



Investigations on upper limb prosthesis control with an active elbow

Manelle M  rad

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**THÈSE DE DOCTORAT
DE L'UNIVERSITÉ PIERRE ET MARIE CURIE**

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présentée par

Manelle MERAD

pour obtenir le grade de :

DOCTEUR DE L'UNIVERSITÉ PIERRE ET MARIE CURIE

Sujet de la thèse :

**Investigations on upper limb prosthesis control with an active
elbow**

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À mes parents, Fadila et Mokhtar.

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Résumé

Les progrès de la mécatronique ont permis d'améliorer les prothèses du membre supérieur en augmentant le catalogue des mouvements prothétiques. Cependant, un fossé se creuse entre les capacités technologiques de la prothèse et leur méthode de contrôle. La commande myoélectrique, qui est la méthode la plus répandue, reste complexe, notamment pour les personnes amputées au niveau trans-huméral qui peuvent avoir un coude actif en plus de la main et du poignet motorisés. Une approche intéressante consiste à utiliser la mobilité du membre résiduel, présente chez la plupart des amputés trans-huméraux, pour contrôler des articulations prothétiques distales comme le coude. Les mouvements du coude sont couplés aux mouvements du membre résiduel selon un modèle de coordination épaule/coude saine. Cette thèse étudie une stratégie de commande d'un coude prothétique utilisant les mouvements du membre résiduel, mesuré par des centrales inertielle, et nos connaissances du contrôle moteur humain. Pour cela, un modèle de la coordination épaule/coude a été construit à partir d'enregistrements de gestes sains de préhension. Ce modèle, implémenté sur un prototype de prothèse, a été testé par des individus sains équipés du prototype afin de valider le concept, puis par 6 personnes amputées. Ces dernières ont aussi réalisé la tâche avec une commande myoélectrique conventionnelle afin de comparer les résultats. La commande couplant automatique les mouvements de l'épaule et du coude s'est montrée satisfaisante en termes de facilité d'utilisation et de réduction des stratégies de compensation.

Mots-clés : Prothèses du membre supérieur, amputation trans-humérale, coude prothétique, coordinations inter-articulaires, stratégies de compensations, régression RBFN

Abstract

Progress in mechatronics has enabled the improvement of upper limb prosthetics increasing the catalog of grasping postures. However, a gap has been growing between the prosthesis technological possibilities and the methods to control it. Indeed, common myoelectric control strategy remains complex, especially for transhumeral amputees who can have an active elbow in addition to a prosthetic wrist and hand. Since most transhumeral amputees have a mobile residual limb, an interesting approach aims at utilizing this mobility to control intermediate prosthetic joints, like the elbow, based on the shoulder/elbow coordination observed in healthy movements. This thesis investigates the possibility of controlling an active prosthetic elbow using the residual limb motion, measured with inertial measurement units, and knowledge of the human motor control. A primary focus has been targeting the reaching movement for which a model has been built using regression tools and kinematic data from several healthy individuals. The model, implemented on a prosthesis prototype, has been tested with healthy participants wearing the prototype to validate the concept, and with six amputated individuals. These participants also performed the task with a conventional myoelectric control strategy for comparison purpose. The results show that the inter-joint coordination-based control strategy is satisfying in terms of intuitiveness and reduction of the compensatory strategies.

Keywords: Upper limb prosthetics, Transhumeral amputation, Prosthetic elbow, Inter-joint coordination, Compensatory strategies, RBFN regression

List of publications

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Proceedings

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Nomenclature

ADL Activities of Daily Living

ANN Artificial Neural Network

DoF Degree of Freedom

EIAS Anterosuperior iliac spine

EMG ElectroMyoGraphy/ElectroMyoGraphic

IMU Inertial Measurement Unit

IRR Institut Régional de Médecine Physique et de Réadaptation

LDA Linear Discriminant Analysis

LWR Locally Weighted Regression

PC Principal Component

PCA Principal Component Analysis

RBFN Radial Basis Function Network

RMSE Root Mean Square Error

sEMG Surface EMG

Chapter I

Context and introduction

I.1 Upper limb amputation and prostheses

Upper limb amputation is rare and represents less than 10% of amputation surgeries, with half of all upper limb amputations occurring at a low level (fingers) ([Bradway et al., 1984](#); [Dillingham et al., 2002](#)). The number of amputees in France is estimated at 40000, 15% of which with an upper limb amputation. There are few epidemiological results on the upper limb amputee population, thus it is difficult to find accurate data. Eighty percent of upper limb amputation surgeries are caused by a traumatism after which limb re-implantation was impossible or failed ([Dillingham et al., 2002](#); [Lamandé et al., 2014](#); [Østlie et al., 2011b](#); [Raichle et al., 2008](#)). According to these studies, transhumeral and transradial amputations are more common than other major amputation levels (illustration in [Fig. I.1](#)): transhumeral and transradial amputations represent respectively 23% and 22 % of all major upper limb amputations, whereas 8% concern higher amputation levels, and 3% are bilateral amputations. The upper limb amputee population is young: 67% of them are below 40 years old at the time of amputation ([Barouti et al., 1998](#)). Deprivation of one (or two) upper limb(s) affects one's daily living, and the impairment increases with the amputation level. In order to perform Activities of the Daily Living (ADLs), and to improve their life quality, upper limb amputees can be equipped with a prosthesis that substitutes the missing limb, depending on their needs and lifestyle.

Upper limb prostheses

An amputee chooses to be equipped with a prosthetic equipment that matches his/her life project, needs, and residual capabilities. However, it is common to see upper limb amputees that chose not to wear a prosthesis, sometimes because they do not need one (often patients with low amputation levels, or agenesis), or because the prosthesis is a burden to them. The latter case is considered as a device rejection, and is still very common in the upper limb amputee population. In ([Raichle et al., 2008](#)), 43.9% of the 107 upper limb amputees participating in the study answered that they were not wearing their prosthesis; in ([Biddiss and Chau, 2007a](#)), they were 28% of the 242 participants. It is important to note that these number may be wronged by the fact that studies are conducted through rehabilitation centers that do not have access to individuals who chose not wear their device, and that only individuals with

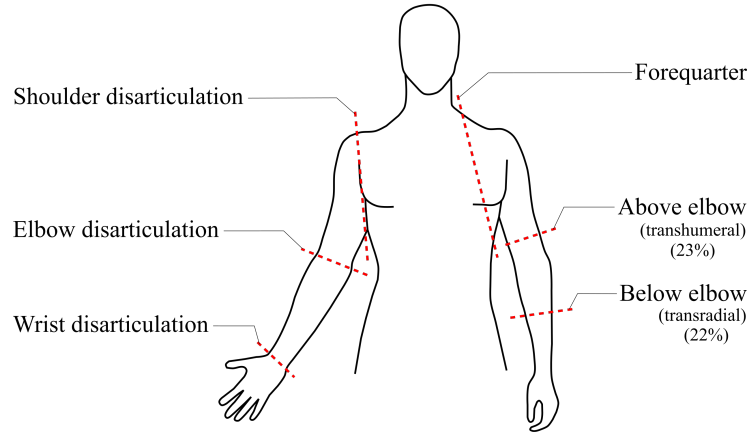


Figure I.1 – Levels of upper limb amputation and disarticulation.

positive prosthetic experience are more predisposed to answer the questionnaires. In comparison, only 16.1% of the 752 lower limb amputees interviewed in (Raichle et al., 2008) rejected their device.

For those who choose to wear a prosthesis, there are mainly two types of devices: the prosthesis can be cosmetic, used for social purposes with moderate functional gain, or functional, used to assist in the realization of ADLs. The first available functional devices were body-powered: the user opens/closes the end-effector with a shoulder protraction (i.e. shoulder's forward motion), pulling a cable that runs from the contralateral shoulder to the prosthetic joint (Cupo and Sheredos, 1998; Doeringer and Hogan, 1995). These mechanical devices present several advantages that satisfy many users: for instance, they are robust, low cost, and they provide some feedback (proprioceptive and force) that is lacking in other systems. Developed in the 60s, myoelectric prostheses are externally-powered by electric motors controlled by the contractions of the user's residual limb muscles (Popov, 1965; Scott, 1967). Young generations seem to prefer externally-powered to body-powered devices (McFarland et al., 2010), however there are no evidence in the literature proving that body-powered devices are outperformed by myoelectric prostheses (Carey et al., 2015). The different types of prosthetic equipment are shown in Fig. I.2.

For the past five years, the progress in mechatronics has made possible the development of realistic anthropomorphic prosthetic limbs (Lenzi et al., 2016), especially prosthetic hands (Belter et al., 2013; Bennett et al., 2015; Deimel and Brock, 2016; Laliberté et al., 2010; Xiong et al., 2016). These solutions are capable of reproducing various human grasp patterns, although the need for numerous independently-motorized degrees of freedom (DoFs) is questioned (Montagnani et al., 2016). Since the commercialization of these multi-articulated hands, a budget issue has been raised. Specifically, the prosthesis is at the State's expense in most European countries, meaning that one has the right to be equipped with the prosthetic device of one's choice, up to a budget decided by a national commission. For instance in France, the i-LimbTMUltra (Touch Bionics) is covered by social security since March 2015 whereas it was commercialized in 2011. Newer more sophisticated prosthetic hands are not yet available unless the patient provides the full payment. The main reason for such a



Figure I.2 – A: From left to right, examples of a cosmetic hand, a body-powered hook, and a myoelectric hand. B: Evolution of myoelectric prosthetic hands (top to bottom, left to right) with the MyoHand VariPlus (Ottobock[®]), the i-Limb Ultra (Touch Bionics), the BeBionic (Ottobock[®]), and the Michelangelo (Ottobock[®]). C: State-of-the-art prosthetic elbows (top to bottom, left to right) with the E-TWO electric elbow (Hosmer, Fillauer), the Utah Arm 3+ (Motion Control, Fillauer), and the 12K100 (Ottobock[®]).

delayed response from the social security is the lack of evidence concerning the benefits of the system to the patients' daily lives.

Prosthetic needs of transhumeral amputees

Transhumeral amputees need a prosthetic elbow in addition to the transradial ensemble composed of a prosthetic hand mounted eventually on a motorized wrist for pronation/supination motion, as depicted in Fig. I.3. Regrettably, among commercialized prosthetic solutions, few have been developed for patients with a transhumeral or higher amputation level concerning the elbow joint, and even fewer have been designed by research entities (Bennett et al., 2016; Lenzi et al., 2016). Elbow substitution includes passive prosthetic elbows, like the 12K44 ErgoArm® Hybrid Plus (Ottobock®) that can be mechanically- or myoelectrically-locked into a desired position, and active prosthetic elbows, like DynamicArm 12K100 (Ottobock®), and the UtahArm3+ (Motion Control, Inc.), as illustrated in Fig. I.2. The latter, not covered by social security systems in most developed countries, are not affordable for most patients that are fitted with simpler less expensive prosthetic elbows; the Ottobock's 12k50 elbow is priced at 7000 euros in France, whereas its electric counterpart costs about 50000 euros. Most transhumeral amputees report that current prosthetic devices lack functionality and do not provide the expected assistance in ADLs (Biddiss and Chau, 2007a). Subsequently, transhumeral amputees are more likely to reject their prosthesis than transradial amputees (Biddiss and Chau, 2007a; Wright et al., 1995). Most amputees wish to have a more efficient utilization of their prosthesis: in the study of Engdahl et al. (2015), 44% of the 104 interviewed upper limb amputated individuals were satisfied with the functionality of their prosthetic equipment.

I.2 Overview of prosthetic control methods

A myoelectric prosthesis substitutes actively for the missing limb of an amputee, but its actuators require control inputs that reflect the user's volition to move the device. Myoelectric control is based on the residual limb's muscular electrical activity, also known as electromyographic (EMG) activity, and it is the most common method to control an externally-powered prosthesis. Today, a race to the ultimate human-machine interface has started, and the number of methods to capture and process the neural signal is escalating quickly (Lee et al., 2014).

I.2.1 Conventional myoelectric control

Invented in the 1950s (Battye et al., 1955), myoelectric control is still implemented on today's prostheses. It associates the electrical activity from the residual limb's muscle groups (generally biceps and triceps brachii for transhumeral amputees) to a prosthetic function: for instance, a biceps contraction closes the prosthetic hand, and a triceps contraction opens it. An on/off strategy is applied by thresholding the EMG signals from the two group muscles. Since each active prosthetic joint composing the substituting limb is controlled with the same two control inputs, the user needs to



Figure I.3 – A transhumeral prosthesis is composed of several elements: the prosthetic joints (hand, wrist, and elbow) that can be passive or active depending on the patient's life project, the prosthesis body that contains the batteries and the electronics for externally-powered joints, the socket (in contact with the wearer's residual limb and in which the eventual myoelectric electrodes are placed), and a harness responsible for keeping the socket in place.

indicates to the prosthesis which joint to activate. A combination of muscle contractions, or a co-contraction (i.e. simultaneous contraction of two agonist-antagonistic muscles) is then required to switch from one joint (e.g. hand closing/opening) to another (elbow flexion/extension), as shown in Fig. I.4. In addition or in supplement of co-contractions, switching between prosthetic joints and functions can be performed by detecting multiple signal states from one muscle site (Dorcas and Scott, 1966; Philipson et al., 1981; Sauter et al., 1985; Scott and Parker, 1988). As illustrated in Fig. I.4, the amplitude and the rate of change of the myoelectric signal corresponding to one muscle's contraction are used to control two joints. For instance, a fast strong contraction of the biceps muscle group yields wrist pronation, and a slow moderate contraction of the biceps yields hand closing.

The electrical activity from the two main residual limb's muscle groups is measured at the skin surface; myoelectric signals are also referred to as the surface EMG (sEMG) signals. The latter are measured via two skin electrodes embedded inside the socket and placed over the residual muscles' motor point. Often described as unreliable (Bottomley, 1965), sEMG signals are impeding the implementation of advanced signal processing techniques (Castellini et al., 2014). Indeed, these signals are influenced by several factors, like electrodes placement, skin impedance, muscle fatigue, and muscle cross-talk (conduction of neighboring muscle electric activity) (Day, 2002). To prevent undesired prosthesis activation, the prosthesis' detection thresholds are set to high values, forcing the user to produce strong and fatiguing muscle contractions.

Since the same control inputs are utilized to control multiple prosthetic joints or grasping modes (e.g. pinch, tri-digit grasp, index flexion etc...), the resulting control strategy is sequential, with successive control over each joints. Moreover, switching between prosthetic joints requires generally additional muscle contractions that are not associated with any prosthesis action. Whereas the biceps/triceps couple in a healthy scheme is responsible solely of elbow flexion/extension, they are also controlling the wrist and the hand movements when wearing a prosthesis. Unlike movements performed with a healthy limb during which one focuses on hand action, controlling a prosthesis requires anticipation and concentration on the muscle contractions to achieve the desired prosthetic movement. Thus, the myoelectric control interface requires long training in order to use the device efficiently. Transhumeral amputees achieve eventually good control of hand and wrist, but have difficulties in general when an active prosthetic elbow is added to the prosthetic arm. Even today, due to sequential and slow prosthetic control, a prosthetic elbow is mostly used for forearm lifting motions and then locked, instead of being involved in global upper limb movements.

Finally, the counter-intuitive sequential control strategy for current myoelectric prostheses, device weight, socket discomfort and lack of feedback, are the main causes of device abandonment in the transhumeral amputee population (Atkins et al., 1996; Biddiss and Chau, 2007b; Wright et al., 1995).

I.2.2 Advanced myoelectric control

Given the limitations of conventional myoelectric control and the users requirements, research groups have been focusing for the last two decades on user-centered control strategies that could improve the functionality of upper limb prosthetic devices

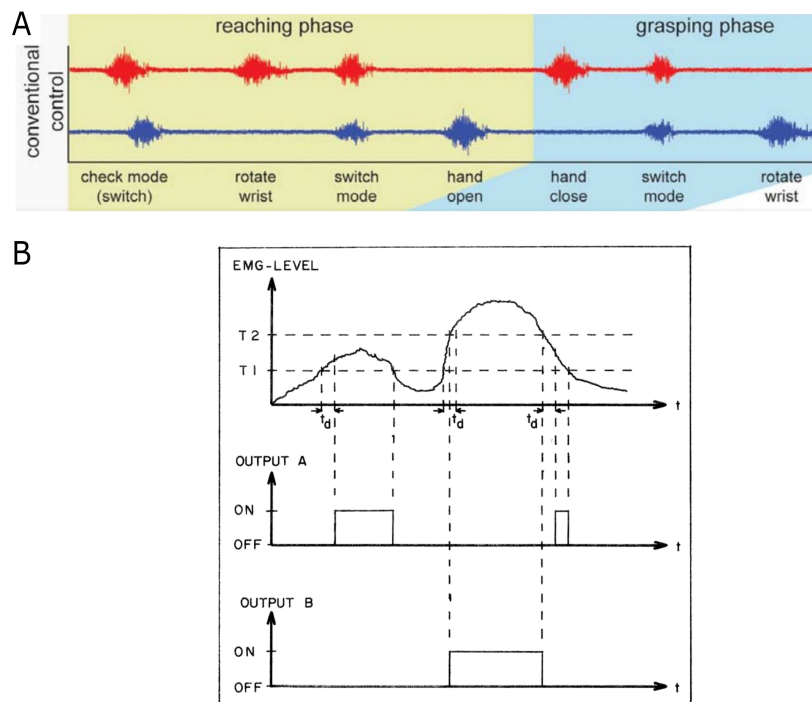


Figure I.4 – A: Illustration of conventional dual-site myoelectric control with a joint switch activated by co-contractions (Farina et al., 2014). B: Proportional control accounts for the signal intensity to switch between joints; two threshold on the same signal enables the control of two joints without doing co-contractions (Philipson et al., 1981).

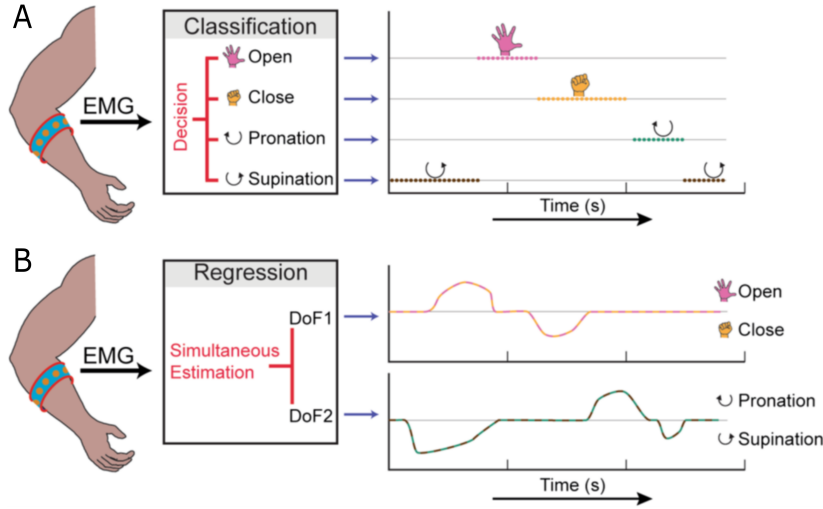


Figure I.5 – Surface EMG classification and regression approaches as illustrated by Roche et al. (2014). A: The sEMG pattern recognition technique uses classification algorithm to interpret features extracted from the sEMG signals, and attribute a class (for instance, hand flexion, or wrist pronation) that is sent to the prosthesis controller. B: The regression approach takes into account the signal intensity to proportionally control several DoFs simultaneously.

(Castellini et al., 2014; Peerdeman et al., 2011; Roche et al., 2014).

Pattern recognition on myoelectric signals has been initiated by Graupe and Cline (1975) and Graupe et al. (1982), but it is not until the work of Hudgins et al. (1993) that a great interest grew for sEMG signals analysis and classification applied to prosthetic control (Farina et al., 2014; Huang et al., 2005; Micera et al., 2010; Scheme and Englehart, 2011; Zecca et al., 2002). Whereas conventional myoelectric control is based on signals amplitude or rate of change, pattern recognition-based techniques extract more information from the EMG signals (Farina et al., 2004), and thus, increase the number of controllable DoFs while using the same number of EMG channels (Khushaba et al., 2012). Most of these approaches share the same signal processing procedure illustrated in Fig. I.5. A large number of features combinations and classification methods have been investigated in the literature in order to discriminate the EMG inputs (Englehart et al., 2001; Englehart and Hudgins, 2003; Englehart et al., 1999; Graupe et al., 1982; Hudgins et al., 1993; Oskoei and Hu, 2007; Shenoy et al., 2008; Zecca et al., 2002).

Although the number of control inputs increases by processing the raw EMG signals with a pattern recognition algorithm, the control strategy remains sequential with one state recognized for each input value. Simultaneous control is a feature that is being developed by several groups (Ortiz-Catalan et al., 2014b; Smith et al., 2016b; Young et al., 2014); commonly, single-movement classes (e.g. hand opening, or wrist pronation) are combined to create additional classes for complex movements.

Even if a couple of decades have passed since the development of pattern recognition approaches, they are not implemented on commercialized prosthetic devices yet. At first, computer power was a major obstacle, leading research groups to focus on achieving real-time sEMG classification (Tenore et al., 2008). Nowadays, the main

disadvantage of pattern recognition is that it does not account for the signal variations throughout time, for instance due to muscle fatigue, different signal intensity, or electrode displacement: if a pattern has not been encountered during the training, a class may not be recognized even if the user performs the same type of contraction. In order to reduce the class recognition error, research groups have been putting efforts in developing algorithms capable to adapt the user's signals (Pilarski et al., 2013; Sensinger et al., 2009; Tommasi et al., 2013).

Research studies are now following a new track aiming to develop myoelectric proportional control (Ison and Artemiadis, 2015; Parker et al., 2006). Proportional control means that the user is able to control continuously the prosthesis motion, instead of movement classes. It can be achieved using regression techniques that estimate control signals such as joint angles or forces from sEMG inputs (Smith et al., 2016a). Research groups are thus now focusing on simultaneous proportional prosthetic control (Amsuess et al., 2015, 2016; Ison et al., 2016; Jiang et al., 2009, 2014; Muceli and Farina, 2012; Nielsen et al., 2011; Park et al., 2016), as illustrated in Fig. I.5. Recently, D. Farina's group has been investigating a novel approach whereby the EMG signal is considered as an image of the neural peripheral information after transmission through the motor nerves and the muscles; their objective is to trace back the neural coding information from EMG measurements (Martinez-Valdes et al., 2016; Sartori et al., 2016). However, sEMG measurements limit considerably the development of myoelectric signal processing methods, and none of these approaches has been implemented on commercialized devices yet.

