [159] highlighted the importance of coaching to incrementally incorporate gestures in a subject's training

session based on the subject’s capacity to create more separable EMG patterns. Looking at human-centered aspects, Dakpa et al. [51] showed that faster improvement of a classifier’s performance can motivate users to pursue the training, hence leaning toward the use of teacher-led training in our use case. Furthermore, it is likely that such results change with a different machine learner [152], or sensor device. Instead of scrutinizing averaged curricula performances, a promising research follow-up would be to investigate outliers, i.e., participants’ curricula that led to extreme performances—either good or bad, compared to others. Second, we argue that human-oriented assessments, e.g., focused on engagement and comprehension, are more important than model performances to involve users in the role of teacher. A valuable avenue for research would be to explore methods for users to effectively retrain their ML-based prosthesis during daily life activities.

4.6.2 Users’ understanding of gesture classification for prosthesis control

This study also investigated users’ mental model of an ML-based prosthesis control. An accurate functional mental model, i.e., users’ comprehension of the model’s behavior, its strengths and weaknesses can help users adapt their muscular contractions and avoid errors in real-life scenarios. Our evaluation method combined assessment of users’ ability to create and predict the classification of training examples with users’ self-reported perception of the system’s accuracy (obtained through answers to a questionnaire). Both methods indicate the benefit of the learner-led strategy (based on gesture separability) on participants’ mental model. On one hand, participants’ ability to reproduce correctly identified (positive) examples is significantly higher in both the learner-led and the random condition than in the case where participants decided which gesture to train. No differences in demonstrating negative examples were found between conditions. On the other hand, users’ perception of the system’s accuracy was more accurate in the

learner-led condition than in the teacher-led condition.

Two explanations can support these findings. First, the learner-led condition creates a curriculum that focuses on ambiguous classes, hence developing users' understanding of the most unstable gesture classes throughout training. The learner-led condition reflects the learner's progress; the user receives information about which gestures the learner finds difficult. Thus, a better mental model in this mode might be attributed to the additional information provided to the participant regarding the classifier. This explanation corroborates with Cakmak et al. [30], who found that human teachers had a more accurate performance estimate of the learner in active learning modes, including human-controlled active learning, compared to self-directed teaching. The second explanation links with our previous results on the model's final accuracy: model behavior of an accurate model is easier to understand. Such an explanation would align with other empirical findings in earlier works in [94, 174].

Our study yielded one unexpected result: during the mental model assessment phase, participants were more capable of producing negative than positive examples. This finding contradicts the verbalizations reported in section 4.4.2, where participants described demonstrating negative examples as more challenging. Participants' verbalizations also suggest that they approached positive examples differently than in earlier phases. Challenges in creating negative examples are reported in prior research [33]. This observation may be due to an experimental design artifact in the mental model assessment session. The think-aloud protocol, which required participants to demonstrate gestures while explaining their decisions aloud, might have imposed a higher cognitive load, resulting in changes in the execution of positive examples.

Asking participants to perform positive and negative examples is not a standard approach to assess participants' mental model, more

precisely, their predictive abilities about the model’s behavior. To assess participants’ predictive accuracy, Sanchez et al. [174] sampled input data to be shown to participants, who had to guess if their model would correctly or incorrectly recognize the selected input. They also introduced an exploration phase after the teaching session in order for participants to familiarize with the final model’s behavior. Cheng et al. [38] introduced variants of tests that assess participants’ predictive ability about the model. These variants, called *unnamed attributes*, *alternative prediction*, and *decision prediction*, are also based on actual data points and suggested modifications. Querying positive and negative labels to participants from actual input data, as well as the variants introduced in Cheng et al. [38], are not feasible in the context of myoelectric prosthesis control as there is no way to cue a muscular contraction pattern: a signal visualization would not be evocative.

We also gained some insights into participants’ interpretation of a *correct* gesture example, which could explain the disparity between scores for positive and negative examples (the True Positive Rates(TPR) were lower than the True Negative Rates(TNR)). Some participants reported that they exaggerated positive examples by turning the hand a lot or putting more effort into the gesture so that it would be recognized. However, exerting more pressure on muscles may cause the EMG patterns to change and may be more prone to misclassifications. Thus it is important to align users’ actions with the algorithm’s behavior, calling for further research on accurate evaluation of mental models in the context of ML-based myoelectric control.

4.6.3 Impact of training strategy on (human) skill acquisition

The gesture separability measure is used to assess the consistency of the demonstrations, i.e., to what extent gesture examples in the same class are close to each other, but far from examples in other classes. All

conditions showed a trend towards higher separability across phases, with a larger increase from start to end when the least separable gesture is queried. Practice and repetition are necessary to build consistency in any motor movement [148, 160]. The first finding might indicate that participants learned how to perform gestures more consistently throughout the training session, i.e., participants improved their motor skills in the execution of gestures. In our case, the learner-led condition favored repetition between gestures of identical classes, suggesting that participants improved their motor skills better in this condition.