Targeted muscle reinnervation

For high amputation levels, the number of muscle groups that can be contracted independently is low; in most cases, only two antagonistic groups are involved in the conventional control strategy. A surgical technique, referred to as targeted muscle reinnervation, increases the number of active myoelectric sites by rerouting unused nerves – force instance amputated ulnar and radial nerves – towards parts of muscle groups like biceps and triceps. The implanted nerves are capable of transmitting the neural information even after amputation. As a result, newly innervated muscle groups can be contracted voluntarily, increasing the number of myoelectric inputs, and thus, the number of controllable prosthetic functions without requiring co-contractions. Kuiken et al. extended the technique to shoulder-dislocated patients by implanting several chest muscle with brachial plexus nerves (Kuiken, 2003; Kuiken et al., 2004, 2009, 2007), as shown in I.6. Miller et al. (2008) demonstrated that in comparison with conventional dual-site myoelectric control, targeted muscle reinnervation of arm or chest muscles can improve the performance in terms of task completion time. Unfortunately, targeted muscle reinnervation requires a non-vital surgery that most patients will not agree upon given the little improvement of control yet (Engdahl et al., 2015).

Most techniques, including most of the approaches presented subsequently, consist in monitoring muscle contractions. For transradial applications, muscle contractions are directly linked to the missing limb, for instance when measuring forearm's muscular activity to predict finger forces. However, in the case of higher amputation levels, the muscle activity used for conventional dual-site myoelectric control is not related to

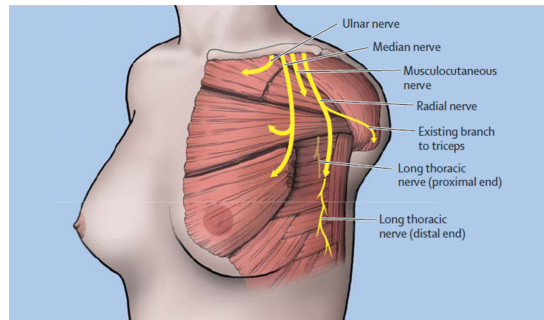


Figure I.6 – Illustration of targeted muscle reinnervation of chest muscles in high-level amputation (Kuiken et al., 2007)

the controlled prosthetic function (i.e. the biceps groups is responsible for controlling the prosthetic hand, and wrist movements), increasing the control complexity of a prosthetic device. A promising solution that does not require surgery, neither long not fatiguing training, is to utilize the phantom limb mobility to evoke several EMG patterns that are different for each phantom movements, and that are associated with a concrete movement for the users: Jarrassé et al. (2017) showed that by classifying these signals, the prosthesis users were able to use intuitively the prosthesis by moving their phantom limb.

I.2.3 Beyond myoelectric control

"Given the difficulty of robust control solely by using EMG, the use of other sensor modalities seems necessary for the control of complex devices" (Jiang et al., 2012). Because of the sEMG signal-related control issues, research groups are now investigating new means of transmitting the user's intention to move the prosthetic limb. Novel control interfaces are being developed (Lobo-Prat et al., 2014), whereby alternative control sources are considered, in substitution of or in addition to myoelectric signals.

Sonomyographic signal

Medical ultrasound imaging uses ultrasound waves and their reflection of tissues to construct a two-dimension map of the probed media. Placed in contact with the skin surface, the probe emits the ultrasound signal that propagates through the biologic media, and it receives the reflection signal. The reflected signal, termed as sonomyographic signal (Zheng et al., 2006), is analyzed to determine the properties (e.g. distance to probe) of the obstacles encountered by the emitted signal. The sonomyographic signal is used to describe the muscles' structural and morphological changes (Castellini, 2014; Tanaka et al., 2003). These muscular contraction-based signal variations are correlated with joints displacements such as wrist or finger movements (Guo et al., 2008; Xie et al., 2009b). The sonomyographic input and the established relationships can then be used to predict distal limb or joint motion, and to control a prosthetic device (Akhlaghi et al., 2016; Castellini et al., 2012; Shi et al., 2010; Sierra González and Castellini, 2013). An instance of experimental setup using sonomyographic signals as control inputs is depicted in Fig. I.7.

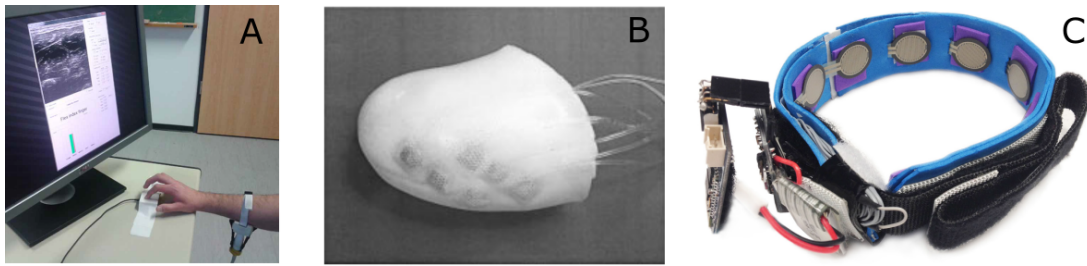


Figure I.7 – Examples of systems designed for the measurement of alternative prosthetic control inputs. A: sonomyography-based control, from [Sierra González and Castellini \(2013\)](#), B: myokinematic socket, from [Curcie et al. \(2001\)](#), C: cuff designed for myokinetic control, from [Cho et al. \(2016\)](#).

Myokinematic signal

Muscle contractions evoke dimensional changes along the muscle's radial axis due to superficial tendons displacement and muscle bulge; measurement of these displacements are named the myokinematic signal. There are two main measurement methods: the first one uses tendon-activated pneumatic foam sensors that capture the pressure differential elicited by superficial displacements ([Abboudi et al., 1999](#)), the second utilizes the Hall effect between a magnet placed on the residual limb and a receiver placed in the prosthesis socket and converts the variations of magnetic flux into voltage output changes ([Heath and Bowker, 1997](#)). Like in myoelectric control, the users can control prosthetic functions by contracting the muscles ([Abboudi et al., 1999](#); [Curcie et al., 2001](#); [Heath and Bowker, 1997](#); [Kenney et al., 1999](#)), except that the control input is the muscle's radial change instead of its electrical activity. A system example that uses pneumatic sensors is shown in Fig. I.7.

Myokinetic signal

The myokinetic signal, or force myographic signal, measures the forces produced at the skin surface that result of contraction-evoked radial changes in the muscle morphology ([Wininger et al., 2008](#); [Yungher et al., 2011](#)). Measured with force sensing resistors placed over the skin ([Sethna et al., 1994](#)), like illustrated in Fig. I.7, the myokinetic signal reflects the person's volition to execute a movement, and thus, it is a potential prosthetic control input ([Cho et al., 2016](#); [Kuttuva et al., 2005](#); [Li et al., 2012](#)).

Mechanomyographic signal

Muscle activity can also be monitored by considering the vibrations generated by muscle fiber activation ([Akataki et al., 2001](#); [Gordon and Holbourn, 1948](#); [Orizio, 2004](#); [Orizio et al., 1995](#)). These low frequency vibrations, termed as mechanomyographic signals, evoke a skin surface displacements of approximately 500 nm, that are detected using accelerometers ([Silva et al., 2003a](#)), microphones ([Courteville et al., 1998](#); [Silva et al., 2003b](#)), or coupled microphone-accelerometer pairs ([Silva and Chau, 2003](#)). Likewise, the mechanomyographic signal can be used as control input of a powered

prosthesis (Silva et al., 2004, 2005). Despite not being influenced by skin impedance nor intramuscular pressure (Søgaard et al., 2006; Xie et al., 2009a), it has a high sensitivity to external mechanical noise sources like heart beat, breathing, and external load exerted on the residual limb.

Unlike sEMG signals, the presented alternative measurement systems are not sensitive to skin impedance variations. However, these signals depend at least as much as myoelectric signals on the sensor location: socket rotation or external perturbation can lead to a misinterpretation of the user's intention.

Control inputs derived from assistive human-machine interfaces

Derived from solutions dedicated to heavily-impaired people, such as quadriplegic patients, all sorts of control signals have been used to control assistive devices (e.g. powered wheelchair). Some of these signals have been used for the control of a prosthetic limb. Ability to voluntarily move the tongue is often one of the last remaining capability of severely impaired patients, hence tongue tracking devices have been developed (Park et al., 2012; Struijk, 2006; Struijk et al., 2009). Used in the control of an upper limb prosthesis (Johansen et al., 2016, 2012), tongue-based interface users cannot use their prosthesis while eating or talking for example, and are often uncomfortable. A similar system called The EagleEye, which is based on eye motion tracking, have been developed for the control of a powered wheelchair (Barea et al., 2002; Gips and Olivieri, 1996), but the concentration required to use the device is too important. Originally utilized for physical medicine (Gilad et al., 1989) and functional electrical stimulation-based rehabilitation (Dai et al., 1996; Peckham et al., 1980), tilt sensors, which are based on inertia measurements, or camera-based motion system's markers, were developed to detect head movements and control a computer mouse cursor (Chen, 2001; Scott and Vare, 2013; Williams and Kirsch, 2015). Voice recognition, developed in many applications, can be used by disabled people to control a wheelchair or to interact with a computer (Mazo et al., 1995; Su and Chung, 2001); these systems have been derived for upper limb prosthesis control (House et al., 2009; Lin et al., 1998; Mainardi and Davalli, 2007; Towers et al., 2005). A recent study by Resnik et al. (2013) presented the DEKA Arm that can be controlled using foot tilts.

Residual limb motion

Body-powered devices are using little residual limb motion to actuate the prosthesis. Despite having a mechanically-fixed shoulder/prosthesis mapping, many amputees appreciate their small weight, functionality, low cost and robustness (Carey et al., 2015).

Despite the fact that most transhumeral amputees can mobilize their residual limb, current externally-powered prosthetic systems are solely based on muscle activity-related signals. Few research groups have been investigating shoulder motion as a potential control input. A first measurement system, developed in (Bayer et al., 1972; Crago et al., 1986) and illustrated in Fig. I.8, converts the shoulder displacements permitted by the scapula (forward/backward and up/down motions), measured with a rod attached between the acromion and the sternum, into an output voltage. Investigation of this concept has led to the conception of 2-axis joysticks able to measure

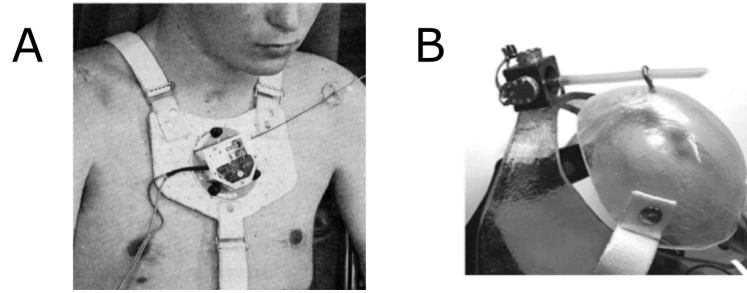


Figure I.8 – Measuring shoulder displacements (scapular protraction and elevation), and use the signals as control inputs of a prosthetic device: system in A is from [Bayer et al. \(1972\)](#), and system in B is from [Lipschutz et al. \(2011\)](#).

shoulder displacements in two directions ([Lipschutz et al., 2011](#); [Losier et al., 2011](#)). Shoulder motion, measured using these sensor designs, can be used to control a neuro-prosthesis ([Humbert et al., 2002](#); [Johnson and Peckham, 1990](#); [Peckham et al., 1980](#)) or a prosthetic arm ([Barton and Sorkin, 2014](#); [Lipschutz et al., 2011](#); [Losier et al., 2011](#); [Williams III, 2005](#)).

These control strategies involve voluntary shoulder motion in order to control a robotic arm, as myoelectric prostheses require voluntary muscle contractions to activate the prosthesis joints. Thus, the overall strategy is still not intuitive for the user that needs to learn an unnatural mapping between his body and the prosthesis. The residual limb motion-based systems previously described only account for shoulder vertical and horizontal motion, i.e. only scapular displacements, whereas shoulder displacements are actually a combination of scapula, clavicle, and humerus movements, increasing the number of potential movements. In a more general approach, [Lee et al. \(2016\)](#) presented a control strategy that maps the overall body movements to the displacements of a cursor; the technique, although it uses the whole body for the control of a simple function, is adapted to the residual capacity of the user.

When not wearing their prosthetic limb, most transhumeral amputees can move their residual limb in important ranges of motion. Unfortunately, to prevent the prosthesis to slip and to maintain good contact between the stump skin and the electrodes, the prosthesis socket is generally tightly strapped to the residual limb: the equipment of transhumeral prostheses often includes a harness attached to the contralateral limb (see Fig. I.3). Subsequently, residual limb motion is impaired by the prosthesis equipment. Moreover, due to amputation sequels, residual limb pain, often caused by post-amputation neuroma, is common and prevents the prosthesis users to extend their residual limb ([Geraghty and Jones, 1996](#); [Kooijman et al., 2000](#)).

I.3 Human motor control-based prosthetic control

The current approach in prosthesis control strategy design is based on the association of one neural signal to a unique prosthetic function, supposing that the human brain controls each muscle group, thus each joint, voluntarily and independently. On the contrary, natural movements are task-centered whereby one focuses on hand acti-

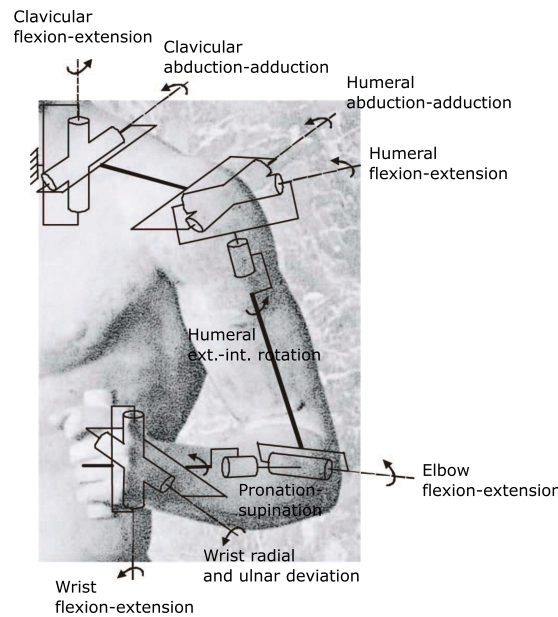


Figure I.9 – Illustration of the upper limb DoFs from [Tondou \(2007\)](#)

ons without voluntarily controlling each muscle/joint motions. A natural movement refers to a movement that is similar to the body behavior of a healthy individual in terms of joint amplitudes, selectivity and synchronicity ([Bernstein, 1967](#)). Replicating this latter control approach to prosthetic control should enable simultaneous intuitive control.

I.3.1 Complexity of human motor control

Upper limb redundancy

The human upper limb, composed of the scapula, the shoulder, the elbow, the wrist, and the hand, is a complex musculoskeletal ensemble. Without considering the finger mobility, the upper limb has 9 DoFs, illustrated in Fig. I.9, that include 2 scapular translations (protraction/depression, protraction/retraction), 3 humerus rotations (abduction/adduction, flexion/extension, humerus internal/external rotation), the elbow flexion/extension, and 3 wrist rotations (flexion/extension, pronation/supination, medial/lateral deviation) ([Tondou, 2007](#)).

The large number of DoFs in the human upper limb yields an infinity of joints configurations for a given hand position. Most tasks consist in positioning and orienting the hand in a 3-dimensional space, and thus require less DoFs than available. Therefore, the human upper limb is redundant with respect to the tasks ([Desmurget et al., 1998](#); [Scholz et al., 2000](#)). The problem is even more complex at the muscle level. Each DoF is actuated by more than one pair of agonist/antagonist muscles, and there are more than 20 teamed muscle groups controlling the whole upper limb, excluding the hand.

Except for rare research designs, externally-powered prosthetic systems do not have coupled actuators that mimic an agonist/antagonist system: generally one prosthetic motor is responsible for bi-directional joint movement (e.g. elbow flexion and exten-

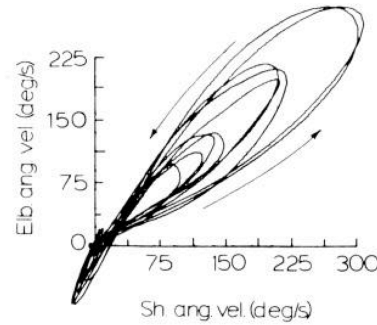


Figure I.10 – Illustration of coupled shoulder/elbow movement during pointing gestures from [Soechting and Lacquaniti \(1981\)](#)

sion). Hence, the human control analysis and the control law design were performed at the joint level. Upper limb prostheses are built in order to replicate the human limb mobility thus they are equipped with more and more DoFs. Although finding a joint solution for a redundant robotic arm is largely achievable, determining the joint configuration of an upper limb prosthesis is still an open challenge ([Li et al., 2015](#)). Indeed, in addition to functional optimization, the solution must account for the human healthy behavior to yield a natural motion. Current prosthetic systems got round the issue by controlling the joints as individual entities, yielding sequential and decomposed movements. Improving the control of a prosthetic arm towards a more natural strategy requires a better understanding of how the central nervous system solves for the system redundancy.

Inter-joint coordinations

Inter-joint coordinations or synergies are a concept that the neuroscience community has agreed upon of how muscular groups are controlled: a synergy is a group of muscles which are contracted in a coordinated way to realize a desired movement. Instead of controlling each muscle fiber's contractions, the central nervous system controls synergies, which thus decreases the overall system's dimension ([Bizzi et al., 2008](#)). Synergies are also defined at the joint level: in most upper limb movements, the hand is brought to a desired position and orientation thanks to a coordinated and simultaneous motions of the joints ([Latash et al., 1999](#)). Muscles or joints are controlled such that the overall output result is close to the desired outcome, leaving however some internal co-variation uncontrolled ([Latash, 2010](#)). Previous research studies on human motor control have shown evidence of invariant characteristics in upper limb movements, and of the coordinated aspect of joints motion ([Bockemühl et al., 2010](#); [Desmurget and Prablanc, 1997](#); [Paulignan et al., 1990](#); [Roby-Brami et al., 2000, 2003](#); [Soechting and Lacquaniti, 1981](#)). Especially, coupled motion of shoulder elbow is often reported ([Lacquaniti et al., 1982](#); [Lacquaniti and Soechting, 1982](#); [Lacquaniti et al., 1986](#); [Micera et al., 2005](#); [States and Wright, 2001](#)): the data set depicted in Fig. I.10 shows the coordination between shoulder and elbow angular velocities.

Altering the inter-joint coordinations

The elbow is required in most healthy upper limb movements and ADLs (Magermans et al., 2005; Morrey et al., 1981; Sardelli et al., 2011); its normal range of motion varies between 30 and 130 degrees (Fornalski et al., 2003; Morrey et al., 1981; Sinha et al., 2010). By constraining the elbow joint only, Vasen et al. (1995) and Fradet et al. (2015) focused on the body reaction of healthy participants after constraining the elbow during ADLs: achieving the task required the participants to develop alternative body movements, referred to as compensatory strategies. Effects of constrained elbow motion were further investigated by Cooper et al. (1993) and de Groot et al. (2011) who found a larger range of motion of unconstrained joints, especially of the shoulder, and by Bland et al. (2008) who observed a decrease in hand function when more proximal joints were impaired.

Amputation affects clearly the inter-joint coordination patterns: the impairment evokes the development of large compensatory strategies that cause shoulder, back, and contralateral limb disorders (Østlie et al., 2011a). Wearing an active prosthesis does not fulfill its duty which is to substitute for the missing limb. Because of a complicated control over their device, most prosthesis wearers still use their whole body to achieve a task, and overuse their contralateral limb instead of the prosthetic limb (Carey et al., 2008). Metzger et al. (2012) explains most compensatory trunk movements by an impaired elbow motion, either limited with transradial prosthesis sockets, preventing full flexion of the residual limb, or blocked with transhumeral amputees.

I.3.2 Inter-joint coordinations in prosthetic control

The coupling between healthy upper limb joint movements has been widely observed in the past, and several studies focused on modeling the recurrent relationship between the joint kinematics (Flash and Hogan, 1985). A pioneer promising prosthetic design was proposed by Gibbons et al. (1987): it linked the residual shoulder motion to the prosthetic elbow and wrist rotations, allowing the user to position the elbow and the wrist simultaneously by flexing the shoulder based on predefined coupling pattern. One of the main objective of modeling the inter-joint coordination is the prediction of distal joints movements from the measurements of proximal joints kinematics. In an attempt of replication a human-like movement pattern, regression techniques are preferred because they allow a continuous kinematic prediction, in opposition to classification-based movement prediction (Kundu et al., 2008). If there is a model for the inter-joint coordination relationship, then distal joint motion can be predicted from proximal joints' measurements (Hanneton et al., 2011; Prokopenko et al., 2001).

The invariant components of the inter-joint coordinations have been generally identified with linear decomposition, such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) (Bizzi et al., 2008; Bockemühl et al., 2010; Crocher et al., 2012; Gioioso et al., 2013; Jarrassé et al., 2014; Santello et al., 1998; Soechting and Flanders, 1997). The approach has been applied to lower limb prosthetics (Vallery et al., 2011; Vallery and Buss, 2006; Vallery et al., 2009): the missing limb's motion was predicted based on residual and contralateral limb measurements. The study by Belić and Faisal (2015) used a PCA-based inter-joint model identification to predict

partial hand movements. Linearization of the shoulder/elbow coupling supposes that there is a finite number of configurations for which an adequate scaling coefficient is found. The results of [Popovic and Popovic \(1998\)](#) demonstrated that the inter-joint relationship was on the contrary nonlinear. Acknowledging this property, the inter-joint coordinations have been modeled by several groups using nonlinear regression methods, such as inductive learning ([Popović and Popović, 2001](#)).