Conversely, increasing the variability of practice has been shown to improve the acquisition of motor skills [28]. This means that it is preferable to switch from one task to another rather than repeat the same task until it has been learned. This improvement in learning has been demonstrated in terms of retention and transfer. In particular, it has been shown that creating motor interference by switching task from one trial (or block of trials) to another decreases the rate of motor learning but increases retention [186]. An analogous observation in our case is that the randomized training curriculum prevented gesture class repetition by design. It is also likely that the teacher-led condition involved fewer repetitions than the learner-led strategy. Hence, investigating the learning effect, measured by gesture consistency, during the retention phase (typically after several days) presents a significant research opportunity. The insights gained could profoundly influence the application of such training protocols in real-world scenarios.

4.6.4 Limitations

Our study had some limitations. First, results from this study are from able-bodied participants. Past research [177] suggests that the relative performance of machine-learning algorithms is consistent between amputees and able-bodied participants. Further investigations with an amputee population are necessary to understand whether this finding

also applies to different training strategies.

Second, we assessed the participants on the basis of a signal which was the average EMG signal over two seconds of data collection. In doing so, we discarded the gestural strategies used by the participants to arrive at the final postures. Keeping all the EMG data would have allowed us to extend our assessment of users' ability to control a prosthesis by inspecting the extent to which they could achieve a given gesture. In particular, it would be interesting to examine the model predictions temporally during these two seconds of gesture stabilisation. Taking into account all the classification decisions made from the beginning to the end of the two seconds would have made it possible to measure the regularity with which a user was able to maintain the desired position once it had been reached and to devise more refined guidance strategies.

4.7 Conclusion

In this chapter, we looked at how to design an adaptive algorithm to build a machine learning model which can be used to control a prosthetic arm. We took a multi-disciplinary approach, encompassing findings and guidelines in myoelectric control, motor learning and interactive machine teaching. Our results highlight the potential of these teaching strategies in the context of prosthesis control and suggest the benefits of using demonstration queries to organize the curriculum.

In the next chapter, we discuss findings and implications of this research on Co-learning and user interactions in adaptive learning systems.

General discussion

This thesis investigated two use-cases and algorithms to schedule motor tasks. The two studies are distinct, and thus do not permit a common reflection on the type of algorithm used and the learning strategies. However, we will, where possible try to find common points regarding the idea of curriculum generation. In the following sections, we reflect on our findings and discuss insights on designing more effective learning systems, enhancing the performance of both human and machine learners, and assisting learners in constructing more accurate mental models of machine learning, particularly in the context of developing adaptive control systems for prosthetic limbs.

5.1 Challenges in Human-Machine Co-learning

A key aspect of this research was the concept of *Co-learning*, which is the simultaneous learning processes of both human and machine. This mutual adaptation process requires both parties to modify their behavior to achieve learning goals in the interest of the human. We examined *Co-learning* in two distinct scenarios, each characterized by varying degrees of human-machine adaptation. In the first study, the machine learned to schedule tasks for the human, who received performance feedback but did not explicitly adapt movements based on the algorithm's recommendations. The interaction in the second study involved a dual-learner problem. Here, the goal of Machine Learning was to enhance the decoding of human intentions, facilitating improved control of prosthetic limbs. The goal was for the human participant to

create a more effective classifier by performing more consistent and distinguishable gestures. Consequently, the model's performance is contingent on the human's ability to produce stable muscle contractions.

One of the challenges of *Co-learning* is to calibrate the learning algorithm to the human learner. The first study necessitated the exploration and exploitation of tasks to assess their contribution to learning. As with other machine learning algorithms, bandit algorithms have one or more hyper-parameters, such as the degree of exploration. We realized that it was not straightforward to select the exploration rate for the participant. Previous studies simulated this parameter. We adjusted this parameter during a pilot study, but this remains impractical because we still use a group average. We maintained a constant exploration parameter, although it could potentially be decreased over time. The impact of this exploration parameter on human learning remains to be determined. In interactive machine learning, model performance is intrinsically linked to human interaction. Thus, works in Human-Machine interaction have explored the consequences of user interaction to make algorithm choices through the interface, with the goal of providing better user experiences and more effective learning systems [196, 70, 7]. These works encouraged the inclusion of end users in all stages of design, to explore and refine the behavior of the system. One way of doing this is to provide interfaces which allow to users to directly manipulate the machine's parameters. For example, Thomaz and Breazeal provided an interface which allowed participants to guide a learning agent to take certain actions through a reinforcement learning framework [196]. Their results provided insights on how humans want to teach agents through feedback. In light of these implementations, it could be interesting to investigate how to use these principles in this work. For example, exposing an exploration parameter (e.g, through a slider on screen) for the user to tune in real-time could provide insights on learners' recommendation preferences, in addition to providing more agency to the user.

Another significant calibration challenge is how to balance adaptation and stability, i.e. how to reconcile the acquisition of new behaviors with the retention of previously learned ones. In the second study, we chose to update the model by retraining it after each teaching example provided by the human participant. This design choice impacts the rate of human learning in a complex manner. Kristoffersen et al. [116] mentioned this dilemma in their work on myoelectric control, noting that a model frequently retrained can lead users to focus excessively on adapting to system changes without enhancing their EMG pattern quality. Conversely, the performance is contingent upon the model's quality, and inadequate robustness can hinder the user's ability to effectively operate the prosthesis.

Another factor which should be considered to decide on the frequency of retraining is concept-drift. In our Co-learning setting, both the machine learning algorithm and the users operating the prosthetic arm are learners, engaged in a closed-loop mutual learning environment. In this environment, users are also discovering their capabilities, adjusting their movements based on feedback. Concept drift, which refers to changes in data over time due to learning, or other factors like fatigue, can influence the system's performance. Participants may introduce concept drift intentionally or unintentionally. Usually, retraining the model with the most recent data helps the model adapt. However, as mentioned above, this can impact human adaptation. The interplay between human learning and frequency of retraining should be further investigated, e.g. by comparing the effects of maintaining a constant ML algorithm versus frequent retraining on human learning.

5.2 Curriculum-based learning for motor skill acquisition

An analysis of the task counts reveals that the adaptive strategy sampled certain tasks more often than others, providing insights into the relative ease or difficulty participants experienced with these tasks. For instance, in the first study (3), the algorithm selected tasks of intermediate difficulty more frequently. In the second study (4), the adaptive algorithm scheduled more instances of confusing classes (e.g., close hand and open hand) and fewer instances of stable classes (e.g., rest hand).

Further research is necessary to examine the effects of curriculum designs on various aspects of skill acquisition. The adaptive learning approach in our first study demonstrated benefits in enhancing movement smoothness. However, it remains to be seen how different curriculum designs can improve other aspects of motor skills. Curricula could be developed by sampling subsets of tasks based on skill level. In prosthesis control training, a manual strategy involves gradually expanding the set of gestures the user can practice until the full set is mastered, a method known as scaffolding, which has proven effective in training users to control their prostheses with machine learning [160]. Combining this technique with adaptive algorithms could potentially further enhance learning outcomes, but this would require strategic decisions about when to expand the task set, such as when accuracy with the current classes reaches a specific threshold. Pairing this technique with adaptive algorithms could further improve learning results, but would require making decisions regarding when to expand the set, e.g., when accuracy of the current classes reaches a certain threshold.

Additionally, the tasks examined in this thesis were independent and discrete. We did not investigate how the scheduling of one task might affect subsequent tasks. This consideration is important for rehabilitation tasks, which often require retraining sequences of movements to

perform goal-directed activities [197].

5.3 Understanding how people perceive algorithms and build mental models of adaptive systems

Another key aspect of this thesis was to understand and address how people perceive adaptive learning systems and what they expect from. It helped gain insights on how to design these systems to enhance learning outcomes and increase their chances of adoption. Aligning the user's comprehension of how the learning system works, with how the system actually works, is important to reduce frustration, confusion and errors. To achieve this, it is first necessary to evaluate people's mental models of these systems. Mental models are internal representations or explanations that people build of how things work. They help people understand the world around them and solve problems.

We consider that it is just as important to test to what extent people understand how to take actions using the system and how they perceive the system's weaknesses and strengths as it is to help people perform well. In both studies, we employed research methods in HCI, such as asking participants to fill a questionnaire after using the system regarding their perception of how the system or algorithm works or asking them to articulate their thought process as they work through the task and video-taping their actions. Through these elicitation methods, we gained insights on how people recall their experiences during training and to what extent they understand certain concepts.

In this research, we focused on the teaching strategies rather than how to help the human improve their teaching abilities. To offer prescriptive strategies for fostering more accurate mental models beyond the curriculum, it could be important to provide guidance on how to

rectify actions in cases of failure. Without appropriate intuitions about the sources of misclassification errors, users may struggle to correct their actions, such as by providing better training examples in subsequent trials. Research has demonstrated that assisting human teachers in understanding how machine learning systems work can enhance the accuracy of mental models [119, 33]. In the context of prosthesis control, guidance in the form of feedback about movement (biofeedback) or the curriculum itself should be studied. Guidance can also take the form of interactive explanations of what went wrong [38]. Nonetheless, prior research on the effects of explanations on mental models has highlighted that excessive information can detract from user experience by demanding considerable time and attention [120].

These challenges illustrate the difficulty of assessing and building accurate mental models. Combining several methods to evaluate mental models and using more rigorous approaches can contribute to acquiring a more accurate picture of users' mental models. Much work remains to be done in this direction, but recent research have shown an interest in developing frameworks to model people's perceptions of AI systems [107, 21] as well as in identifying approaches to provide appropriate explanations tailored to specific domains, use cases and users [36].