Artificial Neural Networks (ANNs) have been used in the general literature to approximate nonlinear functions, and specifically to predict distal joint kinematics. The study by [Kaliki et al. \(2008\)](#) and [Ramírez-García et al. \(2010\)](#) used an ANN-based architecture to estimate offline distal joint kinematics from recordings of healthy individuals' pointing movements: the ANN's set of inputs selected by [Kaliki et al. \(2008\)](#) required the measurement of three shoulder angles and two shoulder translations to predict the elbow flexion angle and the forearm rotation. [Iftime et al. \(2005\)](#) derived an upper limb inter-joint coordination model from kinematic data of healthy individuals moving objects placed on a plane surface: a Radial Basis Functions Network (RBFNs)-based regression was used to approximate the shoulder/elbow relationship. Despite the good results in the literature, training data recorded with camera-based motion capture systems, like in the study of [Martin et al. \(2014\)](#), cannot be used in daily life environments. It is only recently that the development of accurate embedded motion sensors like Inertial Measurement Units (IMUs) (fusion of accelerometer's, gyroscope's and magnetometer's data) and the improvement of the micro-controllers' computing power have enabled the implementation of an inter-joint coordination model-based control strategy. Nonetheless the approaches and models presented in the literature have not yet been tested on prosthetic devices. In the studies by [Mijovic et al. \(2008\)](#) and [Farokhzadi et al. \(2016\)](#), elbow flexion could be estimated offline with accelerometer-based shoulder kinematic measurements. Similarly, the recurrent relationship between humerus elevation (i.e. angle between the humerus longitudinal axis and the trunk vertical axis) and wrist pronation/supination was investigated by [Montagnani et al. \(2015\)](#) with an IMU-based training data set and a PCA-based regression method. [Bennett and Goldfarb \(2017\)](#) used IMU-based measurements of the shoulder abduction/adduction angular velocity to control wrist rotation. Most recent results combine IMU-based shoulder kinematics data and residual limb's myoelectric activity to build the inter-joint coordination model ([Akhtar et al., 2012](#); [Alshammmary et al., 2016](#); [Blana et al., 2016](#); [Lauretti et al., 2016](#)). In the study by [Akhtar et al. \(2012\)](#), sEMG signals from the arm's and deltoid' muscle groups were added to the shoulder angles as inputs of an ANN-based model: elbow and forearm rotation angles were estimated offline using a training data set recorded with healthy participants. Comparably, a set of coefficients linearly relating the humerus elevation angle and the sEMG signals to the elbow angular velocity was found in the study by [Alshammmary et al. \(2016\)](#); they were used in real time by healthy individuals to control a virtual prosthesis.

I.4 Contribution

The mapping between shoulder and elbow kinematics depends on the performed task. Given the ADLs and movements assessed in studies investigating the functional

elbow motion and upper limb movements (Morrey et al., 1981; Sardelli et al., 2011), it seems that most upper limb activities are a combination of the four following types of movements:

- Hand goes towards a targets
- Hand returns to the body
- Object manipulation/displacement
- Hand goes to the face

Most studies have been focused on the reaching motion because it is the most common and easy gesture for healthy individuals. Conversely, the reaching movement is a gesture that a transhumeral amputee rarely performs with his/her prosthesis since it requires a rapid elbow extension, synchronized with shoulder flexion. Yet, a prosthetic elbow, whether or not externally-powered, is mostly used to lift the hand position while maintaining the residual limb along the trunk. The joint is then locked, and the user switches to end-effector control, focusing on hand action. Subsequently, the elbow motion is not part of the overall upper limb movement.

The global aim of this dissertation is to design a movement-based control approach that automatizes the motion of proximal joints (here the elbow joint). Instead of being responsible for the control of the whole prosthesis, myoelectric signals are re-routed towards the end-effector and wrist actuators, which is generally achieved efficiently by most amputees. The general idea is to design control bricks (one for each of the four types of gestures described previously) that describe the elbow behavior depending on the residual limb kinematics. Depending on the performed task and the users needs, a global intelligence would then switch between the different control bricks that also include a voluntary elbow control mode whereby the user explicitly conveys to the prosthesis the will to place the forearm in a desired position. The achieved control strategy enables simultaneous control of proximal joints and end-effector for daily gestures. This work is focused on the first building step of a global automatic control strategy; it investigates the reaching gesture, considered as one of the most basic upper limb movement. Future developments will include more daily gestures in the control strategy in order to offer the users with a complete prosthesis solution.

Previous literature results have proven that the coupling between upper limb joints for pointing or reaching movements can be modeled with regression techniques, and then utilized to predict distal joints motions. Despite promising offline estimation results (using camera-based motion capture systems, healthy participants, and virtual environment testing methods), the inter-joint coordination-based control approach has not been tested on a prosthesis and in a realistic daily life scenario since the work of Gibbons et al. (1987).

The main objective of this thesis is to assess with transhumeral amputees the outcomes of a control approach whereby prosthetic elbow motion depends on shoulder movements. An inter-joint coordination model approximating the shoulder/elbow relationship is driving automatically the elbow motion during reaching movements; the model is derived from healthy upper limb movements recorded with 10 individuals. State-of-the-art embedded sensors enable accurate orientation measurements, and are more and more involved in the tracking of human body kinematics. That is why wearable IMUs were chosen to measure the shoulder kinematics of the healthy individuals. The inter-joint coordination model building method is detailed in Chapter III.

A prosthesis prototype, including a motorized elbow joint and controlled by the developed inter-joint coordination model, has been first utilized by 10 healthy individuals who wore it in parallel to their own forearm; the concept validation and the performance results are reported in Chapter IV. The tested control strategy, further referred to as the automatic control mode, is then tested with 6 transhumeral patients with two different types of sockets, as described in Chapter V: a first group of patients had a conventional external socket maintained to the body with a harness, and a second group had an osseointegrated implant to attach their prosthesis. For all the individuals who tested the system (healthy and amputees), the data analysis is focused on their body behavior and compensatory strategies developed while achieving the task in order to determine the possible benefits of a residual limb motion-based control approach.

Chapter II

Experimental protocol

We concluded from a bibliography analysis that the reaching motion is one of the four primary gestures needed for the achievement of ADLs, the three other gestures being the displacement of an object from one location to another, the return of the hand to the body, and the hand going towards the face (Morrey et al., 1981; Sardelli et al., 2011). Currently, transhumeral amputees do not perform pointing or reaching movements with their prosthesis, or if they do, it comes at the cost of heavy body compensations. Focusing on the reaching motion, the objective of this work is to investigate the outcomes of a shoulder/elbow coordination-driven prosthetic elbow in comparison with conventional myoelectric control.

Two main experiments were conducted in the context of this thesis. The first experimental step consisted in building a generic model of healthy shoulder/elbow coordinations during a reaching task; the recruited individuals' movements were recorded using IMUs and a camera-based motion capture system. For the second experiment, healthy and amputated participants were equipped with a prosthesis prototype to test the developed control strategy; their movements were also recorded using a motion capture system.

This chapter aims to describe the main experiment design, from which all the protocols were derived. The experiments shared the same experimental setup, task and data processing methods. The variations between the different protocols will be further detailed in the Chapters III, IV, and V.

II.1 Participants

This work was carried out in accordance with the recommendations of the Université Paris Descartes ethic committee CERES, which had approved the protocol covering experiments at ISIR with healthy participants and at the Louis Pierquin Center (Institut Régional de Médecine Physique et de Réadaptation, IRR) in Nancy with amputated individuals in April 2016. In addition, a collaboration was developed with Chalmers University to test the developed elbow control strategy with osseointegrated transhumeral amputees. The protocol was approved by the local ethic committee of Goteborg, Sweden in February 2017. The approval letters are depicted in Appendix A. All subjects gave written informed consent in accordance with the Declaration of Helsinki.

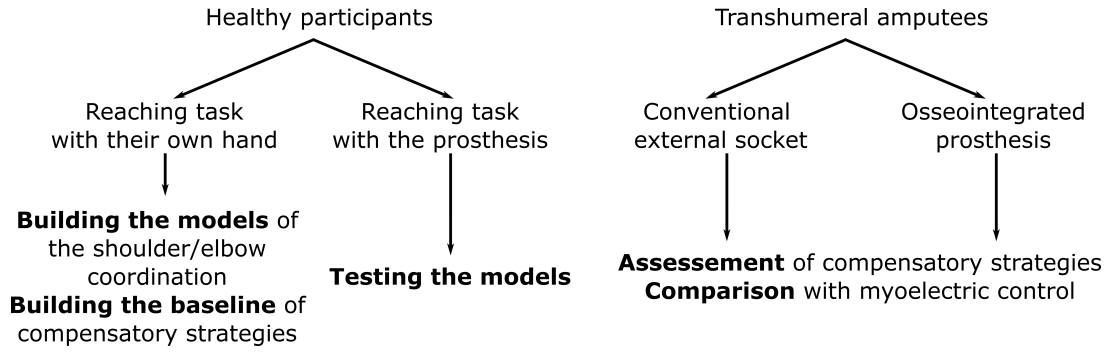


Figure II.1 – Organization and objectives of the experiments.

Several experiments with different groups of participants were conducted; however they all shared the same setup and protocol. There were two major experiments: one dedicated to the recording of healthy reaching movements, the other to the test of elbow control strategies with a prosthesis. Only healthy participants (20 individuals) were recruited in the first experiment, whereas healthy (10) and amputated (6) individuals took part in the control test. For experiments with healthy participants, the upper limb (left or right) performing the task was chosen arbitrary prior to the experiment, independently of their dominant side. The experiments' organization is depicted in Fig. II.1.

II.2 Experimental setup

All the experiments shared the same experimental setup. The participants were asked to reach the targets located in front of them. There were 18 targets split in two distances (I, II), numbered from 1 to 9 for each distance and attached to three sticks, as illustrated in Fig. II.2. The targets' positions were adjusted for each subject depending on their arm length and shoulder height. The Target 8 was aligned with the subject's shoulder (left if the task was performed with the left limb, right if performed with the right limb) such that the subject could reach it by extending fully the arm. Distance I was defined as the arm length minus 10 cm, and Distance II corresponded to Distance I minus 15 cm, as shown in Fig. II.2. The distance between the center and lateral targets, i.e. between Targets 1 and 2, and 2 and 3, was arbitrary fixed to 30 cm.

II.3 Protocol

The protocol was the same for all participants, although there were minor variations between the experimental sessions, especially in terms of repetitions. All participants were asked to reach the 18 targets located in front of them; a reaching movement is described in Fig. II.2C. Healthy individuals performed the task with their own hand, and all participants equipped with a prosthesis prototype (described subsequently) used the prosthetic hand to reach the targets. The instruction given to the participants was to bring the hand fingers around the circular targets, as shown in Fig. II.3.

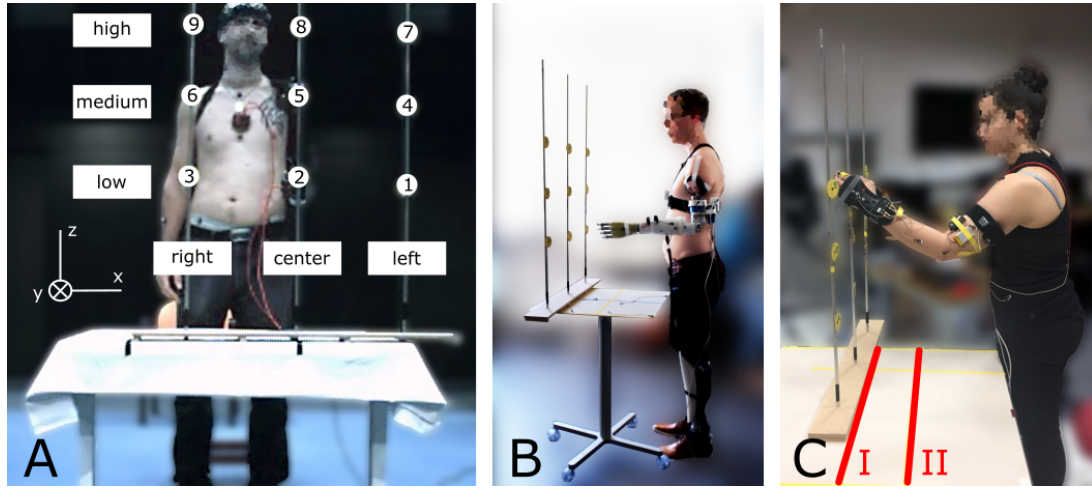


Figure II.2 – Experimental setup with healthy and amputated participants. A: A left-amputated participant is standing in the initial position; there are 9 targets for each distance. B: The same setup and protocol are used for all participants who are equipped with 2 IMUs (chest and arm) measuring the shoulder kinematics. Here a transhumeral osseointegrated patient is wearing the prototype. C: An healthy participant is reaching Target 8 (Distance I).



Figure II.3 – Hand position with respect to the target when successfully performing the reaching task.

The initial position, depicted in Fig. II.2B, was defined with the elbow flexed at 90 degrees and the wrist rotated as if the participant wanted to grasp a cylindrical object (see Fig. II.3). Participants performing the reaching task with the prosthesis prototype were instructed to use only the prosthetic elbow to achieve the task, even though the hand and wrist were myoelectrically-controlled. Healthy participants were equipped with a wrist splint to prevent flexion and deviation movements.

For each reaching movement, the subjects stayed immobile in the initial position until told the target number to reach, then brought the hand the closest to the target, stayed immobile until instructed to come back to the initial position. No particular instruction was given to the subjects concerning movement duration, speed, or target reaching strategy.

II.4 Materials

Motion capture for off-line analysis

A camera-based motion capture system recorded the subjects' upper body kinematics at a frequency of 100 Hz; the data were used for off-line analysis. Two systems were utilized: a Codamotion system (Charnwood Dynamics, Ltd.) was used during experiments that took place at ISIR and at Chalmers University in Sweden, and a Vicon[®] system (Vicon Motion System, Ltd.) was used during experiments at IRR of Nancy. In addition, one or two video cameras recorded the scene.

A Nintendo[®] Wii Balance Board was utilized in the experimental setup with Codamotion to have a recording of the force applied by the feet (Leach et al., 2014). The experimental setup at IRR included two force plates recording the force applied by each foot at a frequency of 1000 Hz.

Controller's inputs measurement

All participants were equipped with two IMUs (x-IMU, x-io Technologies) that were placed on the chest and on the arm – or socket for amputated subjects – as depicted in Fig. II.4. The IMU on the chest was attached to a specific harness used with all participants. During the experiments involving prosthesis control, the arm IMU was placed in a dedicated box attached to the prosthesis. With healthy subjects, the arm IMU was tightly strapped to the arm. The shoulder kinematics, derived from the two wearable sensors (details provided in the subsequent paragraph), were utilized to build the inter-joint coordination model or fed to the prosthesis' controller, as explained in Chapter III. In addition for amputated participants, the signals from their own myoelectric electrodes (Ottobock myoelectrodes 13E125 with a 50 Hz filter, commonly used by prosthetists) were used to control the prosthesis; they were unplugged from their prosthetic device and plugged to a prosthesis prototype. The electrodes were measuring the residual muscular activity of the biceps and triceps groups.

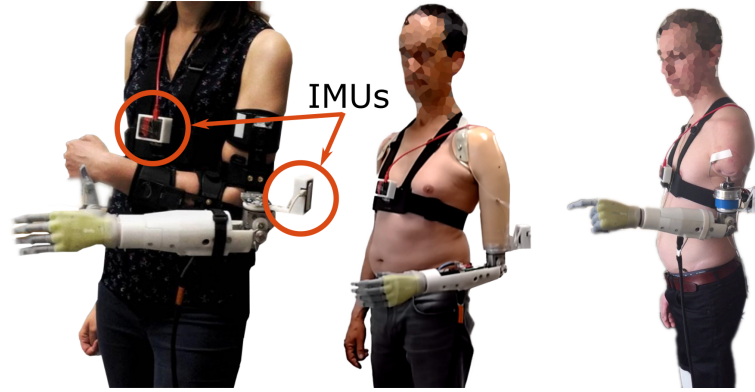


Figure II.4 – Healthy and amputated participants wearing the prosthesis prototype. The prosthesis controller is connected to two IMUs, placed on the chest and the socket, from which is derived the orientation of the trunk and the arm/residual limb. The prosthetic elbow joint rotation axis, when the prototype was mounted on a sound limb, was aligned with the subject's own elbow joint center.

II.5 Prosthesis prototype

Some participants (healthy and amputated) were recruited to test a novel control strategy for the elbow joint whereby shoulder movements drove automatically the elbow extension. For these control tests, the subjects were equipped with a prosthesis prototype which was substituting the amputated participants' own prosthesis, or was worn as a "third" arm by healthy participants, as shown in Fig. II.4.

The prototype was built at ISIR by É. de Montalivet (ISIR/UPMC engineer) and Dr. N. Jarrassé (ISIR/CNRS researcher). Commercialized pieces like a conventional electronic wrist rotator (model 10S17, Ottobock[©]), and an E-TWO electric elbow (Hosmer, Fillauer) were assembled to form a two-DoF prosthetic forearm, as depicted in Fig. II.5. Any myoelectric prosthetic hand with the Quick Disconnect system could be interfaced with the prototype. A Raspberry Pi 3[©] controlled the prosthesis electronics, as well as the motor controller (Ion Motion Control[©]) in charge of elbow's and wrist's motor speed control. An encoder was added to the elbow motor for closed-loop control purpose. The forearm structure, in which most of the electronics was located, had been printed in ABS and reinforced with metal parts. The prosthetic forearm weighed 810 g without a prosthetic hand attached to it. When worn by an amputated participant, the prosthesis prototype was mounted onto the subject's own socket, and the two myoelectric electrodes, located within the prosthesis socket, were connected to the prototype's controller. For all participants, the latter also read the data from the two IMUs and piloted the prosthetic joints accordingly to different input signals and the selected control mode. More details about the prototype's architecture and controller are provided in Appendix B. Moreover, the control strategy to actuate the prosthetic elbow is detailed in Chapters III, IV and V.

The bandwidth of the elbow prototype (with its PID velocity control loop) was experimentally characterized. To this end, sinusoidal velocity signals (with different frequencies) were sent to the prototype's controller, and the absolute velocity output

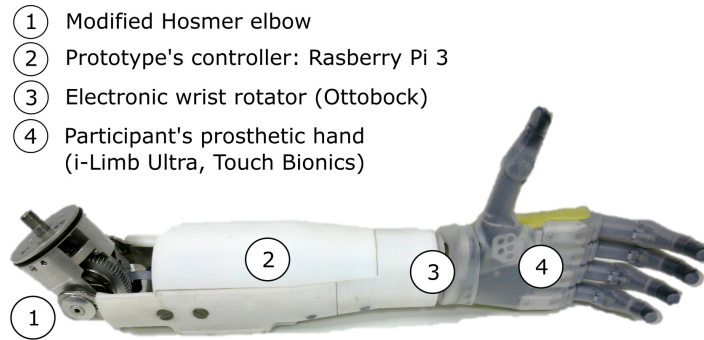


Figure II.5 – The two-DoF forearm prototype includes a motorized elbow (1) and an electronic wrist rotator (3). The participant’s prosthetic hand is connected to the forearm (4). The prosthetic components are controlled by a Raspberry Pi 3 (2) reading the myoelectric signals from the participant’s surface electrodes and from two IMUs.

of the prototype was measured with a camera-based motion capture system (Codamotion). The identified bandwidth of the prototype was [0-6 Hz]; the bode phase diagram (see Fig. B.3 in Appendix B), indicated a 90-deg phase shift for frequencies over 6 Hz. Thus, such performance allowed the prototype to be used to reproduce natural human upper limb movements. Indeed, it is known that healthy individuals exhibit a control bandwidth of 1 to 2 Hz for newly introduced actions, and a bandwidth of 2 to 5 Hz for repetitive actions (Brooks, 1990).

II.6 Deriving the shoulder kinematics from two IMUs

This work presents a control strategy that predicts the elbow kinematics from shoulder kinematics; the latter are derived from two IMUs. This approach has been encouraged by the fact that most transhumeral amputees have a good residual limb mobility, and that inertial sensors can be used to track human kinematics accurately (Chen, 2013; Dejnabadi et al., 2005; Hyde et al., 2008; Luinge et al., 2007; Yun and Bachmann, 2006; Zhang et al., 2011), and especially upper limb angles (El-Gohary and McNames, 2015; Kortier et al., 2015). In addition, their socket and harness can be easily equipped with inertial sensors. Each x-IMU has an embedded fusion algorithm (developed by (Madgwick, 2010)) that computes the orientation based on each device’s accelerometer, gyroscope, and magnetometer measurements. Despite active research on the matter, magnetometer-related drift is still an issue of commercialized IMUs. In the context of this thesis that does not focus on improving the IMUs drift, short recordings are preferred: although the experimental sessions lasted between 1 and 3 hours, the IMUs were re-calibrated every couple of minutes. By using two IMUs, one on the arm/residual limb and the other on the trunk, only the relative motion of the arm with respect to the trunk’s movements are considered, hence disturbances applied to the two sensors will not affect the measure. The procedure to obtain the relative motion between arm and trunk, independently of the sensors’ position on the subject’s

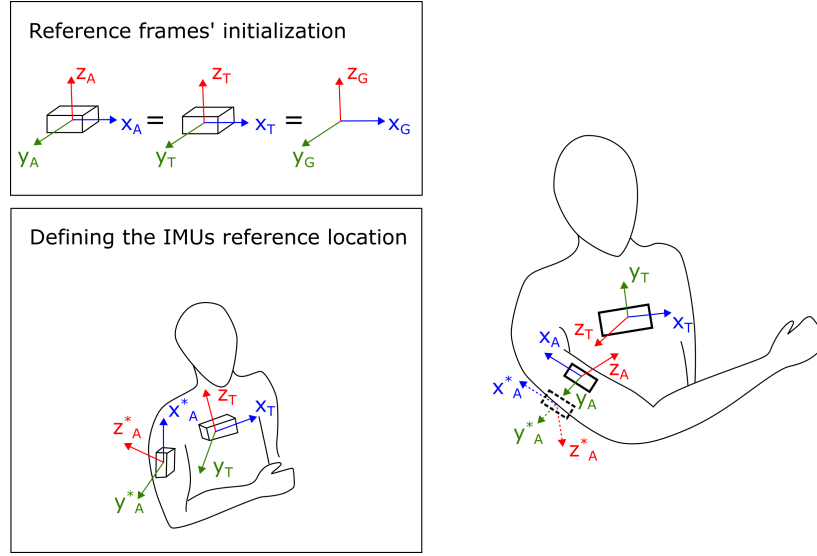


Figure II.6 – Calculating the relative orientation of the IMU placed on the arm with respect to the one placed on the trunk.

body, is described subsequently.