5.4 Human initiative in Co-learning interactions

Educational tools employing machine learning to adapt learning tasks often impose specific learning items or paths on users. Nonetheless, learners may have personal goals and preferences for achieving them, emphasizing the importance of allowing learners to take ownership of their learning process. This includes decisions on how active or passive they wish to be in acquiring knowledge and skills, as well as whether they agree with the system's proposed actions. Active participation of humans in motor learning is associated with increased motivation and

improved performance [11]. A pertinent question arises: Is it desirable to use a Machine Learning system which results in better learning outcomes, even if its recommendations are unpredictable and its underlying approach is unknown to the learner? It is crucial that both learners and educators can confidently rely on the system and influence the algorithm in desirable directions. For instance, an educator might choose an alternative approach for a specific learner.

Research in Human-AI interaction aims to design systems that are more interactive, personalized, and provide greater control to users during task performance. This has led to a body of works called mixed-initiative interaction, which considers the human and intelligent agent as working in a team to yield more effective interactions. Horvitz defines mixed-initiative interaction as *methods that explicitly facilitate an efficient and natural integration of contributions from users and automated services*. In the second study presented in Chapter 4, we examined a scenario where the human assumes the role of a teacher with the objective of training a machine to recognize gestures. The interaction mode itself allowed users to decide how to adapt their movements, with these physical adaptations being considered by the updated model after retraining. This teaching scenario provided users with greater control over the system compared to an offline training protocol, offering opportunities to test the system while training the ML algorithm.

We investigated various strategies for selecting training examples for the teachers to demonstrate, each involving different human-machine initiative. In the Teacher-led strategy, the human had the initiative to design the teaching curriculum. Allowing users to design their curriculum led a more balanced dataset at the beginning of the training, compared to the Learner-Led strategy (Appendix B). Participants may have been selecting gesture classes to both achieve balance and provide instances of classes which were not well recognized. Although this trend did not persist throughout the entire training period, it underscores the value of allowing human input in machine training. Humans

may possess intuitions or strategies that enhance the accuracy of certain gestures.

Cakmak et al., [30] demonstrated that human-controlled active learning — where humans decide when to receive queries from the system was the most preferred interaction method when training a robot to understand complex concepts. This strategy maintained user engagement while providing some degree of control. The fact that human initiative may improve other aspects of learning besides performance (e.g. motivation), should be taken in consideration when designing adaptive control systems using machine learning.

5.5 (Not) modeling the learner in adaptive systems for motor learning

Tutoring usually involves providing learning interventions for an individual. Knowing how to guide the learner requires an understanding of how people learn (or teach). When designing adaptive systems to facilitate motor learning, one question to consider is how to model the learner, i.e., identify and analyze relevant information to track the learning evolution.

In this research, we investigated performance outcomes following training for tasks outcomes following training for tasks that lack standardized procedures for solving them. In the work presented in Chapter 3, we aligned with the positioning of previous work in the field of cognitive and movement learning and consider that constraints in creating an elaborate model of the learner can be relaxed due to limited understanding of the learner's cognitive and motor processes [44, 169]. Consequently, rather than identifying parameters that characterize learners' knowledge of the task, we rely on estimations of learners' competence levels by computing their learning progress. Similarly, in Chapter 4,

we did not measure learners' knowledge against that of experts, given the user-specific nature of controlling a prosthetic arm. Instead, we estimated the learner's proficiency in controlling a prosthetic arm by evaluating the performance of the machine learner.

A growing body of works in complex domains have relied on online estimations of learners' characteristics to avoid depending too strongly on a cognitive model [44, 145, 169, 24]. This trend may indicate the efficacy of such an approach, or at the very least, suggest its potential to simplify the design process of adaptive systems in the context of movement learning.

However, it might be argued that there are some cases where modeling provides some advantages. For example, attempts at modeling cognition have led to improvements in our understanding of our brains [9]. Similarly, even if they do not show the full picture of learning, attempts at modeling aspects of learning motor skills may illuminate our understanding of how we acquire these skills.

Conclusion

In this thesis, we aimed to design adaptive algorithms to propose tasks for motor learning and to understand how individuals perceive and develop mental models of these algorithms after training machine learning (ML) models. Our first study concluded that using ML to schedule tasks offers notable benefits. Compared to an alternative adaptive practice that scheduled poorly performed tasks, the ML-based adaptive strategy provided more uniform training and improved a specific dimension of motor learning, namely movement smoothness.

The second study explored how humans comprehend and interpret the behavior of ML algorithms used to develop adaptive control systems. It involved investigating various interaction strategies for selecting which class to train in a prosthesis control task. Our findings indicated that employing a strategy where the system actively selects training examples had benefits. Specifically, using an adaptive algorithm enhanced individuals' mental models and overall performance gains.

Our research contributes to both HCI and cognitive science. We explored some challenges of designing Co-learning interactions, namely calibrating the system for the human and balancing adaptation and stability of the machine learning model. Recent machine learning paradigms such as interactive machine learning, which include users in the development of user-facing applications, create opportunities to provide more agency to users, leading the way to exciting research directions.

As a direct extension of this work, it would be interesting to explore adaptive learning over an extended time period within a more ecological context. As emphasized by research in motor skill learning, moving

beyond the desktop environment is likely to be beneficial as laboratory settings cannot replace actual training. When designing curricula for motor learning, it is imperative to work with users over several weeks or months. This approach allows for a deeper understanding of user needs and the lasting effects of various interventions. For instance, conducting a long-term study in the home of a rehabilitation patient offers a more realistic setting, potentially revealing the benefits of certain strategies over others. Although this approach presents greater challenges, both in terms of tools and methodologies used, it ensures that subsequent learning system designs target the most relevant learning metrics.

Lastly, other motor learning factors which may benefit from curriculum-based learning should be investigated. In this thesis, we studied the impact of curriculum-based learning on human performance and Machine Learning model performance. Previous works have shown that adapting learning tasks to provide optimal challenge is conducive to greater motivation and confidence [50]. Motivation and confidence being crucial elements of learning, it would be interesting to investigate how they are impacted by the adaptive systems implemented in this research.

This thesis paves the way to Human-Machine Co-learning. It provides insights which may enhance the design of personalized learning interventions for motor skills, balance control in human-AI interactions and foster sounder mental models of users.

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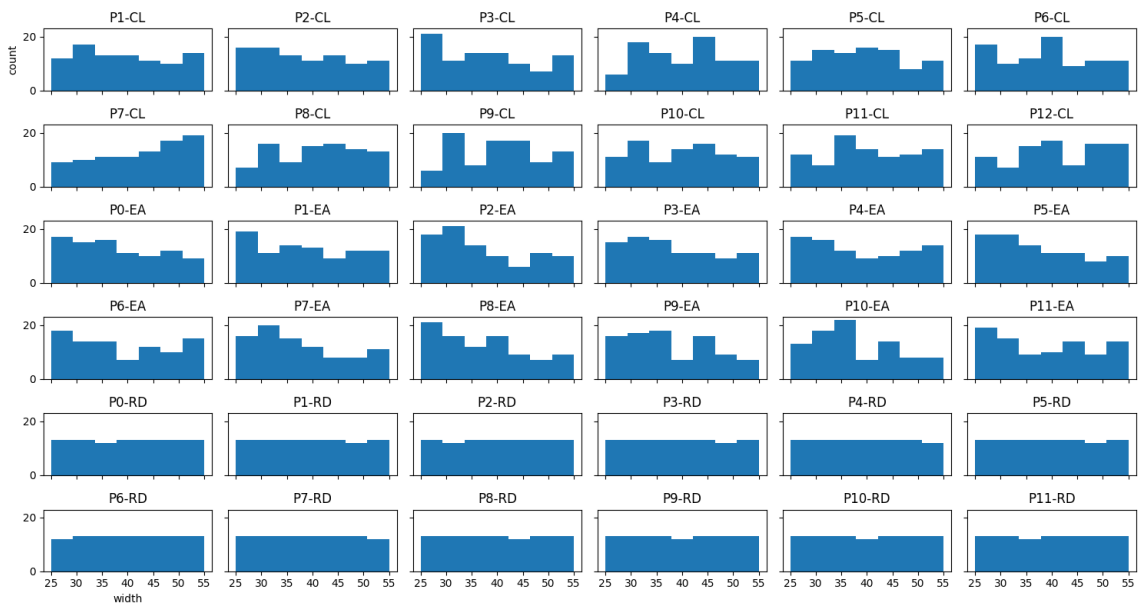
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.1 Appendix A

.1.1 Frequency of tasks in each practice schedule

Figure 1 shows the histograms of task widths (25 to 55 pixels) which were scheduled during the practice phase, for each participant and condition, denoted by Px-CL|EA|RD for Curriculum-based learning, Error adaptation and Random. In general, the shapes of the histograms are more variable for the Curriculum-based Learning condition than the others. Based on the taller bars at the beginning of the histograms, the Error Adaptation condition seems to schedule harder tasks than easier ones.

Fig. 1: Histograms of task widths for each learning schedule : Curriculum-based learning - CL, Error Adaptation - EA, and Random - RD.



.1.2 Questionnaires

In the context of the study presented in Chapter 3, we carried out a subjective analysis of learners' perception of the schedules. First, we asked them whether they found the schedule to be random or having a certain discernible structure. Then, we asked them to rate how appropriate they found the practice schedule to perform the post-test task. Figures 2 and 3 shows the questionnaires we employed.

Fig. 2: Day 1 questionnaire.

11/07/2024 13:14 Questionnaire 1

Questionnaire 1

- PID

- What is your age group?
Une seule réponse possible.
 - 18-24
 - 25-34
 - 35-44
 - 45-54
 - 55-60
 - 60+
- What is your dominant hand?
Une seule réponse possible.
 - Left
 - Right
- What is your gender?
Une seule réponse possible.
 - Male
 - Female
 - Prefer not to say
 - Other

Fig. 3: Day 2 questionnaire.

11/07/2024 13:13

Questionnaire 2

Questionnaire 2

1. PID

2. How much do you think you were good at this activity before training?

Une seule réponse possible.

1 2 3 4 5

Very Very good

3. Do you feel that the training schedule was appropriate for the task you had to learn?

Une seule réponse possible.