The two IMUs (arm and trunk) provide information on their own orientation with respect to an initial reference frame. An inertial reference frame G attached to the ground is defined during a calibration phase whereby the two sensors are aligned to each other, as illustrated in Fig. II.6. The reference frame A (resp. T) is attached to the IMU on the arm (resp. on the trunk), and its orientation is given by the quaternion value ${}^G_A q$ (resp. ${}^G_T q$).

The measure of the relative motion between the two IMUs varies depending on the sensor placement on the participant's body. Thus, in order to have comparable inter-individual measurements, the calculation of the transformation between reference frame T and A should account for the initial position of each IMU. The time t_0 denotes the time at which the IMUs are placed on the subject's body after sensor calibration. The corresponding reference frame attached to arm IMU (resp. trunk IMU) is denoted A_0 (resp. T_0), and its orientation is given by ${}^{G_0}_{A_0} q$ (resp. ${}^{G_0}_{T_0} q$). An ideal sensor position was defined at a time t_0^* , arbitrary chosen. The corresponding relative orientation ${}^{A_0^*}_{T_0^*} q$ between reference frames A and T at t_0^* , denoted A_0^* and T_0^* , was used in further calculations as the sensor position of reference. Specifically, the measure of each IMU's orientation was then rectified such that their placement was realigned with the ideal placement on the arm and the trunk. Since the trunk IMU was fit in a dedicated rigid attachment device onto the harness, it was assumed that the trunk IMU position was always correct when placed on the subject, meaning that $T_0^* = T_0$. Thus, the relative orientation between the two corrected IMUs' positions, measured at t_0^* with a unique subject, and is given by

$${}^{T_0}_{A_0^*} q = {}^{G_0}_{A_0^*} q \left({}^{G_0}_{T_0} q \right)^{-1}. \quad (\text{II.1})$$

For all further measures, the objective is to calculate the value of ${}^{T_0}_{A_0^*} q$, i.e. the

relative transformation between the trunk IMU and the arm IMU at the corrected position, that can also be written as the rotation matrix $R_{T \rightarrow A^*}$. Then $R_{T \rightarrow A^*}$ can be written as

$$R_{T \rightarrow A^*} = R_{T \rightarrow G} R_{G \rightarrow A} R_{A \rightarrow A^*}. \quad (\text{II.2})$$

Because all movements measured by the arm IMU are assumed to come from arm movements and not sensor displacements, the transformation from reference frame B and B* is supposed to be constant. Hence, using II.2, $R_{T \rightarrow A^*}$ can be written as

$$\begin{aligned} R_{T \rightarrow A^*} &= R_{T \rightarrow G} R_{G \rightarrow A} R_{A_0 \rightarrow A^*} \\ &= R_{T \rightarrow G} R_{G \rightarrow A} R_{A_0 \rightarrow G} R_{G \rightarrow T_0} R_{T_0 \rightarrow A^*}, \end{aligned} \quad (\text{II.3})$$

which in terms of quaternions is equivalent to

$${}^T_{A^*}q = {}^{T_0}_{A_0^*}q \ {}^G_{T_0}q \ \left({}^G_{A_0}q\right)^{-1} \ {}^G_Aq \ \left({}^G_Tq\right)^{-1}. \quad (\text{II.4})$$

with the value of ${}^{T_0}_{A_0^*}q$ given in II.1. The obtained quaternion value ${}^T_{A^*}q$ is then used to derive the humerus orientation relative to the trunk motion in terms of Euler angles. By definition, the rotation matrix associated with the quaternion ${}^T_{A^*}q$ can be written as

$$R_{T \rightarrow A^*} = \begin{pmatrix} 2q_0^2 - 1 + 2q_1^2 & 2(q_1q_2 + q_0q_3) & 2(q_1q_3 - q_0q_2) \\ 2(q_1q_2 - q_0q_3) & 2q_0^2 - 1 + 2q_2^2 & 2(q_2q_3 + q_0q_1) \\ 2(q_1q_3 + q_0q_2) & 2(q_2q_3 - q_0q_1) & 2q_0^2 - 1 + 2q_3^2 \end{pmatrix}, \quad (\text{II.5})$$

where ${}^T_{A^*}q = [q_0 \ q_1 \ q_2 \ q_3]$, and q_0 is the real part. The decomposition in three consecutive rotations yields

$$\begin{aligned} R_{T \rightarrow A^*} &= \begin{pmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi & \cos\phi \end{pmatrix}, \\ &= \begin{pmatrix} c\psi c\theta & -s\psi c\theta + c\psi s\theta s\phi & s\psi s\theta + c\psi s\theta c\phi \\ s\phi c\theta & c\psi c\phi + s\psi s\theta c\phi & -c\psi s\phi + s\psi s\theta c\phi \\ -s\theta & c\theta s\phi & c\theta c\phi \end{pmatrix}, \end{aligned} \quad (\text{II.6})$$

where ψ , θ , and ϕ correspond to the three Euler angles in the sequence ZYX. Identifying the terms between the equations II.5 and II.6 yields

$$\tan(\psi) = \frac{R_{T \rightarrow A^*}\{2\}\{1\}}{R_{T \rightarrow A^*}\{1\}\{1\}}, \tan\theta = \frac{-R_{T \rightarrow A^*}\{3\}\{1\}}{\sqrt{1 - (R_{T \rightarrow A^*}\{3\}\{1\})^2}}, \tan\phi = \frac{R_{T \rightarrow A^*}\{3\}\{2\}}{R_{T \rightarrow A^*}\{3\}\{3\}}. \quad (\text{II.7})$$

The Euler angles' values, which describe the relative orientation of the arm longitudinal axis with respect to the trunk vertical axis, are used subsequently as inputs of the shoulder/elbow coordination model, as detailed in Chapter III.

II.7 Describing the upper body motion

There are several nomenclatures describing upper body movements, and especially upper limb motions. This paragraph aims at defining how kinematic data from camera-based motion capture systems are processed prior to compute the metrics relevant

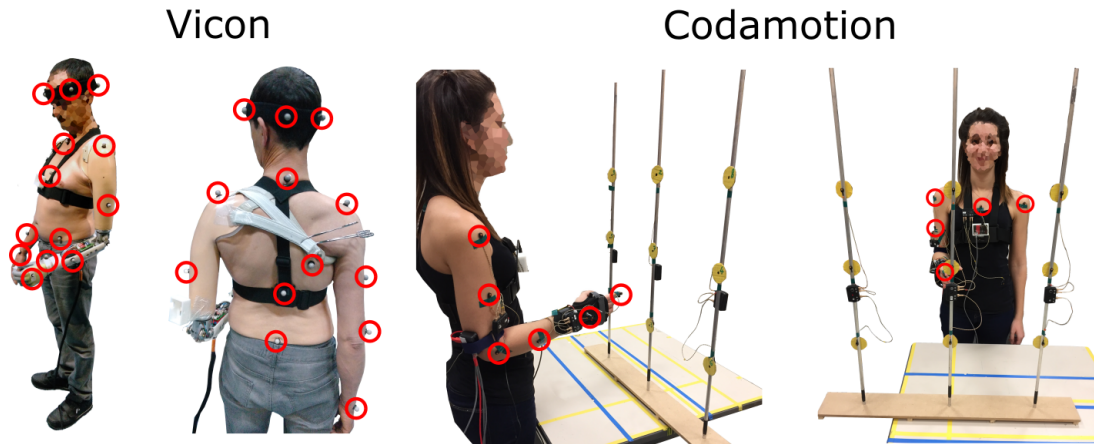


Figure II.7 – Marker positions for the camera-based motion capture systems – Vicon[©] on the left and Codamotion on the right.

to the assessment of the participant's body movements that will be utilized in the subsequent chapters.

II.7.1 Position of the motion capture markers

As previously explained, two different camera-based motion systems were used to measure the body kinematics: the Codamotion system was used during experiments with healthy participants at ISIR and osseointegrated patients at Chalmers University in Sweden, and the Vicon[©] system was used with IRR patients in Nancy. For both motion capture systems, the main markers locations were:

- Index's middle phalanx
- Hand's back
- Forearm
- Elbow lateral epicondyle
- Upper arm
- Left and right acromions
- Suprasternal notch
- Xiphoid process
- Left and right anterosuperior iliac spines (EIAS)

The marker locations are listed in Table II.1.

II.7.2 Kinematic quantification of the body movements

The following paragraph details the kinematic model analysis from the camera-based motion capture recordings. Since a reduced number of markers was used in the Codamotion setup, only markers common to the two setups were utilized in the analysis. The procedure is adapted from the work of Carey (2008) (see Chapter 4, p. 35 in Carey's dissertation) and the recommendations of the International Society of Biomechanics (Wu et al., 2005). The upper body is divided in three blocks for the motion analysis: 1) the trunk, 2) the arm, and 3) the forearm, and a reference frame is attached to each block to describe the relative movement of one bloc, to respect to the others.

	Codamotion	Vicon
Ipsilateral limb	Index middle phalanx (Finger) Hand's back × × Forearm Lateral epicondyle × Upper arm Acromion	Wrist A Wrist B Medial epicondyle
Contralateral limb	× × × × × × Acromion	Hand's back Wrist A Wrist B Lateral epicondyle (Elbow) Medial epicondyle Upper arm
Chest	Suprasternal notch (CLAV) Xiphoid process (STRN) Left EIAS (LEIAS) Right EIAS (REIAS)	
Back	× × ×	C7 T10 Sacrum
Targets	Target 1 to Target 9	

Table II.1 – Markers locations for both camera-based motion capture systems (Vicon[©] and Codamotion). They are depicted in Fig. II.7.

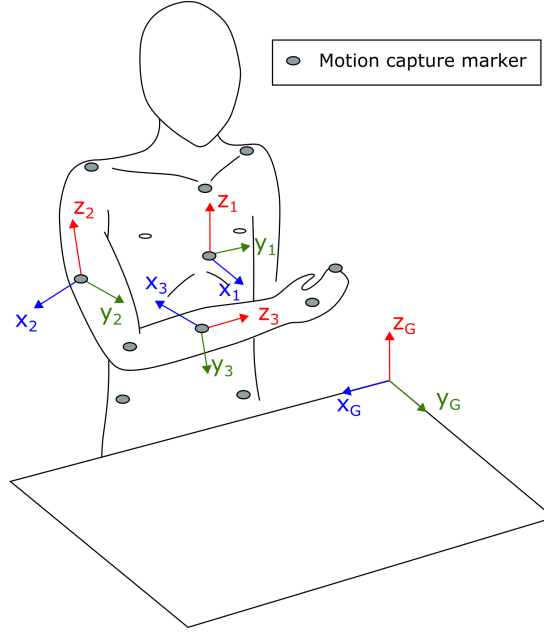


Figure II.8 – Main markers location and reference frames attached to the body (trunk, arm, and forearm).

First the reference frame G , attached to the room in which the experiment takes place, is defined as the reference frame in which the data from the motion capture systems are given. The origin of reference frame G is the fixed point O arbitrary placed in the room, and G 's coordinate system is $\{\mathbf{x}_G, \mathbf{y}_G, \mathbf{z}_G\}$, as illustrated in Fig. II.8. The reference frame 1 is attached to the subject's trunk, with the sternum marker as origin; the coordinate system associated with this reference frame is defined as $\{\mathbf{x}_1, \mathbf{y}_1, \mathbf{z}_1\}$. The vector $\mathbf{z}_1$ is built as the unit vector between the STRN and CLAV markers. The CLAV markers and one marker EIAS (LEIAS for pointing movements with the right hand, REIAS for pointing movements with the left hand) are utilized to build a secondary unit vector. The latter is crossed with the first vector $\mathbf{z}_1$ to define $\mathbf{x}_1$, pointing forward. The y-axis is defined as the result of the crossing of $\mathbf{z}_1$ and $\mathbf{x}_1$. Reference frame 2 is attached to the upper arm segment, and has the UPA marker as origin, and its associated coordinate system is denoted $\{\mathbf{x}_2, \mathbf{y}_2, \mathbf{z}_2\}$. The axis $\mathbf{z}_2$ is defined as the unit vector between the elbow and acromion marker. The x-axis is defined as the crossing of the line between the UPA and acromion markers and $\mathbf{z}_2$. The z-axis and x-axis are crossed to defined $\mathbf{y}_2$. Reference frame 3 is attached to the forearm segment, and its origin is the forearm marker; $\{\mathbf{x}_3, \mathbf{y}_3, \mathbf{z}_3\}$ denotes the reference frame's coordinate system. Its z-axis is defined as the unit vector along the line between the elbow markers and the hand marker. The x-axis is defined as the crossing of the line between the elbow and forearm markers with $\mathbf{z}_3$. Finally, the y-axis is defined as the crossing of $\mathbf{z}_3$ and $\mathbf{x}_3$.

Few studies have been focusing on analyzing the trunk motion during ADLs (Bouwsema et al., 2014; Carey et al., 2008; de Groot et al., 2011; Fradet et al., 2015; Petuskey et al., 2007). Here, trunk displacements are assessed in the three anatomical planes,

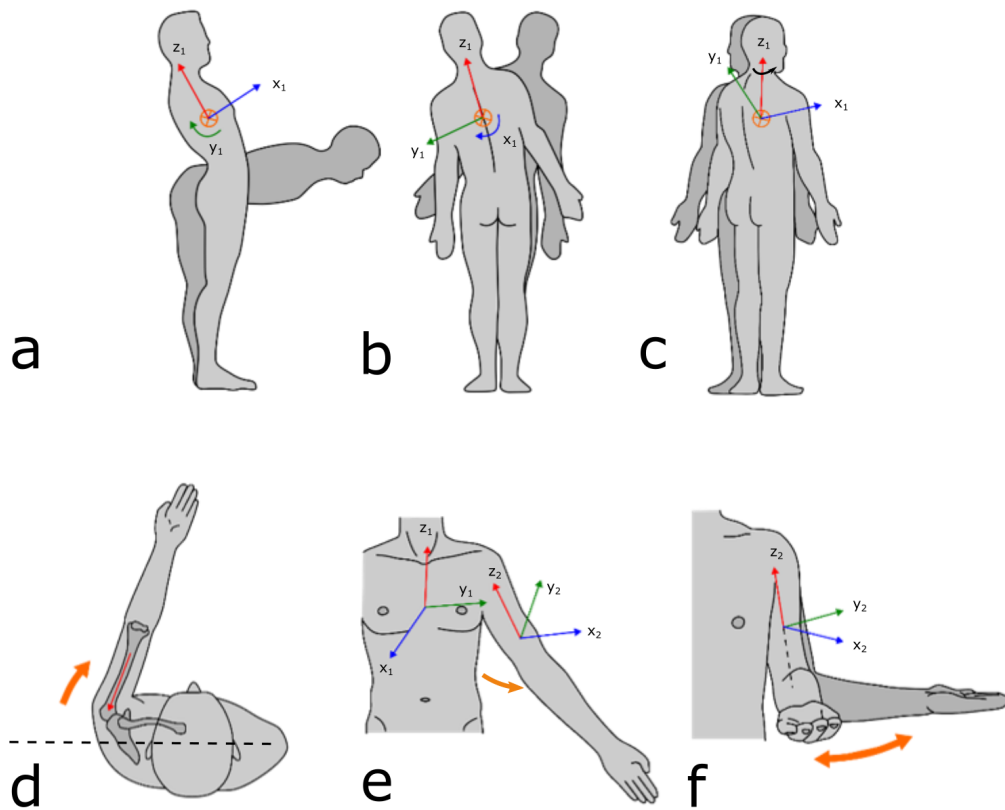


Figure II.9 – Trunk movements are composed of three rotations: anteroposterior bending (a), mediolateral bending (b), and torsion (c). The humerus motion is described by the anatomical angles corresponding to the plane of elevation (d), the elevation (e), and the humerus axial rotation (f).

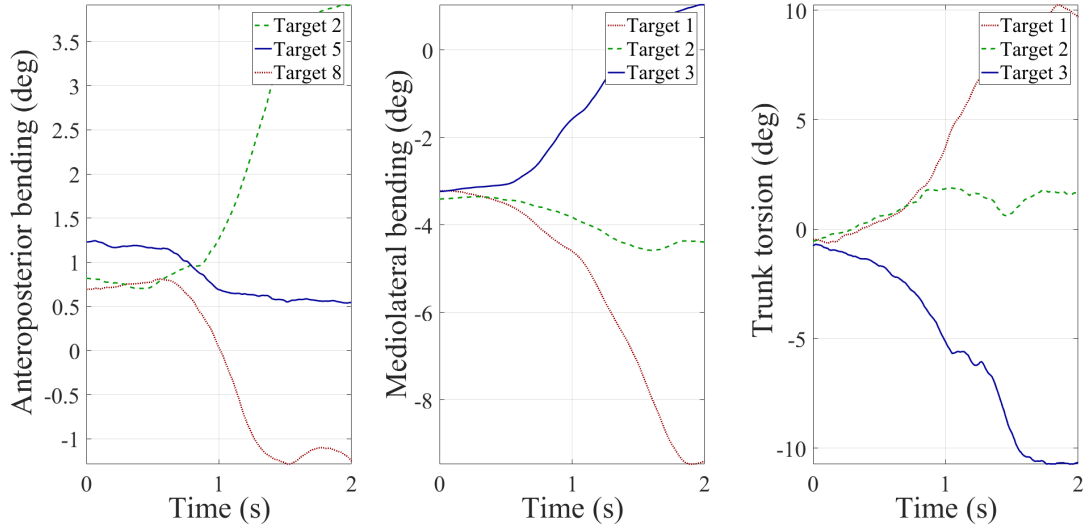


Figure II.10 – Angular variations of the three trunk angles θ_{ap} , θ_{ml} , and θ_t . The values correspond to the recording of an healthy individual doing reaching movements with his left upper limb towards Targets 1, 2, 3, 5, 8 of Distance I.

as depicted in Fig. II.9. The **anteroposterior bending angle** θ_{ap} is defined as the angle between the trunk vertical axis $\mathbf{z}_1$ and its initial position $(\mathbf{z}_1)_0$ projected in the sagittal plane, the **mediolateral bending angle** θ_{ml} is defined as the angle between the trunk vertical axis $\mathbf{z}_1$ and its initial position $\mathbf{z}_{10}$ projected in the frontal plane, and the **torsion angle** θ_t is defined as the angle between the trunk direction axis $\mathbf{x}_1$ and its initial position $\mathbf{x}_{10}$ in the transverse plane, such that

$$\tan(\theta_{ap}) = \frac{\mathbf{z}_1 \cdot \mathbf{x}_{10}}{\mathbf{z}_1 \cdot \mathbf{z}_{10}}, \tan(\theta_{ml}) = \frac{-\mathbf{z}_1 \cdot \mathbf{y}_{10}}{\mathbf{z}_1 \cdot \mathbf{z}_{10}}, \tan(-\theta_t) = \frac{\mathbf{x}_1 \cdot \mathbf{y}_{10}}{\mathbf{x}_1 \cdot \mathbf{x}_{10}}. \quad (\text{II.8})$$

It should be accounted that the angles θ_{ml} , and θ_t as calculated in Eq. II.8 correspond to the configuration whereby the task is performed with the left hand, and that the opposite value should be considered for a right configuration. The angular values of the three angles θ_{ap} , θ_{ml} , and θ_t for an healthy individual doing pointing movements towards targets located at Distance I is depicted in Fig. II.10. The value of θ_{ap} increases when bending was forward, and decreases for backward bending motion. The mediolateral bending angle value θ_{ml} decreases during lateral bending (i.e. bending towards the side of the limb performing the movement). The value of θ_t decreases for medial trunk rotation, i.e. towards the contralateral side. The angular variations, defined as the difference between the final and initial angular values, were derived from the three trunk angles.

Trunk compensatory movements are also characterized by the distance covered by the trunk's reference frame's origin STRN, like it is done by Metzger et al. (2012). The **trunk cumulative path**, normalized by the movement duration, is calculated as the sum of the distances between two consecutive points of the trunk center's trajectory, divided by the time needed to movement duration. In addition, changes in the weight distribution during the movements, referred to as the **weight distribution variation**,

are assessed by computing the difference between the final and initial amount of force applied by the ipsilateral foot with respect to the total force applied by both feet.