1 2 3 4 5

Not Appropriate

4. How much do you think you've learnt the movement?

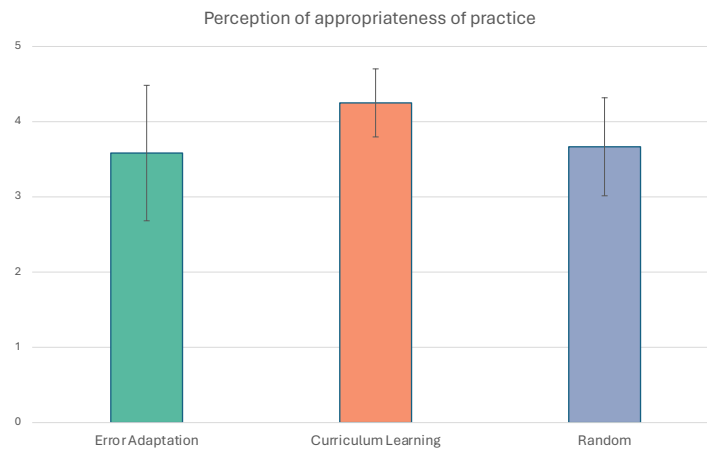
Une seule réponse possible.

1 2 3 4 5

Not Very well

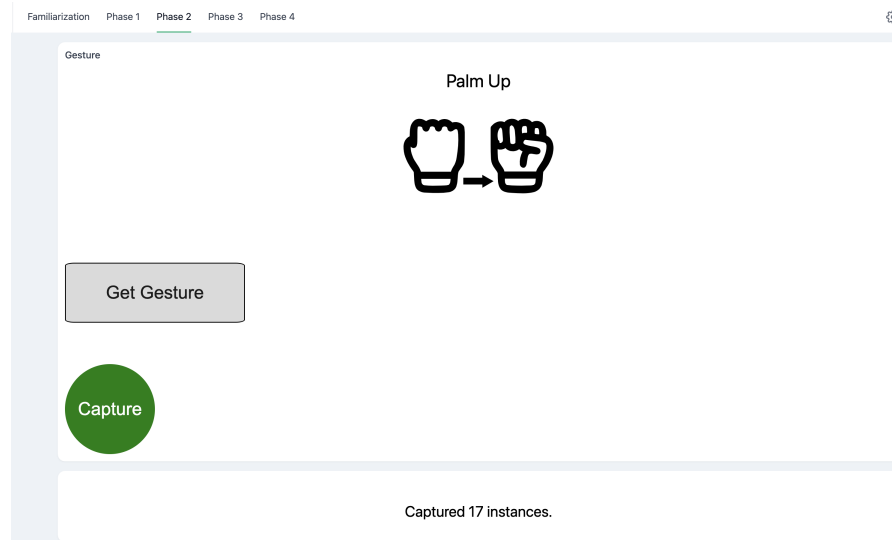
We analyzed how they perceived the structure of the practice schedules. Individual T-tests showed that the participants of the error-adaptation and curriculum-based learning who correctly perceived that the schedules were structured did not answer randomly ($p < 0.05$). The, we inspected participants answers regarding the appropriateness of the schedules. Our results showed that participants considered the schedules of curriculum-based learning to be appropriate for learning ($F(2, 36) = 3.300, p < 0.05$) compared to the other two schedules. Figure 4 shows these results.

Fig. 4: Appropriateness of practice. Perception of how appropriate each type of practice was for learning the test task, on a 5 point Likert scale.

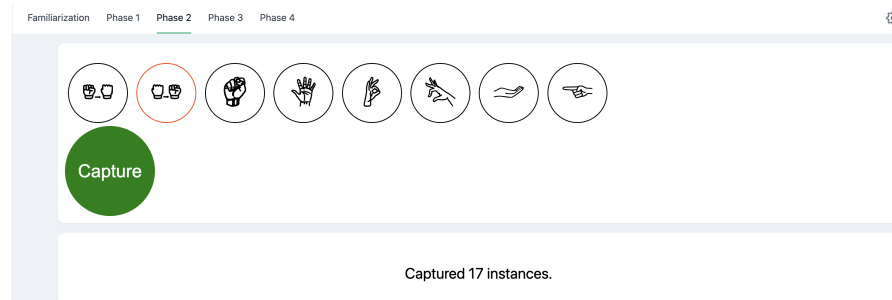


.2 Appendix B

.2.1 Interface for the Learner -Led and Teacher -Led conditions



(a) Interface for the Learner-Led condition. Clicking on the "Get Gesture" button queries the next gesture.



(b) Interface for the Teacher-Led Condition. Participants select gestures by clicking on icon buttons. The button border turns red to indicate that a gesture has been selected.

Fig. 5

.2.2 Post-Training Questionnaire

According to your experience, after having taught the system to recognize the 8 gestures, how accurately will the system recognize each one? (0% - the system never recognizes the gesture to 100% - the system always recognizes the gesture)

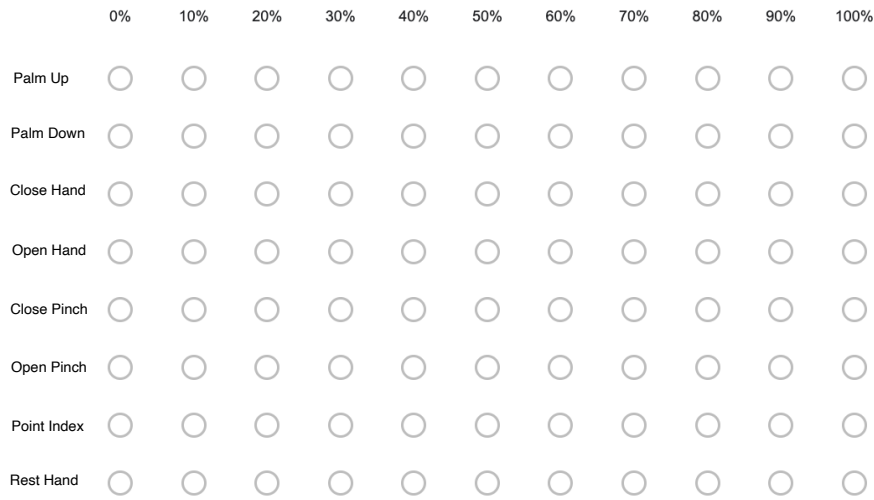


Fig. 6: Post test questionnaire: participants' perception of the machine's accuracy for each gesture.

.2.3 Histograms of tasks for each strategy

The plots below are the histograms of the gesture instances generated by participants for each each condition. The first three plots show the histograms for the full training period (120 trials). The next three plots show the histograms for the first 60 trials. Compared to the Learner-Led condition, the count of gestures is more balanced in the Teacher-Led condition (see figures 7 and 8). For some participants, the Learner-Led condition scheduled fewer than 5 gestures for the Rest hand gesture and more than 20 gestures for Open hand (see figure 8). This trend is also seen before 60 training trials, which also corresponds to the phase where the TLC condition and the random condition show faster accuracy increase than the LLC condition (see Chapter 4, figure 4.5). Extreme class imbalance may be responsible for the slower increase in accuracy for the LLC condition.

Fig. 7: Count of gestures performed by participants assigned to the Teacher-Led condition.

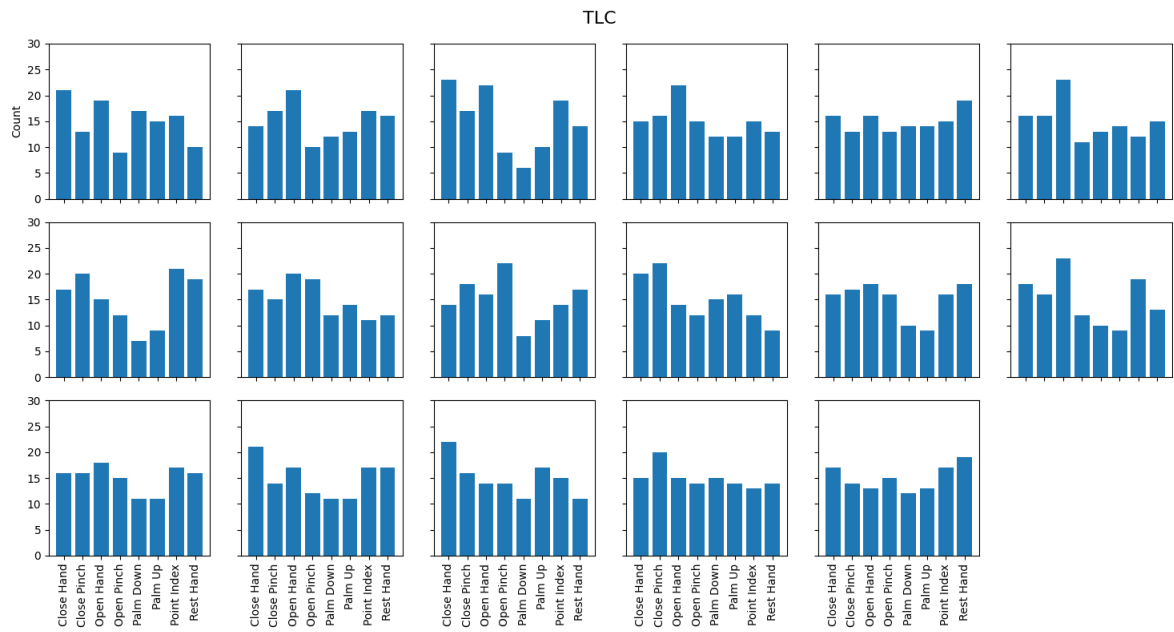
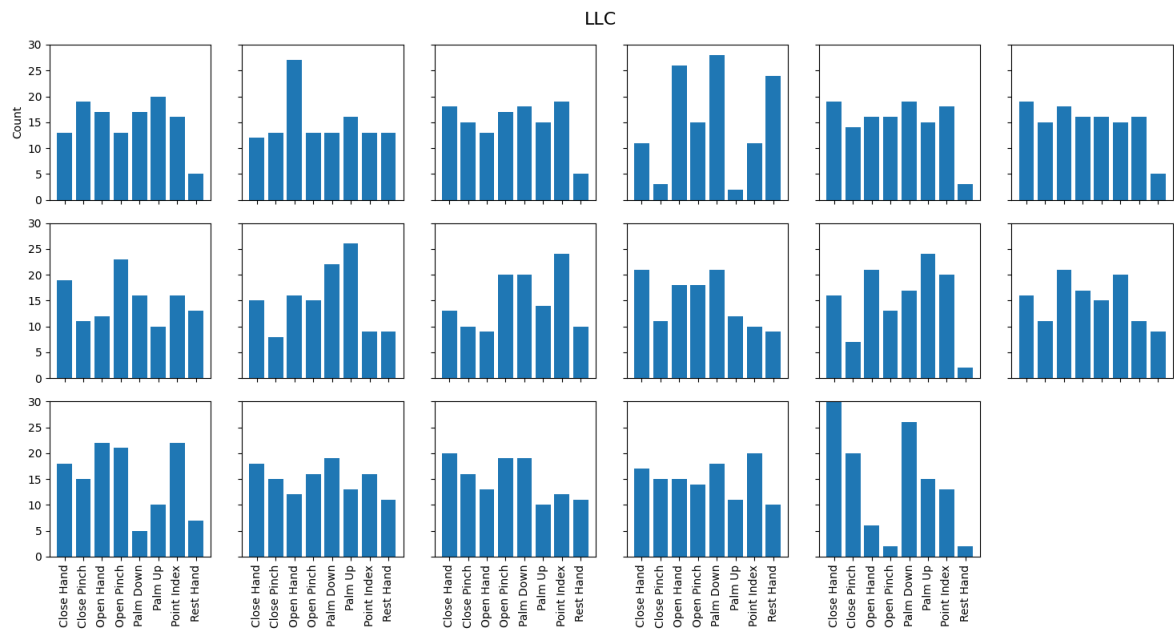