Assessment of trunk movements:

- Angular variation of the **anteroposterior bending angle**
- Angular variation of the **mediolateral bending angle**
- Angular variation of the **torsion angle**
- **Trunk cumulative path**
- **Weight distribution variation** on the force plate

Shoulder kinematics are often measured to quantify compensatory strategies (Bouwsema et al., 2014; de Groot et al., 2011; Deijs et al., 2016; Kasten et al., 2009; Magermans et al., 2005; Major et al., 2014; May-Lisowski and King, 2008; Petuskey et al., 2007; Romilly et al., 1994). As recommended by the International Society of Biomechanics (Wu et al., 2005), three angles describe the humerus movements, as illustrated in Fig. II.9. The **plane of elevation** is described by the angle γ_{GH_1} that characterizes the direction in which the humerus was pointing; it is calculated as the angle between the shoulder line and the humerus longitudinal axis $\mathbf{z}_2$ projected in the horizontal plane. The **elevation angle** α quantifies the humerus amplitude with respect to the trunk vertical axis $\mathbf{z}_1$. The **humeral axial rotation** corresponds to the humerus internal/external rotation about its longitudinal axis and it is described by the angle γ_{GH_2} . The angle values are computed using the rotation matrix $R_{1 \rightarrow 2}$ corresponding to the transformation between the reference frame 1 (attached to the trunk) and the reference frame 2 (attached to the arm). This rotation matrix can be written as, using the ZYZ Euler decomposition

$$R_{1 \rightarrow 2} = \begin{pmatrix} c_{\gamma_1} c_{\gamma_2} - s_{\gamma_1} c_{\alpha} s_{\gamma_2} & -c_{\gamma_1} s_{\gamma_2} - s_{\gamma_1} c_{\alpha} c_{\gamma_2} & s_{\gamma_1} s_{\alpha} \\ s_{\gamma_1} c_{\gamma_2} + c_{\gamma_1} c_{\alpha} s_{\gamma_2} & -s_{\gamma_1} s_{\gamma_2} + c_{\gamma_1} c_{\alpha} c_{\gamma_2} & -c_{\gamma_1} s_{\alpha} \\ s_{\alpha} s_{\gamma_2} & s_{\alpha} c_{\gamma_2} & c_{\alpha} \end{pmatrix}, \quad (\text{II.9})$$

where c_{γ_1} (resp. s_{γ_1}), c_{α} (resp. s_{α}), and c_{γ_2} (resp. s_{γ_2}) are short notations for $\cos(\gamma_{GH_1})$ (resp. $\sin(\gamma_{GH_1})$), $\cos(\alpha)$ (resp. $\sin(\alpha)$), and $\cos(\gamma_{GH_2})$ (resp. $\sin(\gamma_{GH_2})$). The rotation matrix $R_{1 \rightarrow 2}$ can also be written as

$$R_{1 \rightarrow 2} = (R_{G \rightarrow 1})^{-1} R_{G \rightarrow 2} = (R_{1 \rightarrow 2} \{i\} \{j\})_{i=1..3, j=1..3}, \quad (\text{II.10})$$

where $R_{G \rightarrow 1}$ (resp. $R_{G \rightarrow 2}$) denotes the rotation matrices between the reference frame G (attached to the lab) and reference frame 1 (resp. reference frame 2). The associated coordinate systems are used to compute $R_{G \rightarrow 1}$ and $R_{G \rightarrow 2}$, as following

$$R_{G \rightarrow i} = \begin{pmatrix} \mathbf{x}_i \cdot \mathbf{x}_G & \mathbf{y}_i \cdot \mathbf{x}_G & \mathbf{z}_i \cdot \mathbf{x}_G \\ \mathbf{x}_i \cdot \mathbf{y}_G & \mathbf{y}_i \cdot \mathbf{y}_G & \mathbf{z}_i \cdot \mathbf{y}_G \\ \mathbf{x}_i \cdot \mathbf{z}_G & \mathbf{y}_i \cdot \mathbf{z}_G & \mathbf{z}_i \cdot \mathbf{z}_G \end{pmatrix}_{i=1,2}. \quad (\text{II.11})$$

The three anatomical angles can be calculated by identifying the terms between II.10 and II.9, such that

$$\tan(\gamma_{GH_1}) = \frac{R_{1 \rightarrow 2} \{1\} \{3\}}{-R_{1 \rightarrow 2} \{2\} \{3\}}, \quad \cos(\alpha) = R_{1 \rightarrow 2} \{3\} \{3\}, \quad \tan(-\gamma_{GH_2}) = \frac{R_{1 \rightarrow 2} \{3\} \{1\}}{R_{1 \rightarrow 2} \{3\} \{2\}}. \quad (\text{II.12})$$

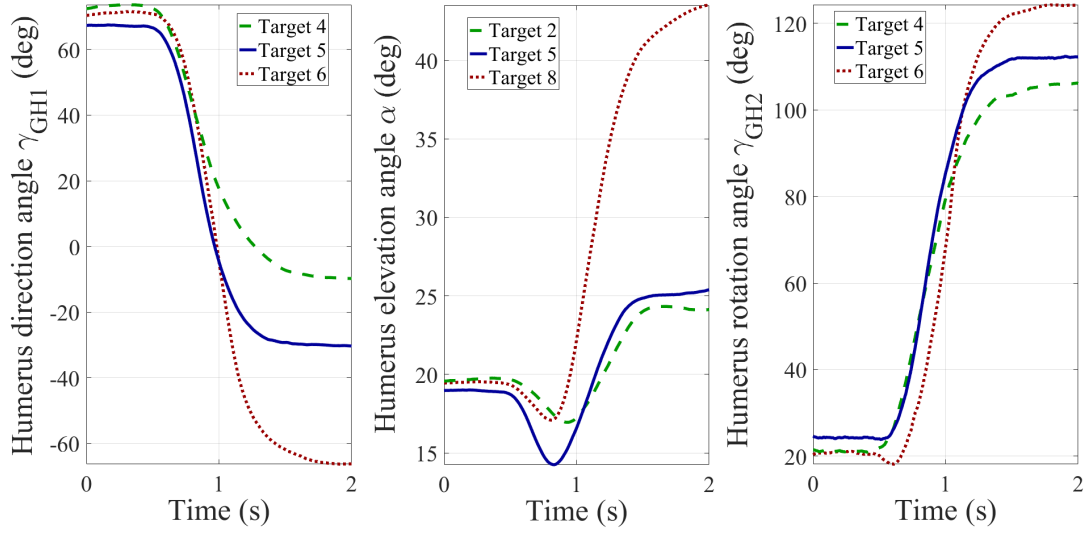


Figure II.11 – Angular variations of the three shoulder angles γ_{GH_1} , α , and γ_{GH_2} . The values correspond to the recording of an healthy individual doing reaching movements with his left upper limb towards Targets 2, 4, 5, 6, 8 of Distance I.

It should be accounted that the angles γ_{GH_1} , and γ_{GH_2} as calculated in Eq. II.12 correspond to a left-amputee configuration, and that the opposite values should be considered for a right-amputee configuration. The angular variation of the three angles γ_{GH_1} , α , and γ_{GH_2} for an healthy individual doing reaching movements towards targets located at Distance I is depicted in Fig. II.11. The value of α increases with the targets' height; it is null when the humerus longitudinal axis is aligned with the trunk vertical axis. Humerus medial (i.e. internal) rotation increases the value of the angle γ_{GH_2} .

Elbow joint motion is assessed with the **flexion/extension angle** β such that $\cos(\beta) = \mathbf{z}_2 \cdot \mathbf{z}_3$. The angle β decreases with elbow extension, and the initial elbow position is 90 degrees. All angle values for the trunk and upper limb are calculated as a variation of movement, i.e. as the difference between the final and initial value taken by the considered angle. All metrics are compared to the baseline values obtained with the healthy participants' data from the model training data set acquisition experiment (i.e. reaching movements without a prosthesis), referred to as the control situation.

Moreover, the shoulder/elbow coordination is assessed numerically by doing a PCA on the joints kinematic data, i.e. the values of humerus elevation angular velocity and elbow extension angular velocity (Bockemühl et al., 2010). For each participant, the difference between his own inter-joint coordination and a coordination of reference is computed as the angle between the first principal components of the respective PCA.

Assessment of shoulder and elbow movements:

- Angular variation of the **plane of elevation**
- Angular variation of the **elevation angle**
- Angular variation of the **humeral axial rotation**
- Angular variation of the **elbow flexion/extension angle**
- **Inter-coordination angle**

Chapter III

Construction of the inter-joint coordination model

This chapter presents the first step of developing an automatic control mode of an prosthetic elbow joint, i.e. modeling the shoulder/elbow coordination relationship. Since an amputee's own inter-joint coordinations cannot be measured, an approach whereby inter-joint coordination patterns from several individuals are combined is investigated. Building on previous literature results, the shoulder and elbow coordinations for the reaching task is modeled using healthy participants' data recorded with wearable sensors.

Experiment overview

The experiment aimed to acquire the model training data, and it consisted in recording upper limb reaching movements of several healthy individuals. Two IMUs, placed on the participants' chest and arm, measured the shoulder kinematics, while the overall upper body kinematics were measured with a motion capture system, as described in Chapter II. The recorded data were utilized offline to build shoulder/elbow coordination models; several training data sets and modeling techniques were investigated.

III.1 Materials and methods

Participants Fourteen healthy individuals (7 women, 7 men) participated in the study. The only inclusion criterion was a good physical condition. The average age was 24 years old (± 2.1 yo), and the average height was 174 cm (± 10 cm). The participants were mainly recruited from graduate students at ISIR, where the experiment took place. Information on the subjects is grouped in Table III.1.

Protocol All participants performed thrice the task consisting in reaching 18 targets (9 targets at 2 distances) with their hand (see Chapter III). The hand with which they did the task was selected arbitrary prior to the experiment, independently to their dominant side. As explained in Chapter II, the targets were adjusted to each participant's height and arm length. For every reaching movement, the subject started in the initial position (i.e. the elbow flexed at 90 degrees), brought the hand to the designated target, stayed immobile until told to come back to the initial position. In

	Gender M/F	Age	Height	Side [†] Right and/or Left
S1	M	25 yo	182 cm	R/L
S2	M	28 yo	175 cm	R/L
S3	F	25 yo	173 cm	R/L
S4	F	22 yo	163 cm	R
S5	M	23 yo	192 cm	R/L
S6	F	23 yo	160 cm	L
S7	M	21 yo	185 cm	R
S8	F	21 yo	167 cm	L
S9	F	25 yo	171 cm	R
S10	M	27 yo	190 cm	R/L
S11*	F	23 yo	167 cm	R/L
S12*	F	23 yo	167 cm	L
S13*	M	24 yo	174 cm	L
S14*	M	26 yo	175 cm	R

[†] Side corresponds to the upper limb with which the task was performed (e.g. left means that the participant performed the task with the left hand).

* Experimental sessions during which a Wii Balance Board was used to measure the forces.

Table III.1 – Healthy participants' general information

order to avoid concentration-related reaching mistakes, the participants were asked to focus on the target to reach before doing the main reaching movement at one go.

Experimental setup The participants were equipped with motion capture markers from the Codamotion system. The shoulder kinematics were measured with two IMUs: one placed on the arm with a Velcro strip, the other was attached to the trunk thanks to a chest harness. A Wii Balance Board was used during the last experimental sessions to record the force distribution during the movements. The participants were asked to click the heels on the platform at the beginning of each recording session: this movements, seen by the three measurement systems (Codamotion, IMUs, Wii Balance Board) was used as a signal cue during the offline synchronization phase. More details about the experimental setup are provided in Chapter II.

III.2 Model building methods

The objective was to approximate the relationship between the shoulder and the elbow kinematics. Several regression methods were investigated. RBFN- and PCA-based regressions are the most used in the literature to assess the correlation between proximal and distal joints kinematics, and locally weighted regression (LWR) was tested as an alternative. The influence of the input set was studied with the RBFN-based regression, since it is the modeling approach with the best results in the literature. Regression techniques aim to find the best-fitted model relating a selected input/output set (shoulder/elbow kinematics in this case) during the training step; during the testing step, this model is used to estimate the output (elbow angular velocity) based on a measured input value (shoulder angular velocities). The testing step can be performed

offline, or online using input values measured in real time. The data acquired from the healthy participants were split in two groups, whether the task was performed with the right or left limb.

The inputs and outputs are chosen in the velocity space since it makes the models free of the initial position. The participants are asked to return to the same initial position for the shoulder and the elbow without control from the experiment designers, certainly yielding some variability that was desired by the experiment designers. Having a system robust to changes in the initial position is necessary in the development process: prosthesis users should not pay attention to the initial position when they want to actuate their device.

Model data preparation

Data from the two measurement systems (Codamotion and x-IMU) were synchronized offline. Three angles, derived from the measurements of the two IMUs, were utilized to describe the humerus orientation (see paragraph II.6). The angle β represented the elbow flexion/extension angle, and was derived from the Codamotion measurements. Shoulder and elbow angular velocities were computed numerically from angular position measurements. The data were partitioned for each movement (18 targets, 3 trials, 10 subjects for each side, i.e. 540 movements) such that only the reaching motion was conserved. The angular velocity were low-pass filtered with a cutoff frequency of 5 Hz.

RBFN-based regression

Several studies in the literature, like the one presented by [Iftime et al. \(2005\)](#), have investigated the outcomes of a regression that uses radial basis function networks, referred to as RBFN-based regression, to model the shoulder/elbow relationship. As [Stulp and Sigaud \(2015\)](#) explained in their review of regression techniques, the model itself can be represented by an equation of the form

$$\mathbf{y} = f(\mathbf{x}), \quad (\text{III.1})$$

where $\mathbf{x}$ denotes the input set, f is the function approximating the relationship between the selected inputs/outputs sets, and y denotes the output set estimated by f for a given input set $\mathbf{x}$. The RBFN-based regression technique is a nonlinear approximation method in the sense that the output is not a linear combination of the input. The input set is transposed into a feature space, the transformed input values are then linearly combined to obtain the output value. The feature space is the result of the projection of the input into a space of high dimension; ϕ , the projection function, is characterized by the number of features (e.g. Gaussian basis functions) that defines the space dimension, and their parameters. As a result, the equation III.1 can be written as

$$\mathbf{y} = \sum_{e=1}^E w_e \phi(\mathbf{x}, \mathbf{c}_e), \quad (\text{III.2})$$

where w_e denotes E coefficients linearly relating the feature space to the output space, and $\mathbf{c}_e$ denotes the e-th Gaussian basis function's radius. An example is illustrated in Fig. III.1. The selected input corresponds to the time derivative of the shoulder

	Method	Input set	Model form
Model 1	Regression with RBFN	$\mathbf{x} = [\dot{\alpha}]$	$\dot{\beta} = \sum_{e=1}^E w_e e^{-\ \mathbf{x} - \mathbf{c}_e\ _2}$
Model 2		$\mathbf{x} = [\dot{\psi} \quad \dot{\theta} \quad \dot{\phi}]$	
Model 3	PCA-based regression		$\dot{\beta} = P_2 (P_1)_{left}^{-1} \mathbf{x}$
Model 4	LWR regression		$\dot{\beta} = \sum_{e=1}^E \phi(\mathbf{x}, \mathbf{c}_e) (\mathbf{a}_e^T \mathbf{x})$

Table III.2 – Summary table of the four modeling methods used to approximate the relationship between the shoulder and the elbow kinematics.

elevation. Four Gaussian basis functions, uniformly distributed across the input space, are represented as color lines in Fig. III.1; they are weighted with their corresponding coefficients in Eq. III.2. The resulting model is a weighted sum of the Gaussian basis functions.

The RBFN-based regression technique is used to model the shoulder/elbow coordination with two different sets of inputs, yielding ultimately to classes of model. The first input set, associated with the model referred to as **Model 1**, corresponds to the time derivative of the humerus elevation angle, such that $\mathbf{x} = \dot{\alpha}$. Another input set, utilized with a second model referred to as **Model 2**, corresponds to the time derivatives of the three Euler angles describing the orientation of the reference frame attached to the arm with respect to the trunk (see details in Chapter II, paragraph II.6), such that $\mathbf{x} = [\dot{\psi} \quad \dot{\theta} \quad \dot{\phi}]$.

Principal Component-based regression

A common method to assess the inter-joint coordinations is to use PCA on joint kinematics (Crocher et al., 2012; Jarrassé et al., 2014; Santello et al., 1998; Soechting and Flanders, 1997; Vallery and Buss, 2006; Vinjamuri et al., 2014). The number of DoFs of the shoulder/elbow system, denoted by d , exceeds the number of DoFs required to position the hand in a 3-dimension workspace. Hence, there is redundancy with respect to the task. PCA can be performed over a training data set to determine an orthogonal basis in the joints angular velocity space, composed of d PCs $\mathbf{p}_i$. In this analysis, $\mathbf{p}_1$ represents the most variance of the data, and $\mathbf{p}_d$ represents the least variance. Considering the measurement of the shoulder and elbow angular velocities (respectively $\mathbf{x} = [\dot{\psi} \quad \dot{\theta} \quad \dot{\phi}] \in \mathbb{R}^3$ and $\dot{\beta} \in \mathbb{R}$), grouped in the vector $X \in \mathbb{R}^4$, the new coordinates $Y \in \mathbb{R}^4$ represent the vector X expressed in the joint space's basis, such that

$$\begin{aligned} Y &= P^T X, \\ &= [\mathbf{p}_1 \quad \mathbf{p}_2 \quad \mathbf{p}_3 \quad \mathbf{p}_4]^T [\mathbf{x} \quad \dot{\beta}]^T, \end{aligned} \quad (\text{III.3})$$

where P is the matrix formed by the eigenvectors (sorted in descending order of the corresponding eigenvalues) of the covariance matrix calculated with the training data set (i.e. n measurements of $\mathbf{x}$). Transposing Eq. III.3 yields

$$X = PY. \quad (\text{III.4})$$

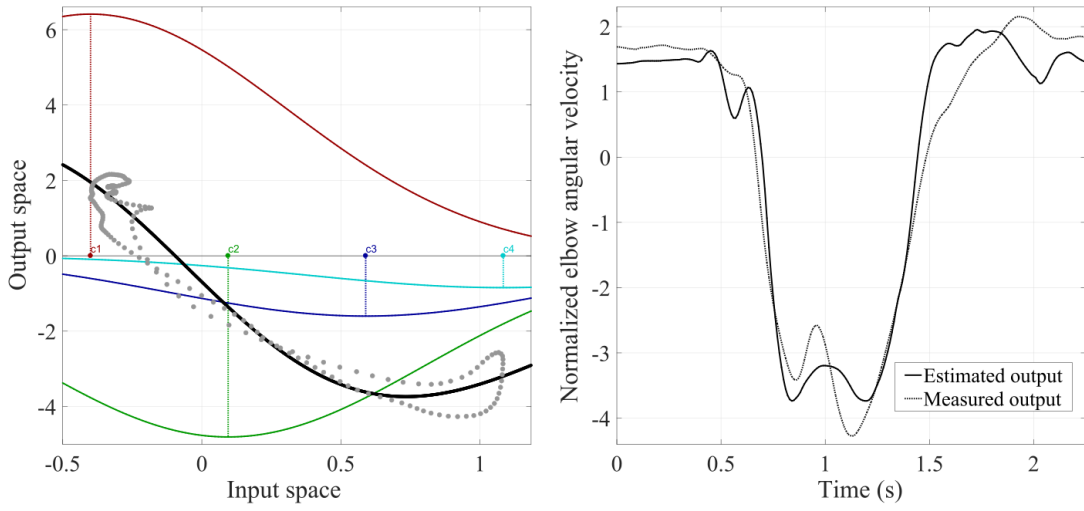


Figure III.1 – Illustration of the RBFN-based regression between a 1-dimension input set (time derivative of the shoulder elevation) and the 1-dimension output set (elbow angular velocity). Left: The four colored plots represent the Gaussian basis functions, scaled by their corresponding weight in the model (Eq. III.2). The resulting approximation function f , represented by the solid black line, corresponds to the sum of the Gaussian components. The grey dots represent the measured data $(\mathbf{x}, \dot{\beta})$ for one reaching movement. Right: The model is fed with a measured input set to estimate the corresponding output values (solid line). As a comparison, the measured output set is represented by the dotted line.

Neglecting the last components of Y is equivalent to omitting the corresponding eigenvectors in P , which can be written as $P = \begin{bmatrix} \mathbf{p}_1 & \mathbf{p}_2 & \mathbf{p}_3 \end{bmatrix}$. Hence, the dimension of Y is reduced to $p < d$ (here, $p = 3$). In addition to dimension reduction, redundancy in the data can also be used for reconstruction of incomplete measurements. Indeed, if part of the vector X is unknown (for instance, the elbow angular velocity value $\dot{\beta}$), it can be computed from the remaining part of X , then equal to $\mathbf{x}$ and the p -first PCs. Hence, the equation in III.4 can be written as

$$\begin{bmatrix} \mathbf{x} \\ \dot{\beta} \end{bmatrix} = \begin{bmatrix} P_1 \\ P_2 \end{bmatrix}, \quad (\text{III.5})$$

with $P_1 \in \mathbb{R}^{3 \times 2}$, and $P_2 \in \mathbb{R}^{1 \times 2}$, which can be separated into

$$\mathbf{x} = P_1 Y, \quad \dot{\beta} = P_2 Y. \quad (\text{III.6})$$

Hence, using Eq. III.6, the missing data can be calculated as

$$\dot{\beta} = P_2 (P_1)_{left}^{-1} \mathbf{x}, \quad (\text{III.7})$$

where $(P_1)_{left}^{-1}$ denotes the left pseudoinverse of P_1 as $(P_1)_{left}^{-1} = (P_1^T P_1)^{-1} P_1^T$. For the current and the following chapters, **Model 3** refers to as the inter-joint coordination model built using a PCA-based regression method.

Locally weighted regression

LWR is an alternative to RBFN-based regression to approximate the nonlinear relationship between the shoulder and the elbow kinematics. As described by [Stulp and Sigaud \(2015\)](#), the approach consists in building E local linear models, each of them weighed by a Gaussian functions of centers $\mathbf{c}_e$. Each linear model is then fitting a part of the data. The resulting model can be written as

$$\mathbf{y} = \sum_{e=1}^E \phi(\mathbf{x}, \mathbf{c}_e) (\mathbf{a}_e^T \mathbf{x}), \quad (\text{III.8})$$

where $\mathbf{a}_e$ denotes the e -th linear coefficient for the e -th local linear model. The solution to locally weighed least squares, which aims at minimizing the sum of residuals, is given by

$$\mathbf{a}_e = \left(X^T W_e X \right)^{-1} X^T W_e y, \quad \text{for } e = 1..E, \quad (\text{III.9})$$

where $W_e \in \mathbb{R}^{N \times N}$ (with N the number samples in the training data set) represents the local weights matrix; W_e is diagonal and its components $w_{e,n=1..N}^n$ are described using normalized Gaussian basis functions, such that $w_e^n = \phi(\mathbf{x}_n, \theta_e)$ where $\mathbf{x}_n$ denotes the n -th sample of the training data set $\mathbf{x}$, and $\theta_e = (\mathbf{c}_e, \Sigma_e)$ denotes the Gaussian basis functions parameters. The function ϕ is described for LWR regression as

$$\phi(\mathbf{x}, \mathbf{c}_e, \Sigma_e) = \frac{g(\mathbf{x}, \mathbf{c}_e, \Sigma_e)}{\sum_{e'=1}^E g(\mathbf{x}, \mathbf{c}_{e'}, \Sigma_{e'})}, \quad g(\mathbf{x}, \mathbf{c}_e, \Sigma_e) = e^{-\frac{1}{2}(\mathbf{x}-\mathbf{c}_e)^T \Sigma_e^{-1} (\mathbf{x}-\mathbf{c}_e)}. \quad (\text{III.10})$$

An example with $E = 2$ is depicted in III.2. A linear model is built on each local interval of input data (i.e. the time derivative of the humerus elevation angle for the chosen example), and the weighed sum of these local models yields the global model. The linear coefficients $\mathbf{a}_e$ associated with each local model are determined using Eq. III.9. However, in the subsequent analysis, the selected input set was the time derivatives of the three Euler angles ($\mathbf{x} = [\dot{\psi} \ \dot{\theta} \ \dot{\phi}]$), and the corresponding modeled was referred to as **Model 4**.

Other modeling approaches can be envisaged. However, the main requirement of the model development phase is to use simple modeling tools and to avoid complex neuronal structures for future embedding steps.

III.3 Offline assessment of the models

Four modeling approaches were implemented in MATLAB scripts. **Model 1** and **Model 2** were built using a RBFN-based regression method with two different sets of input/output data: while for all models the selected output was the elbow angular velocity $\dot{\beta}$, **Model 1**'s input set was the time derivative of the humerus elevation angle, i.e. $\mathbf{x} = \dot{\alpha}$, and **Model 2**'s input set was the time derivatives of the three Euler angles, such that $\mathbf{x} = [\dot{\psi} \ \dot{\theta} \ \dot{\phi}]$. PCA-based regression was performed to build **Model 3** with $\mathbf{x} = [\dot{\psi} \ \dot{\theta} \ \dot{\phi}]$ as the model's input, and **Model 4** was obtained the same input set and LWR regression. The models information and input sets are summarized in Table III.2.

Assessing the models comprised two steps: the training phase, and the testing phase. During the training phase, a training data set (measured set of input/output data $(\mathbf{x}, \dot{\beta})$) was used with several regression techniques to approximate the function relating shoulder to elbow kinematics. The approximated function was used during the testing phase with a testing data set (measured set of input data $\mathbf{x}$) to estimate the elbow angular velocity. Three offline tests were performed to assess the modeled functions:

- **Test A** (intra-individual): the training data set comprised data of 2 out of 3 trials from one of the 10 subjects (10 subjects for the right side, and 10 subjects for the left side), i.e. 2x18 movements. The test was performed on the same subject's remaining trial, i.e. 1x18 movements. This training/testing routine was repeated for each subject.
- **Test B** (inter-individual): data from $k \in \mathbb{N}$ subjects (with k varying from 1 to 9), including all their trials, were mixed in the training data set to build the regression models. The approximation function is tested on the data of the remaining subjects (i.e. $10 - k$ subjects, 3 trials for each subjects).
- **Test C** (spatial generalization): the regression coefficients were derived from the data of 9 out of 10 subjects; their 3 trials were included, except that the number of targets was varying between 1 and 18. The model was tested on the remaining subject's data (i.e. 3 trials x 2 distances x 9 targets).

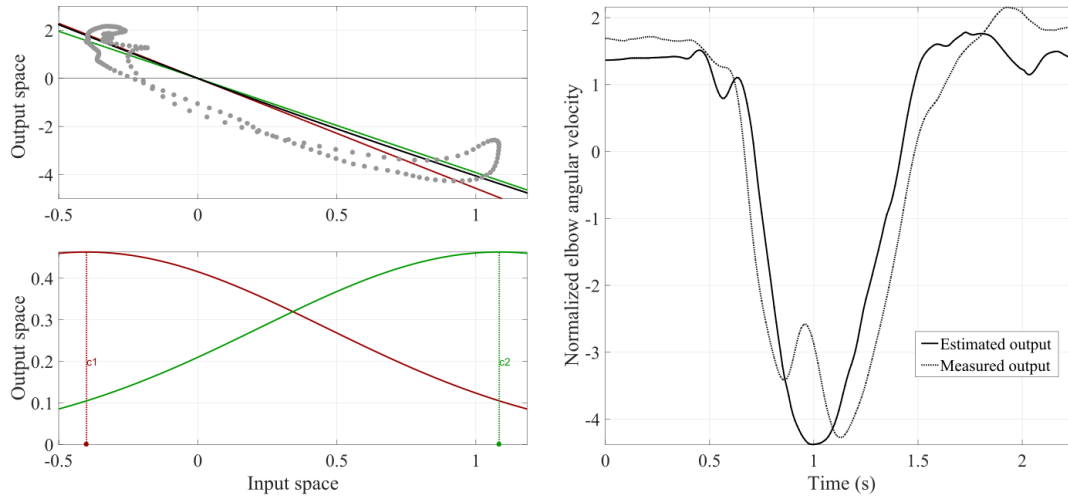


Figure III.2 – Illustration of the LWR regression between a 1-dimension input set (time derivative of the shoulder elevation angle) and the 1-dimension output set (elbow angular velocity). Bottom left: The two colored plots represent the Gaussian basis functions used to calculate the local weights. Top left: The shoulder/elbow approximated coordination model is the result of the weighted sum of local linear models, as described in Eq. III.8, and is represented by the black solid line. The measured elbow angular velocity for the same input is also depicted as the grey dots. Right: the estimated elbow angular velocity using the LWR regression model is represented by the solid black line, along with the measured elbow angular velocity represented by the dotted black line.

Left side			Right side		
	Mean (deg/s)	Peak (deg/s)		Mean (deg/s)	Peak (deg/s)
S1	9.7 ± 8.3	13.5 ± 6.6	S1	7.5 ± 7.5	12.9 ± 9.2
S2	9.7 ± 9.4	17.5 ± 11.7	S2	11.4 ± 11.6	25.2 ± 12.2
S3	10.2 ± 9.8	18.7 ± 9.3	S3	13.5 ± 14.5	37.9 ± 15.0
S5	10.3 ± 9.4	13.1 ± 6.8	S4	10.9 ± 10.0	14.6 ± 9.5
S6	8.3 ± 7.9	13.2 ± 6.6	S5	9.7 ± 8.2	12.2 ± 10.6
S8	8.9 ± 8.4	15.8 ± 10.2	S7	9.7 ± 9.9	22.1 ± 11.1
S11	11.8 ± 13.3	13.8 ± 7.6	S10	6.3 ± 6.1	13.7 ± 7.1
S12	9.0 ± 8.6	13.8 ± 8.9	S11	7.0 ± 7.5	17.1 ± 9.2
S13	10.4 ± 7.8	14.8 ± 8.2	S12	9.2 ± 9.6	14.7 ± 9.7
S14	11.2 ± 11.0	23.4 ± 11.5	S15	8.0 ± 7.5	10.3 ± 5.0

Table III.3 – Intra-individual variability: overall standard deviation of the measured elbow angular velocity averaged over all trials, and peak value variation averaged over all targets and distances.

For each test, the predicted elbow angular velocity values were compared with the Codamotion-based measurements of the elbow kinematics. Several metrics were computed to evaluate the performance of the four regression models, such as root mean square error (RMSE) between measured and estimated elbow angular velocity, denoted $RMSE_{vel}$, the RMSE between measured elbow angle values and reconstructed elbow angle (integration of the estimated elbow angular velocity), denoted $RMSE_{pos}$, and the relative error between the measured and estimated final angular positions, denoted $\Delta_{\beta_{final}}$.

III.4 Simulation results

IMU measurements

In order to quantify the IMU's reconstruction error, a comparison between the Codamotion- and IMU-based shoulder orientation reconstructions was performed after collecting the data. The angular position RMS error between the Codamotion- and IMU-based reconstruction was $2.4 \text{ deg} \pm 3.1 \text{ deg}$ for the trunk inclination angle (i.e. the angle between the trunk vertical axis and the vertical direction), and $7.2 \text{ deg} \pm 4.9 \text{ deg}$ for the humerus elevation angle (i.e. the angle between the humerus longitudinal axis and the vertical direction). In the angular velocity space, the angular velocity RMS error between the two systems was $2.5 \text{ deg/s} \pm 2.5 \text{ deg/s}$ for the trunk inclination angular velocity, and $9.5 \text{ deg/s} \pm 5.2 \text{ deg/s}$ for the humerus elevation angular velocity. The difference between the final angular positions for the Codamotion- and the IMU-based reconstructions was $3.1 \text{ deg} \pm 4.2 \text{ deg}$ for the trunk inclination angle, and $10.5 \text{ deg} \pm 7.5 \text{ deg}$ for the humerus elevation angle.

Intra-individual variability

Measured elbow angular velocities were averaged for each participant, and the corresponding standard deviations were computed to assess the human movement re-

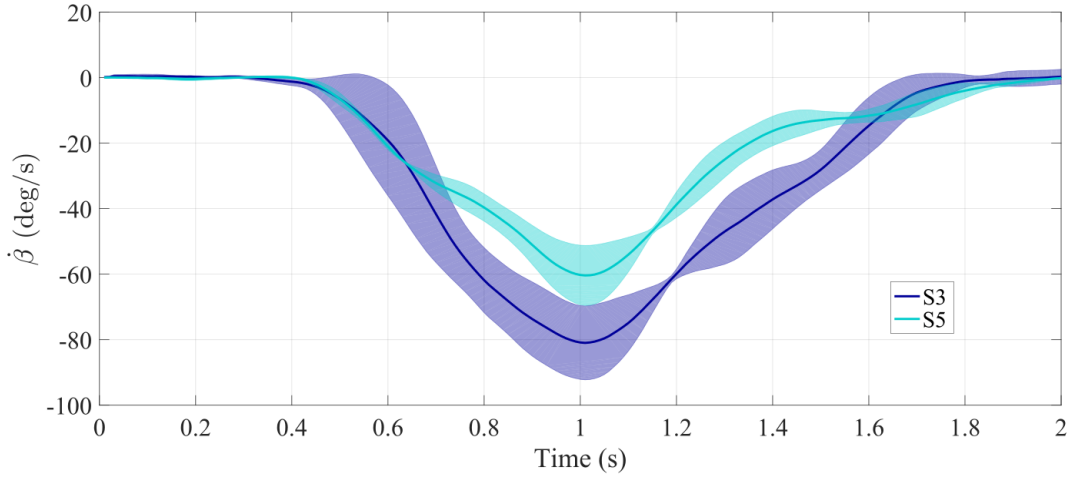


Figure III.3 – Illustration of the intra- and inter-individual variability. The solid lines represent the measured elbow angular velocity for S3 and S5, averaged over the three trials towards Target 4 of Distance I. The shaded areas represent the standard deviation around the mean value for three trials.

peatability, as illustrated in Fig. III.3. The overall variation around the elbow angular velocity mean values was $9.9 \text{ deg/s} \pm 9.6 \text{ deg/s}$ for the left side ($9.3 \text{ deg/s} \pm 9.8 \text{ deg/s}$ for the right side), averaged over all targets, distances, and participants. The peak value of the angular velocity profile is an important feature in the elbow reaching movement. Thus, the standard deviation of the elbow angular velocity peak values for three trials towards the same targets were averaged over all the targets and distances, resulting in a global variability of $15.8 \text{ deg/s} \pm 9.3 \text{ deg/s}$ for the left side ($18.1 \text{ deg/s} \pm 12.7 \text{ deg/s}$ for the right side) for all participants. The variability values for each individual are depicted in Table III.3.

Modeling the inter-joint coordination

The different tests' results are grouped in Table III.4. Test B (resp. C) assessed the performance of the models by increasing the number of individuals (resp. targets) included in the training data set. Only the results for the minimal (min) and maximal (max) number of subjects (resp. targets) included in the training are displayed. In addition, an intermediate score (inter) that corresponds to a training data set including 6 individuals for Test B, and 9 targets for Test C, is shown in the Table III.4. An example of Test B's results is depicted in Fig. III.4, which shows the assessing metrics decreasing with the addition of new data into the model training data set. In addition, an example of the estimation of the elbow angular velocity with the four models for Target 7 of Distance I is depicted in Fig. III.5: in this example, the data set fed to the models for the training phase includes the kinematic data from 9 out of 10 participants, and the testing phase is performed with the 10th individual's data.

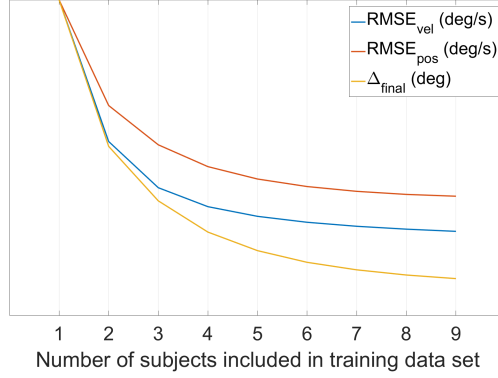


Figure III.4 – Test B results (normalized) with **Model 1**: the error between the measured and estimated angular velocities $RMSE_{vel}$, the error between the measured and estimated angular positions $RMSE_{pos}$, and the final position error $\Delta_{\beta_{final}}$ are depicted for training data sets with an increasing number of individuals for which the data were included.

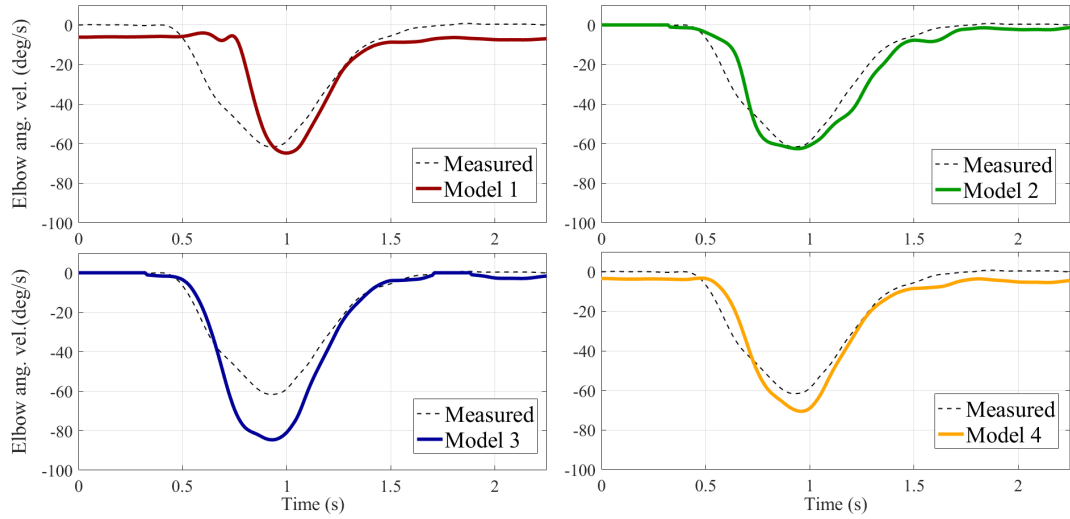


Figure III.5 – Prediction results (elbow angular velocity) with the four models using the input data (shoulder kinematics) of a reaching movement towards Target 7 of Distance I. The corresponding measured elbow angular velocity is represented by a dashed black line.

		RMSE _{vel} (deg/s)		RMSE _{pos} (deg)		$\Delta_{\beta_{\text{hml}}}$ (deg)	
		Left	Right	Left	Right	Left	Right
Model 1	Test A	13.3 $\pm$ 6.6	15.2 $\pm$ 6.7	8.9 $\pm$ 5.5	10.2 $\pm$ 6.2	10.7 $\pm$ 7.8	12.2 $\pm$ 8.7
	Test B	min: 1 inter: 6 max: 9	16.4 $\pm$ 8.2 14.8 $\pm$ 7.6 14.6 $\pm$ 7.5	18.5 $\pm$ 8.1 16.7 $\pm$ 7.3 16.6 $\pm$ 7.3	12.1 $\pm$ 7.9 10.9 $\pm$ 7.2 10.7 $\pm$ 7.0	15.6 $\pm$ 11.2 13.6 $\pm$ 9.5 13.4 $\pm$ 9.5	16.7 $\pm$ 12.3 14.7 $\pm$ 10.8 14.6 $\pm$ 10.7
		min: 1 inter: 9 max: 18	16.6 $\pm$ 8.2 14.8 $\pm$ 7.4 14.6 $\pm$ 7.5	18.9 $\pm$ 8.6 16.7 $\pm$ 7.4 16.6 $\pm$ 7.3	12.7 $\pm$ 8.5 10.8 $\pm$ 7.1 10.7 $\pm$ 7.0	16.9 $\pm$ 12.1 13.6 $\pm$ 9.6 13.4 $\pm$ 9.5	17.6 $\pm$ 12.9 14.8 $\pm$ 10.8 14.6 $\pm$ 10.7
	Test C	14.2 $\pm$ 8.1	17.0 $\pm$ 9.4	9.0 $\pm$ 6.0	10.6 $\pm$ 7.2	11.1 $\pm$ 8.3	13.6 $\pm$ 9.9
Model 2	Test A	21.7 $\pm$ 11.6	21.6 $\pm$ 11.4	13.4 $\pm$ 9.3	13.5 $\pm$ 9.6	17.4 $\pm$ 13.6	17.4 $\pm$ 14.0
	Test B	min: 1 inter: 6 max: 9	14.7 $\pm$ 7.6 14.3 $\pm$ 7.6	14.4 $\pm$ 7.0 13.7 $\pm$ 6.3	10.4 $\pm$ 6.7 10.3 $\pm$ 6.7	13.2 $\pm$ 9.3 13.0 $\pm$ 9.1	13.0 $\pm$ 9.5 12.7 $\pm$ 9.2
		min: 1 inter: 9 max: 18	29.6 $\pm$ 15.1 15.1 $\pm$ 7.8 14.3 $\pm$ 7.6	26.6 $\pm$ 13.6 15.0 $\pm$ 7.4 13.7 $\pm$ 6.4	18.0 $\pm$ 12.8 10.7 $\pm$ 6.9 10.3 $\pm$ 6.7	17.1 $\pm$ 11.9 10.7 $\pm$ 7.1 10.1 $\pm$ 6.5	24.3 $\pm$ 20.0 13.6 $\pm$ 9.7 13.0 $\pm$ 9.1
	Test C	19.5 $\pm$ 9.2	16.0 $\pm$ 6.8	13.2 $\pm$ 8.1	11.3 $\pm$ 7.2	17.1 $\pm$ 14.2	14.4 $\pm$ 10.6
Model 3	Test A	18.0 $\pm$ 10.6	17.6 $\pm$ 8.6	13.9 $\pm$ 10.8	13.9 $\pm$ 9.5	18.7 $\pm$ 16.0	18.5 $\pm$ 13.7
	Test B	min: 1 inter: 6 max: 9	14.9 $\pm$ 7.1 14.7 $\pm$ 7.0	16.0 $\pm$ 7.4 15.9 $\pm$ 7.3	12.4 $\pm$ 8.2 12.3 $\pm$ 8.1	14.1 $\pm$ 10.0 13.9 $\pm$ 9.9	16.2 $\pm$ 11.8 16.0 $\pm$ 11.5
		min: 1 inter: 9 max: 18	20.9 $\pm$ 12.4 14.8 $\pm$ 7.1 14.7 $\pm$ 7.0	19.2 $\pm$ 10.4 16.2 $\pm$ 7.5 15.9 $\pm$ 7.3	17.0 $\pm$ 13.1 10.9 $\pm$ 7.1 10.8 $\pm$ 6.9	23.2 $\pm$ 19.3 14.0 $\pm$ 10.1 13.9 $\pm$ 9.9	20.7 $\pm$ 16.4 16.3 $\pm$ 11.9 16.0 $\pm$ 11.5
	Test C	17.0 $\pm$ 7.5	15.8 $\pm$ 6.2	11.2 $\pm$ 6.8	11.1 $\pm$ 7.0	14.0 $\pm$ 10.7	14.4 $\pm$ 10.9
Model 4	Test A	14.3 $\pm$ 6.9	15.1 $\pm$ 7.1	10.2 $\pm$ 6.6	11.2 $\pm$ 7.4	12.7 $\pm$ 9.2	14.4 $\pm$ 10.6
	Test B	min: 1 inter: 6 max: 9	13.5 $\pm$ 6.6 13.4 $\pm$ 6.6	14.3 $\pm$ 6.7 14.1 $\pm$ 6.6	10.7 $\pm$ 7.1 10.7 $\pm$ 7.0	12.3 $\pm$ 8.8 12.3 $\pm$ 8.8	13.7 $\pm$ 10.0 13.6 $\pm$ 10.0
		min: 1 inter: 9 max: 18	15.4 $\pm$ 7.4 13.6 $\pm$ 6.7 13.4 $\pm$ 6.6	16.2 $\pm$ 7.5 14.3 $\pm$ 6.6 14.1 $\pm$ 6.6	11.1 $\pm$ 7.1 10.0 $\pm$ 6.4 10.0 $\pm$ 6.3	13.9 $\pm$ 10.2 12.5 $\pm$ 8.9 12.3 $\pm$ 8.8	15.2 $\pm$ 11.4 13.7 $\pm$ 10.0 13.6 $\pm$ 9.9
	Test C	14.1 $\pm$ 6.6	14.1 $\pm$ 6.6	10.0 $\pm$ 6.3	10.7 $\pm$ 7.0	12.3 $\pm$ 8.8	13.6 $\pm$ 9.9

Model 1: RBFN-based regression (input: α). **Model 2:** RBFN-based regression (input: $[\psi \ \dot{\theta} \ \dot{\phi}]$). **Model 3:** PCA-based regression (input: $[\psi \ \dot{\theta} \ \dot{\phi}]$). **Model 4:** LWR (input: $[\psi \ \dot{\theta} \ \dot{\phi}]$).

Table III.4 – Results of the comparison between estimated and measured elbow angular velocity for tests A, B, and C. Four models of the shoulder/elbow coordination were built using the data from 10 healthy subjects.

III.5 Discussion

IMU-based shoulder motion capture

The shoulder kinematics were derived from two IMUs placed on the participants' arm and chest, and a comparison between a Codamotion-based and an IMU-based angular reconstruction was performed. The low angular reconstruction error between the two systems justified the use of IMUs as a shoulder kinematic measurement system.

Inter-joint coordination-based elbow motion prediction

Four regression-based models were implemented to approximate the relationship between shoulder and elbow angular velocities. They were obtained using the data from 20 healthy participant who did a reaching task, and tested using different training data sets. The prediction results depicted in Table III.4 demonstrated that IMU-based shoulder kinematics can be used to build an approximation of the shoulder/elbow relationship, and to predict elbow motion during a 3D reaching task. However, the error values were varying depending the modeling methods and input sets.

The aim of Test A was to learn the coordination pattern of one individual, and to test the modeled relationship on the data of the same subject. The results showed that the lowest Δ_{beta_final} was obtained when **Model 1** was used. Kaliki et al. (2013) obtained also good prediction results, although they utilized a camera-based motion capture system to measure the shoulder kinematics, and more ANN input signals (3 shoulder angles, and 2 shoulder translations).

Elbow kinematic information cannot be measured with transhumeral amputees; hence, algorithm estimation results must be robust to inter-individual testing, and capable of predicting elbow angular velocity profile based on a model that was obtained with healthy individuals. This property was tested with Test B that tested the models on individuals' data that were not included in the training data set. For all models (except **Model 1**), a larger error than in Test A's results was found when only one individual was included in the training data set, and increasing the number of different coordination patterns included in the models yielded a decrease in the estimation errors. These results suggest that despite the fact the participants' reaching strategies were different, a generic model that combined several individuals' coordination patterns, and thus included inter-individual variability, could be built and used to predict the elbow extension movement. Moreover, the fact that Test B's prediction errors for **Model 1** increased when coordination patterns from several individuals were included in the training data set, implied that a single-input model could not catch the inter-individual variability. Iftime et al. (2005) had mixed results for inter-individual testing, showing the importance of the model input set: they estimated the elbow angular acceleration during a 2D reaching task, and obtained a correlation coefficient value of 0.94 with the shoulder flexion angular acceleration as the model input value, and -0.96 with the shoulder abduction angular acceleration as the model input value. However, they trained the RBFN-based ANN on goniometer-based data from only one target location and tested the model on the same target location.