Fig. 8: Count of gestures performed by the participants assigned to the Learner-Led condition.



2.4 Histograms of tasks for Learner-Led and Teacher-Led strategies until trial 60

Fig. 10: Count of gestures performed by participants assigned to the LLC condition until trial 60.

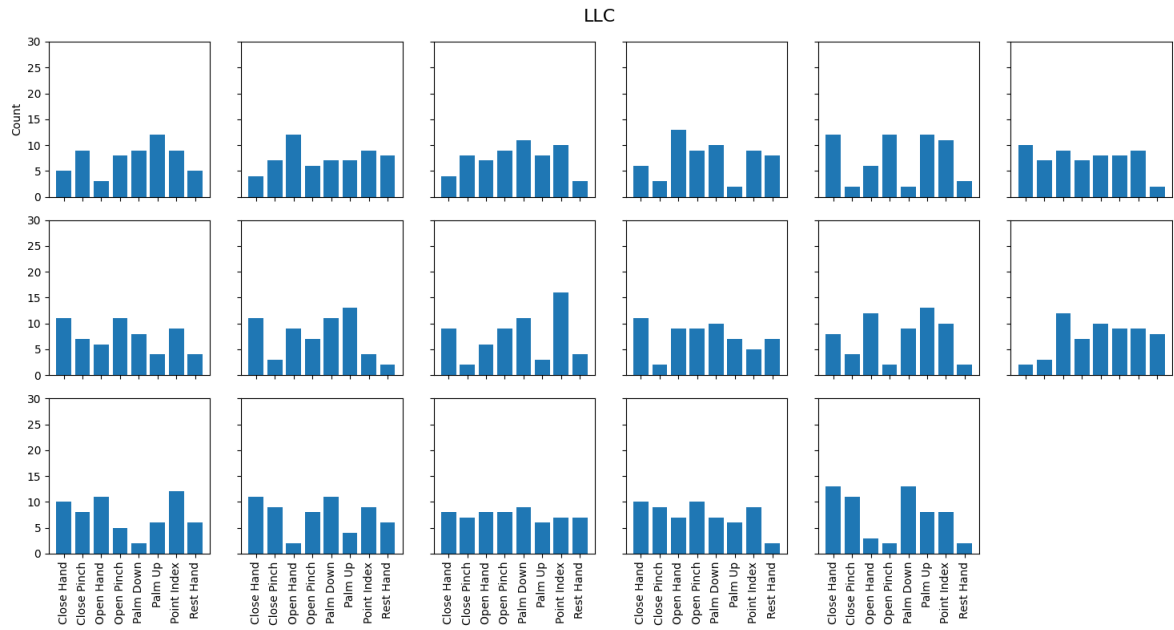


Fig. 11: Count of gestures performed by participants assigned to the TLC condition until trial 60.