Tests A and B were performed on reaching movements towards targets that were included in the training data set. Thus, the simulation results, obtained on a discre-

tized workspace, did not allow to conclude on the system's potential response in real prosthetic applications, where the workspace is continuous. The prosthesis user must be able to bring the prosthetic hand to a location that was not included in the training data set, i.e. in between target locations. Test C justifies the models' ability to predict elbow motion for movements towards targets on which they were not trained. The results when the models were trained on only 9 targets were almost as good as Test B's results, suggesting that the models were possibly over-trained. In comparison, there were between 400 and 500 target locations distributed across the workspace in the study by Kaliki et al. (2013) that also tested the generalization property.

- **Model 1** yielded the best prediction errors for Test A (intra-individual training and testing). However, the performance worsened when kinematic data from different individuals were included (Test B), or when less targets were included in the training data set (Test C), showing the **Model 1**'s limit to adapt to the inter-individual variability or to the workspace generalization.
- **Model 2** had also good Test A's results. The prediction error was constant when more individuals' data (Test B) or less targets (Test C) were included in the training data set.
- **Model 3** had the worse Test A's results. The RMS errors for Test B and Test C were lower than for Test A, reaching values slightly larger than those obtained with **Model 1** and **Model 2**.
- **Model 4**'s Test A results were not satisfying compared to the first two models. However, the prediction errors improved (i.e. lower RMS errors) when more individuals' data and less targets were included in the training data set. The obtained offline performance was similar to the one of **Model 2**. However, **Model 4** had a long computation time for both training and testing phases, limiting its potential utilization in a real time system.

Overall, the models' offline prediction results were acceptable since they remained within the intra-individual variability values. In particular, Test B's and C's RMS errors were smaller than the natural variability of an individual repeating the same gesture towards a target.

III.6 Conclusion

This chapter demonstrates that coordination patterns from several individuals can be combined to build a generic inter-joint coordination model utilized to estimate the elbow motion during a reaching task. Several regression techniques were utilized in the model building process, and the results highlight the importance of the models' training data sets: including data from more than one individual or training the models on a reduced number of targets can improve the prediction results. The four tested models in this chapter yielded good prediction results. Although the RBFN-based regression model with the time derivatives of the three shoulder angles as input signals seemed to be more robust to inter-individual variability and spatial generalization, the overall simulation results did not allow to conclude on a potential best modeling approach. Thus, the next chapter focuses on the testing the different models to assess

an eventual difference in a real prosthesis situation, whereby the automatic elbow control strategy is implemented onto a prosthesis prototype.

A major contribution of this work is that it shows that IMU-based kinematics measurements can provide good results as camera-based motion capture systems that were used in the literature and that limit the transfer potential of the developed solution to embedded solutions for prosthetics. This chapter shows that simple algorithms, chosen for their implementation potential, can provide good prediction results using the inputs from embedded sensors. Finally this chapter extends the literature by showing that a novel prosthetic elbow control strategy based on inter-joint coordination models is ready to be implemented on a prosthesis.

Chapter IV

Control of a prosthetic elbow: Healthy participants

In the previous chapter, healthy kinematic data were collected, and combined to find an approximation of the shoulder/elbow coordination during a reaching task. Four modeling approaches were utilized, yielding four different models that were tested offline. Because they combined inter-joint coordinations from several individuals, the model were referred to as generic models. The subsequent chapter assesses the generic models through the performance of healthy individuals who used a prosthesis prototype driven successively by the four models.

Experiment overview

Ten healthy participants were equipped with a prosthesis prototype including a motorized elbow, and they were asked to use it to perform a reaching task. The prosthetic elbow joint was randomly driven by the four generic shoulder/elbow coordination models build in the previous chapter. The objective of the experiment was to assess the participants' performance in terms of precision and compensatory strategies.

IV.1 Materials and methods

Participants Ten healthy individuals participated in the study; most of them were graduate students at ISIR, where the experiment took place. The age was 24.8 years old in average, and the average height was 173.7 cm. Table [IV.1](#) groups information on the subjects. Half of the group performed the task with the right hand, and the other half used the left hand, independently of their dominant side.

Experimental setup The participants were wearing an elbow orthosis to which the prosthesis prototype was attached, as depicted in Fig. [IV.1](#), blocking their own elbow at a fixed angle of 90 degrees. The prosthesis controller was implemented with the four inter-joint coordination models developed in Chapter [III](#). It was reading the information from the two IMUs, one placed in a dedicated receptacle on the prosthesis, and the other attached to a chest harness. The sensors' placement was similar to one in the model training data acquisition; any sensor position discrepancies were taken care of with the humerus orientation re-calculation, as explained in Paragraph [II.6](#). The

	Gender M/F	Age (yo)	Height (cm)	Hand dominance	Side* Right or Left
S1	M	23	180	Right	L
S2	F	23	169	Right	L
S3	M	26	175	Right	L
S4	M	23	176	Right	L
S5	F	26	163	Right	L
S6	M	26	184	Right	R
S7	M	28	173	Right	R
S8	M	26	170	Right	R
S9	M	22	177	Right	R
S10	F	25	170	Left	R

* Upper limb with which the task was performed.

Table IV.1 – General information about the healthy individuals recruited in the prosthesis control experiment.

prosthesis wrist and hand were not used during the experiment; the wrist and hand position were set at the beginning of the experimental session with the hand full open (similarly to the hand position shown in Fig. II.3). The participants were standing on a Nintendo[®] Wii Balance Board who measured the force distribution. In addition, they were equipped with Codamotion markers that recorded their upper body kinematics (see Chapter III for markers placement).

Control of the prosthesis During the reaching movement, the relative shoulder kinematics (see calculations in Chapter II) were derived from the two IMUs that were connected to the prosthesis controller; the latter estimated in real time the elbow angular velocity based on the IMU-based shoulder kinematics and the regression models built in Chapter III. The participants' elbow was blocked into a constant position with a lockable orthosis, hence only their arm, to which the prosthesis was fixed (see Chapter II), was free to move, as shown in Fig. IV.1. As they rose the arm, the prosthetic elbow automatically extended according to the estimated output of the implemented shoulder/elbow coordination model.

Protocol Each participant was asked to reach 18 targets (9 targets at 2 distances) with the prosthetic hand, as described in Chapter II. The targets positions were adjusted according to the participant's height and upper limb length¹. For every reaching movement, the subject started in the initial position with the prosthetic elbow flexed at 90 degrees (left picture in Fig. IV.1), brought the prosthetic hand to the designated target, stayed immobile until told to come back to the initial position. The participants were asked to do ballistic movements with a naturally paced approach towards the targets, without correcting the end effector position at the end of the reaching motion, even though the elbow locking enabled adjustments. Indeed, the experiment objective was to assess the models through the subjects performance, hence

¹Here the upper limb length is referring to the distance between the acromion and the prosthetic finger when the elbow is extended

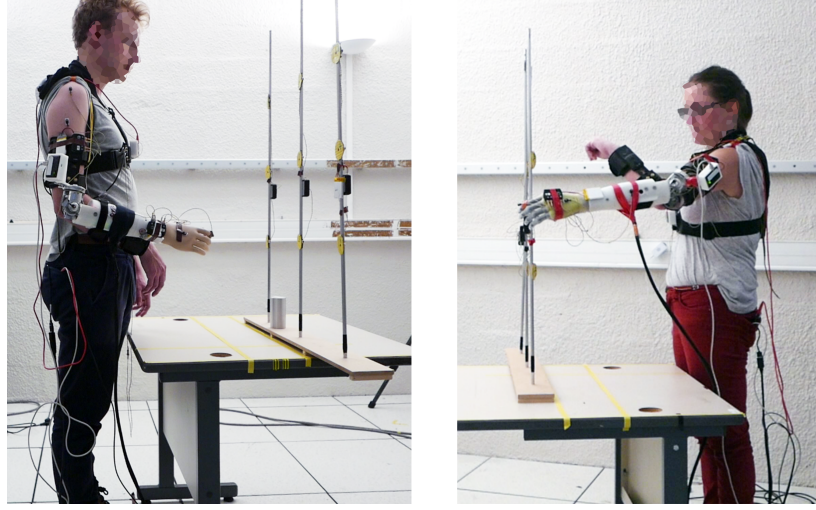


Figure IV.1 – Experimental setup with two healthy participants wearing the prosthesis prototype. Two IMUs (chest and arm), measuring the shoulder kinematics, were connected to the prosthesis controller that used their information to estimate the prosthetic elbow angular velocity using a generic model of inter-joint coordinations. On the left, the subject is waiting in initial position; on the right, the subject is reaching Target 4 of Distance I.

the final distance between the end effector and the target was meaningful in terms of performance analysis.

Since the participants did not have control over the end-effector, they were asked to bring the prosthetic hand around the target without closing the prosthetic fingers, nor rotating the wrist. The participants repeated four times the reaching gesture towards each targets with a different inter-joint coordination model for each movement. The order in which the models were tested was randomized for each target, and the participants were naive in the sense that they did not know that several elbow control laws were being tested. They received the instruction that shoulder movements drove the elbow extension, that they were supposed to move the shoulder as naturally as possible, and not to adjust the end-effector position if the elbow over-extended (yielding possibly to a large distance between the end-effector and the target). Before starting the recording for one target (i.e. four reaching movements), each participant performed two to four training movements towards the target for training purpose. The models driving the prosthesis during these training movements were randomly chosen from the 4 generic models, in order to avoid training the participants with a specific model that would have biased the performance.

IV.2 Data analysis

In the literature, gestures with an upper limb prosthetic device are widely assessed in terms of movement duration (Bland et al., 2008); the outcome of such an analysis is to measure whether the task is achieved. However, the strategy chosen to perform the

task is as important as the completion time, especially since upper limb amputation and musculoskeletal complaints were proven to be correlated: the assessment should also report how the individual performed the task. Yet, few assessment tools quantify the compensatory strategies, and most research groups develop their own compensatory movement quantification tool (Deijs et al., 2016).

In the course of this and the following chapter, the assessment of the task performance was focused on compensatory strategies, in addition to the task precision and duration time. The movement duration was defined as the time needed to reach a target. The precision error was defined as the distance between the target and the end-effector position when the subject stopped the movement. Moreover, the metrics presented in Chapter II assessed the compensatory movements of the trunk and the shoulder. In summary, the following values assessed the participants' performance:

Overall assessment:

- **Task completion time**
- **Precision error**

Assessment of trunk movements:

- Angular variation of the **anteroposterior bending angle**
- Angular variation of the **mediolateral bending angle**
- Angular variation of the **torsion angle**
- **Trunk mean speed**: trunk cumulative path over the completion time
- **Weight distribution variation** on the force plate

Assessment of shoulder and elbow movements:

- Angular variation of the **plane of elevation**
- Angular variation of the **elevation angle**
- Angular variation of the **humeral axial rotation**
- Angular variation of the **elbow flexion/extension angle**
- **Inter-coordination angle**.

IV.3 Results

During the reaching movements, the prosthesis controller estimated in real time the elbow angular velocity using the IMU-based shoulder kinematics and one of the four inter-joint coordination models. The input signals were either the time derivative of the elevation angle for **Model 1**, or the time derivative of the Euler angles for **Model 2**, **Model 3**, and **Model 4**. An instance of the input/output set $([\dot{\psi} \ \dot{\theta} \ \dot{\phi}], \dot{\beta})$ for one reaching movement performed with the prosthesis is depicted in Fig. IV.2. The metrics calculated for the assessment of the participants performance and body movements are grouped in Table IV.2. The movements performed with the prosthetic elbow were compared to those performed by healthy participants using their physiological coordination (referred to as the control situation), which corresponded to the data set recorded in the model training data set acquisition experiment (see Chapter III).

Healthy		Overall
Precision (mm)	58.7 ± 19.8	Model 1 Model 2 Model 3 Model 4 26.6 ± 27.6 38.1 ± 49.0 44.5 ± 50.1 30.2 ± 27.6
Duration (s)	1.1 ± 0.2	Model 1 Model 2 Model 3 Model 4 0.9 ± 0.3 1.0 ± 0.4 1.1 ± 0.3 1.1 ± 0.3
Trunk mean speed (mm/s)	14.0 ± 11.0	Model 1 Model 2 Model 3 Model 4 25.1 ± 15.2 24.4 ± 16.2 23.7 ± 14.1 23.8 ± 15.2
S/E coord. (deg)	×	Model 1 Model 2 Model 3 Model 4 6.2 ± 3.4 4.7 ± 3.4 9.7 ± 4.5 7.6 ± 3.3
T/S/E coord. (deg)	×	Model 1 Model 2 Model 3 Model 4 15.8 ± 7.8 18.5 ± 8.1 17.0 ± 7.5 19.0 ± 8.8

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	
Precision (mm)	Model 1	47.0 ± 34.6	16.1 ± 14.2	24.3 ± 21.1	25.6 ± 24.6	58.7 ± 27.3	10.7 ± 6.1	26.1 ± 41.1	26.5 ± 21.7	17.3 ± 17.6	13.6 ± 13.7
	Model 2	48.0 ± 40.5	20.0 ± 13.9	31.2 ± 24.6	51.2 ± 43.7	103 ± 89.7	10.0 ± 5.9	46.7 ± 61.0	28.8 ± 28.3	32.7 ± 35.0	10.0 ± 9.1
	Model 3	60.9 ± 46.1	26.0 ± 25.4	31.6 ± 24.6	55.4 ± 42.7	96.6 ± 63.2	8.3 ± 6.3	31.1 ± 46.3	76.2 ± 66.9	42.0 ± 48.3	15.9 ± 30.5
	Model 4	25.2 ± 21.9	16.1 ± 20.7	34.7 ± 34.5	30.0 ± 27.2	81.5 ± 54.0	11.7 ± 9.3	19.6 ± 36.6	48.3 ± 42.4	24.6 ± 22.0	10.1 ± 9.8
Duration (s)	Model 1	0.9 ± 0.3	0.8 ± 0.2	0.9 ± 0.1	0.9 ± 0.1	0.8 ± 0.3	1.1 ± 0.3	1.1 ± 0.4	0.9 ± 0.2	0.9 ± 0.2	0.9 ± 0.2
	Model 2	0.9 ± 0.2	0.8 ± 0.2	0.9 ± 0.2	0.9 ± 0.3	1.2 ± 0.5	1.1 ± 0.3	1.1 ± 0.4	0.9 ± 0.2	1.0 ± 0.2	0.9 ± 0.2
	Model 3	1.0 ± 0.3	1.0 ± 0.3	1.0 ± 0.2	1.0 ± 0.3	1.2 ± 0.4	1.2 ± 0.3	1.3 ± 0.4	1.2 ± 0.3	1.2 ± 0.3	1.1 ± 0.4
	Model 4	1.1 ± 0.5	0.9 ± 0.2	1.0 ± 0.3	1.1 ± 0.3	1.2 ± 0.3	1.0 ± 0.1	1.2 ± 0.4	1.0 ± 0.3	1.0 ± 0.2	0.9 ± 0.2
Trunk speed (mm/s)	Model 1	38.0 ± 21.6	24.3 ± 15.4	21.8 ± 12.7	20.6 ± 11.0	34.4 ± 14.6	30.9 ± 14.7	19.3 ± 9.8	15.8 ± 7.7	20.1 ± 13.4	25.1 ± 13.6
	Model 2	40.8 ± 27.7	25.7 ± 15.0	22.3 ± 16.6	21.2 ± 10.7	28.6 ± 11.8	32.2 ± 15.8	18.6 ± 10.0	15.1 ± 8.7	16.7 ± 7.9	23.1 ± 13.4
	Model 3	36.4 ± 22.0	25.8 ± 12.8	19.5 ± 13.5	21.9 ± 12.7	28.4 ± 10.0	29.3 ± 14.7	18.0 ± 9.1	13.9 ± 7.0	19.0 ± 8.1	24.8 ± 13.5
	Model 4	41.4 ± 23.8	23.5 ± 13.9	19.1 ± 11.2	18.9 ± 8.7	30.2 ± 14.5	32.6 ± 13.5	17.5 ± 8.1	14.0 ± 8.2	15.3 ± 8.1	24.6 ± 14.9
S/E coord. (deg)	Model 1	0.1	7.2	4.1	3.5	8.5	2.5	2.9	2.5	11.4	4.2
	Model 2	1.0	8.9	9.9	7.1	7.1	3.5	3.5	7.6	2.8	5.8
	Model 3	4.2	13.7	14.8	10.9	15.4	9.2	7.9	10.8	1.1	8.6
	Model 4	3.0	5.8	8.9	6.7	9.7	5.0	7.2	14.1	4.7	10.6
T/S/E coord. (deg)	Model 1	29.9	19.9	25.5	27.4	15.1	6.0	21.2	9.4	10.3	19.9
	Model 2	21.4	23.0	22.0	24.6	15.3	2.9	17.1	8.9	4.8	18.3
	Model 3	22.0	20.0	23.8	25.8	17.8	8.1	13.0	19.3	1.4	18.3
	Model 4	36.0	19.6	24.4	23.4	13.6	5.6	21.5	16.5	7.7	21.9

* Angle between the Shoulder/Elbow coordinations of healthy participants using the prosthesis and participants in the control situation.

** Angle between the Trunk/Shoulder/Elbow coordinations of healthy participants using the prosthesis and participants in the control situation.

Table IV.2 – Results of the experiment with healthy participants wearing the prosthesis.

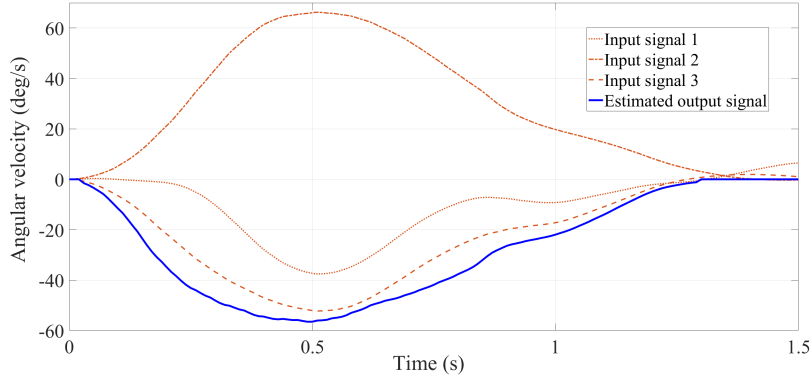


Figure IV.2 – Measured input signal (time derivative of the three shoulder angles) and the corresponding estimated output signal (elbow angular velocity) using **Model 2** for one reaching movement of Subject 8 towards Target 4 of Distance I. The IMU-based shoulder angular velocities (three red lines) are utilized by the **Model 2**-based regression algorithm to compute online the elbow angular velocity (blue line).

IV.3.1 Performance assessment

Precision error In the control situation, the precision error was $5.9 \text{ cm} \pm 2.0 \text{ cm}$. Even though all the participants using the prosthesis achieved the task, there was an offset in the precision error due to the marker placement. Indeed the precision error was computed as the distance between the finger marker and the target marker, hence it was not null when the gesture was well performed (with the fingers around the circular target). For a clearer reading of the values, an offset corresponding to the average precision error of healthy gestures (i.e. 5.9 cm) was subtracted from the values calculated in the present and in the following chapter. As a result, when healthy participants performed the task with the prosthesis, the precision error between the position reached by the prosthesis end-effector and the target, averaged over all targets and all participants, was $2.7 \text{ cm} \pm 2.8 \text{ cm}$ for **Model 1**, $3.8 \text{ cm} \pm 4.9 \text{ cm}$ for **Model 2**, $4.4 \text{ cm} \pm 5.0$ for **Model 3**, $3.0 \pm 4.9 \text{ cm}$ for **Model 4**. The values are depicted in Fig. IV.3A.

Completion time The overall time to reach a target naturally, i.e. with a sound limb, was $1.1 \text{ s} \pm 0.2 \text{ s}$. Values were similar for reaching gestures with a prosthesis: the reaching time was $0.9 \text{ s} \pm 0.3$ for **Model 1**, $1.0 \text{ s} \pm 0.4 \text{ s}$ for **Model 2**, $1.1 \text{ s} \pm 0.3 \text{ s}$ for **Model 3**, and $1.1 \text{ s} \pm 0.4 \text{ s}$.

IV.3.2 Trunk movement assessment

Trunk movements The trunk movements were quantified using the trunk cumulative trajectory normalized by the completion time, i.e. the trunk mean speed. The values are depicted in Fig. IV.4. The mean speed of the trunk's displacements performed with a prosthesis was $25.1 \text{ mm/s} \pm 15.2$ for **Model 1**, $24.4 \text{ mm/s} \pm 16.2 \text{ mm/s}$ for **Model 2**, $23.7 \text{ mm/s} \pm 14.1 \text{ mm/s}$ for **Model 3**, $23.8 \text{ mm/s} \pm 16.2 \text{ mm/s}$ for **Model 4**. For comparison, the mean speed of movements performed with a sound limb

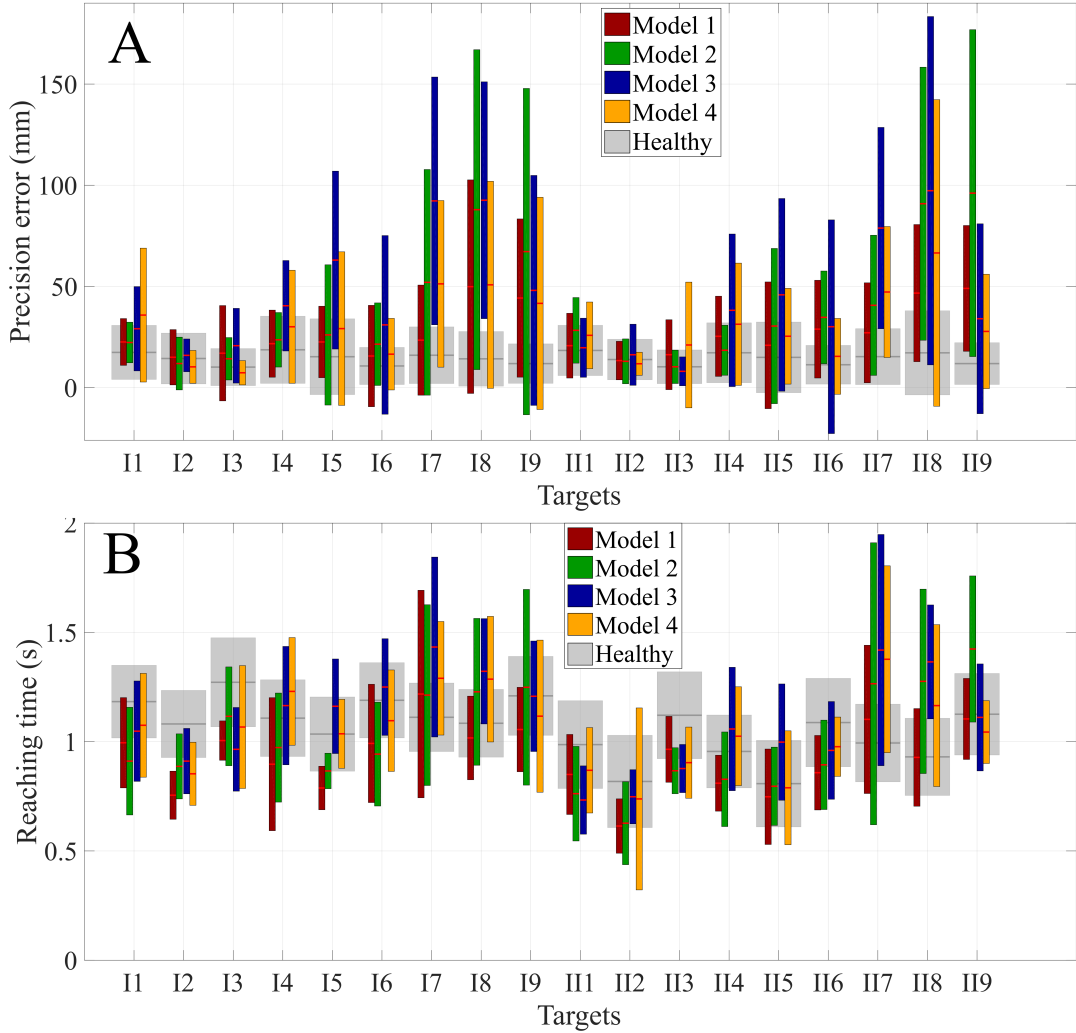


Figure IV.3 – Overall assessment in terms of precision error (A) and task completion duration (B) of healthy participants performing a reaching task with a prosthetic elbow. The latter was randomly driven by four models: **Model 1** (RBFN-based regression, input: $\dot{\alpha}$), **Model 2** (RBFN-based regression, input: $[\dot{\psi} \ \dot{\theta} \ \dot{\phi}]$), **Model 3** (PCA-based regression, input: $[\dot{\psi} \ \dot{\theta} \ \dot{\phi}]$), **Model 4** (LWR, input: $[\dot{\psi} \ \dot{\theta} \ \dot{\phi}]$). The performance with each model is represented with a different color. Each bar represents the mean value of the considered metric over all trials (short red line) plus and minus the standard deviation. In addition, the averaged value of the precision error and task duration for the control situation are depicted with grey bars as a baseline.

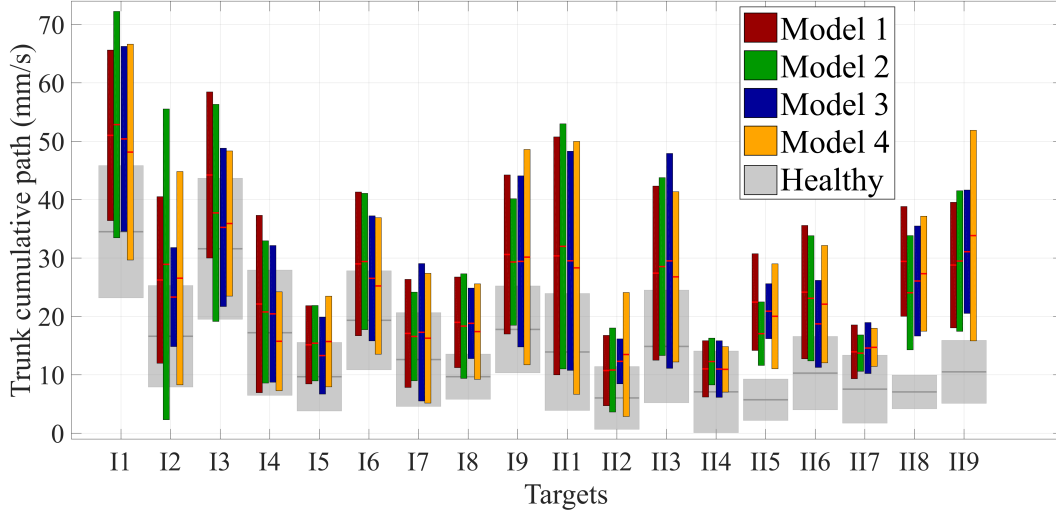


Figure IV.4 – The thorax cumulative trajectory, normalized by the completion time, quantifies the trunk’s displacements during each reaching movements. The corresponding values for the control situation is also depicted as a baseline.

was $14.0 \text{ mm/s} \pm 11.1 \text{ mm/s}$. In addition, the trunk movements were decomposed in three planar movements: anteroposterior bending, mediolateral bending, and torsion motion. The variations of each corresponding angles are depicted in Fig. IV.5.

Weight distribution variation The variation of amount of force exerted by the ipsilateral foot with respect to the total force is depicted in Fig. IV.6. The average values were within the control baseline, however the large standard deviation values showed the inter-individual variability in the weight distribution variations during the reaching movements.

IV.3.3 Upper limb movement assessment

Shoulder movements Humerus motion was assessed with three parameters: humerus direction, elevation, and rotation. Using the prosthesis to reach the targets lead to a significant change in the humerus motion strategy. Especially, the ranges of motion of the humerus direction angle and the humerus rotation angle were importantly reduced, as shown in Fig. IV.7. However, the models did not have an individual influence on the participants’ performance: the shoulder angles’ ranges of motion were similar in between the four tested models.

Elbow movements The elbow angle variation, i.e. the difference between the final and initial elbow angle values, were computed for each target; the values are depicted in Fig. IV.8. The prosthetic elbow utilization was limited in comparison with reaching movements of the control situation for low targets (Targets 1, 2, and 3); however, the models lead to a similar prosthetic elbow joint utilization.

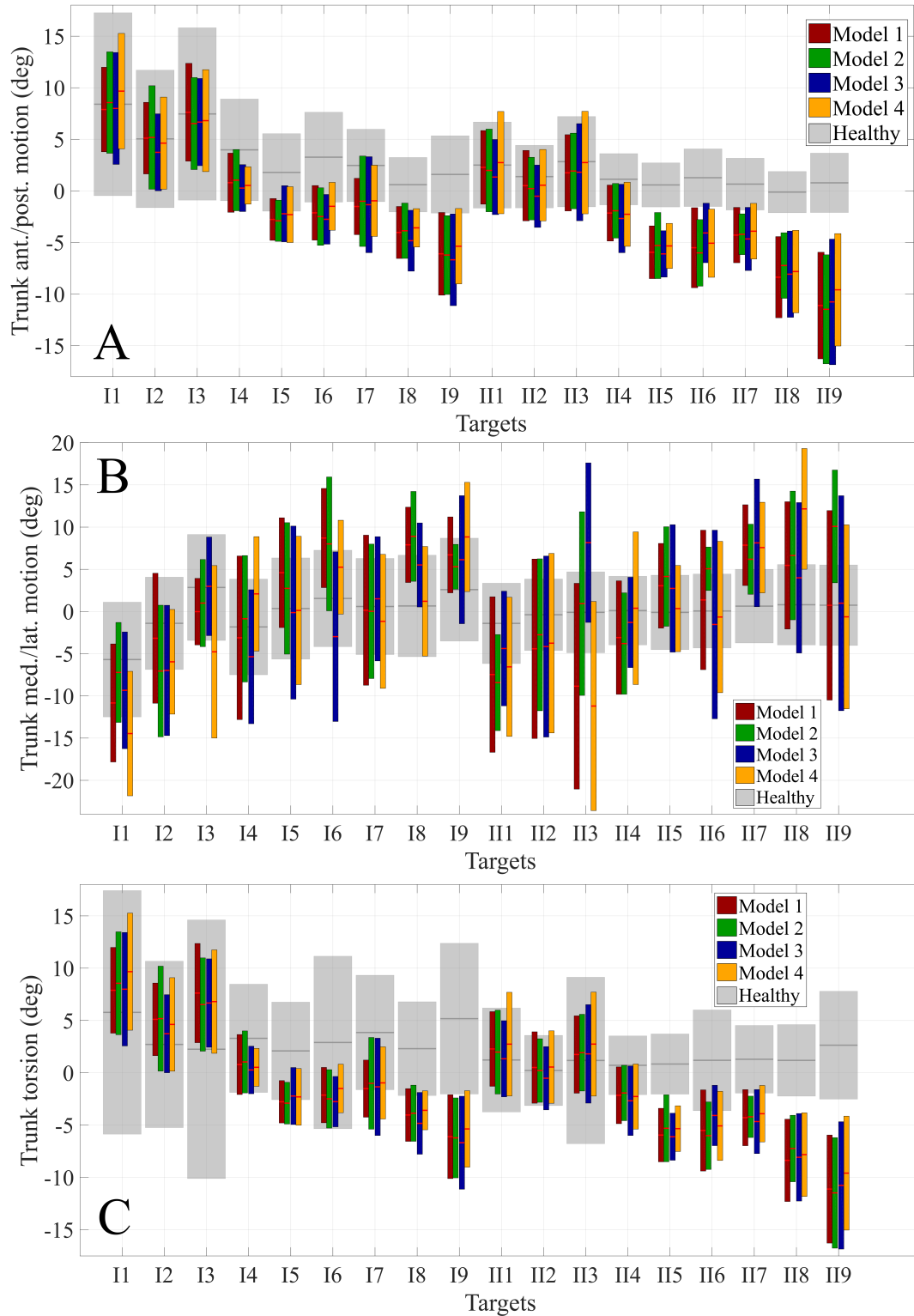


Figure IV.5 – Trunk movements of healthy participants wearing the prosthesis do perform the reaching task were analyzed with three angles: the anteroposterior bending angle, the mediolateral bending angle, and the torsion angle. In addition, the averaged value of the three trunk angles for healthy individuals in the control situation are depicted as a baseline.

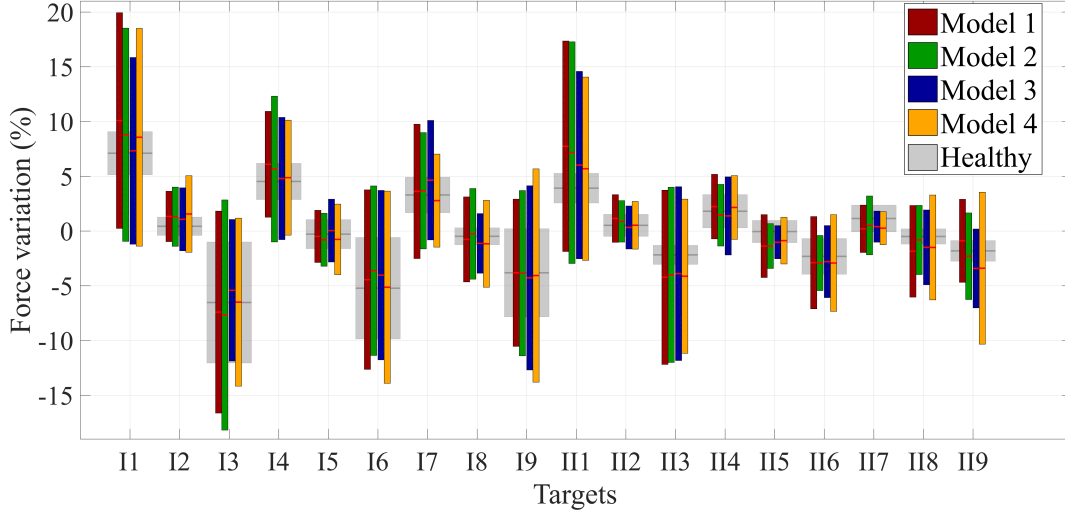


Figure IV.6 – Variation of the amount of force applied by the ipsilateral foot with respect to the total force between the beginning and the end of each reaching movement.

Inter-joint coordination The coordination between shoulder and elbow angular velocities was assessed with the angle between the first PCs of each data set (healthy participants in the control situation versus participants using the prosthesis). An angle value of $4.7 \text{ deg} \pm 3.4 \text{ deg}$ for **Model 1**, $6.2 \text{ deg} \pm 3.4 \text{ deg}$ for **Model 2**, $9.7 \text{ deg} \pm 4.5 \text{ deg}$ for **Model 3**, and $7.6 \text{ deg} \pm 3.3 \text{ deg}$ for **Model 4**, was measured between the coordination of participants performing the task with an automatically-driven elbow, and participants in the control situation. A large angle value meant that the considered coordination was very different from the coordination of reference. Similarly, the coordination between trunk, shoulder, and elbow kinematics was evaluated and compared to the control situation: the angle values were $18.5 \text{ deg} \pm 8.0 \text{ deg}$ for **Model 1**, $15.8 \text{ deg} \pm 7.8 \text{ deg}$ for **Model 2**, $17.0 \text{ deg} \pm 7.5 \text{ deg}$ for **Model 3**, and $19.0 \text{ deg} \pm 8.8 \text{ deg}$ for **Model 4**.

IV.4 Discussion

The 10 participants succeeded in using a prosthesis elbow implemented with a generic model of the healthy shoulder/elbow coordination to reach targets in a 3D workspace. There were four different control laws, corresponding to four generic models built using different sets of input signals or regression methods; construction of these models was detailed in Chapter III. None of the tested models allowed a better performance, however the participants feedback indicated that the prosthesis response with **Model 3** and **Model 4** felt not as natural as with **Model 1** or **Model 2**. Even though the participants' performance with **Model 3** and **Model 4** were similar than with the other models, their complex implementation and their long training model computation time encouraged us not to pursue with these models for further investigations. The performance evaluation showed that **Model 1** (i.e. RBFN-based regression model that used only the time derivative of the humerus elevation angle as

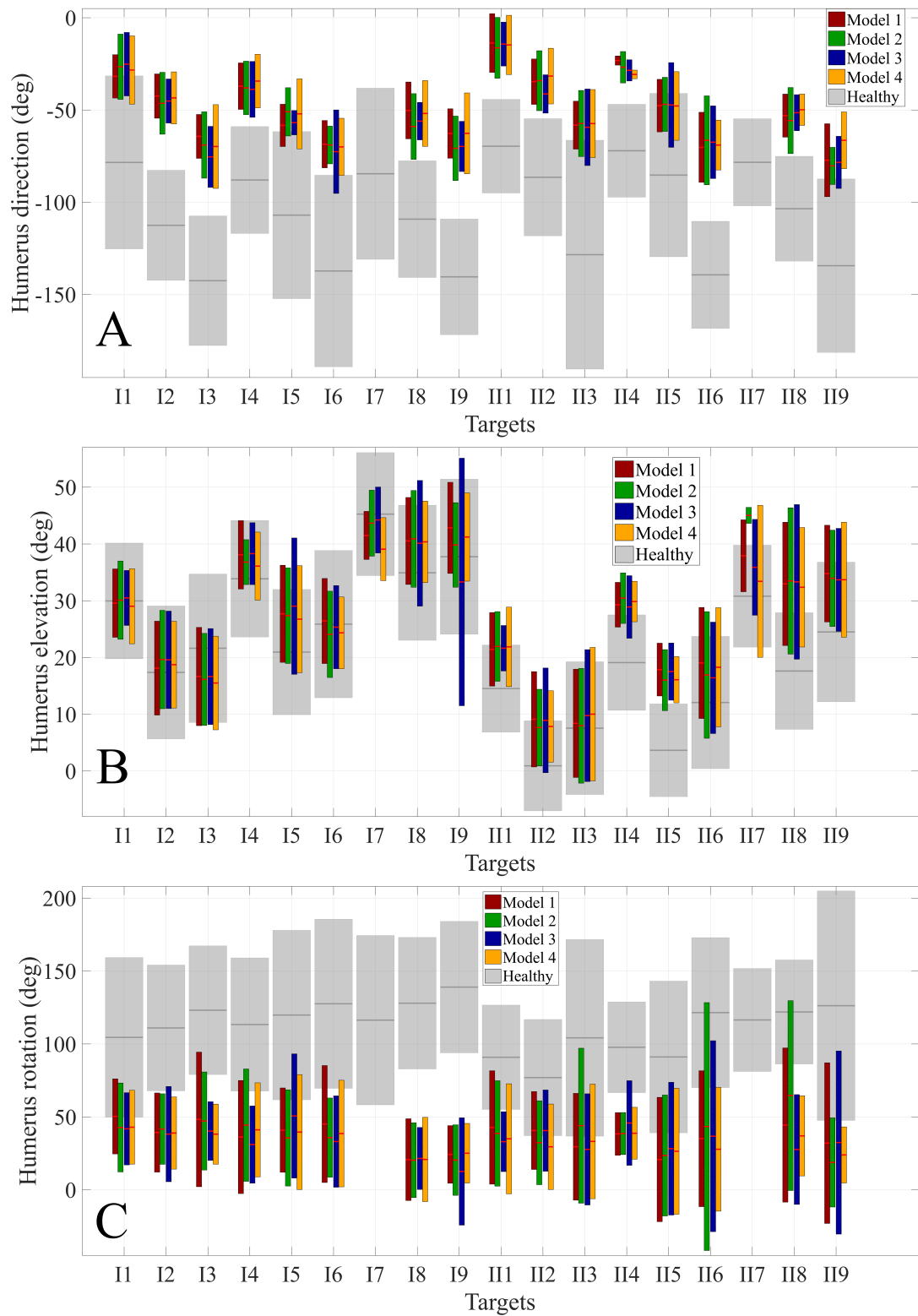


Figure IV.7 – Variations of the three angles describing the humerus motion for each target. A: humerus direction. B: Humerus elevation. C: Humerus rotation.

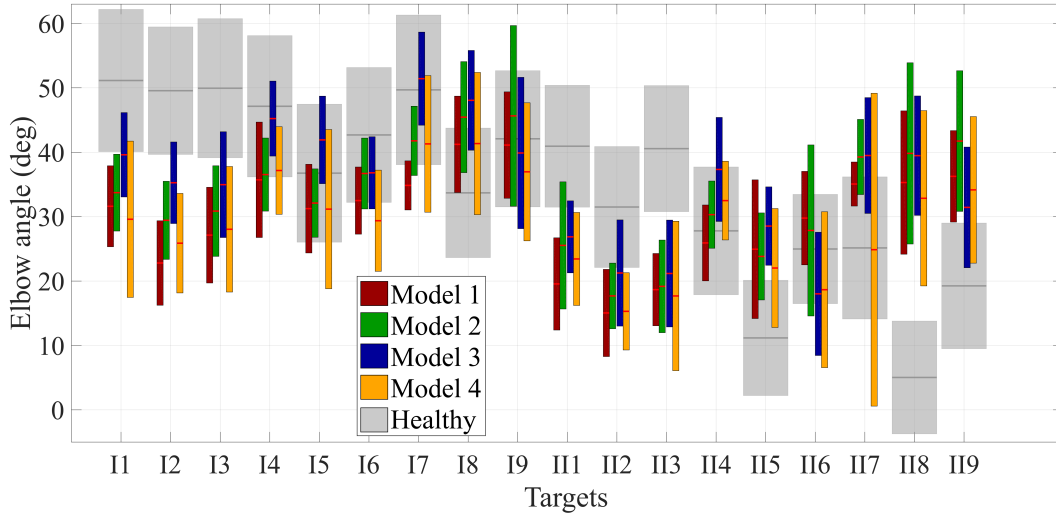


Figure IV.8 – The difference between final and initial elbow angle values, defined the elbow angle variation, is depicted for each target.

input signal) seemed to provide a better precision for high-located targets. The body kinematics assessment indicated that participants using the prosthetic elbow driven by **Model 2** (i.e. RBFN-based regression model that used the time derivative of the three shoulder angles) seemed to have a better upper body coordination between the trunk, the shoulder, and the elbow motions.

The task performance assessment showed that the participants could reach most targets with a precision error inferior to 5 cm. Specifically, the distance between the targets and the end-effector remained within the range of values of healthy individuals performing the same task with their physiological coordination. For some targets (especially Targets 8 and 9 of both distances), several participants noted that the prosthetic elbow over-extended, increasing the distance between the end-effector and the target. In terms of completion time, using a prosthesis did not slow down the reaching gesture. As expected, the movement duration increased for difficult targets, such as high-located targets like Target 7, 8, and 9.

The automatic control strategy for the elbow joint influenced in small proportions the body behavior. The analysis of trunk movements showed that the utilization of the prosthesis lead to an increased posterior bending motion for high-located targets, and an increased range of values of the trunk torsion angle. The results suggested that the trunk was more involved in the reaching gesture when wearing the prosthesis. These modifications of the body behavior could also be evidenced by the changes in the weight distribution. Even though the standard deviations values were larger for participants who used the prosthesis, the mean values were centered on the control values. Hence, it was concluded that the healthy individuals who participated in the experiment compensated the extra weight attached to their arm in order to share the overload between the two feet and maintain an balanced standing posture. The fact that the prosthetic elbow joint center was located few centimeters away from the actual elbow center yielded a mismatch between the humerus and forearm longitudinal axes.

This could explain the larger range of values of the trunk direction and trunk torsion in comparison with control values.

The most notable effects were observed in the upper limb kinematics. First, although the obtained elbow extension angles allowed the participants to reach the targets without evoking too large trunk forward bending variations, the measured prosthetic elbow's ranges of motion were smaller than values measured with healthy individuals in the control situation (except for high-located targets at Distance II, for which the elbow tended to over-extend). This limited elbow motion could explain the increased ranges of motion of the trunk's displacements. Secondly, restricted shoulder angles' ranges of motion indicated that wearing the prosthesis while not being amputated changed the shoulder kinematics. Especially, the range of motion of the humerus axial rotation was constant for all the targets, whereas measurements with healthy individuals without a prosthesis showed that the humerus internal/external rotation depended on the target location. The limited humerus rotation was explained by the way the prosthesis prototype was attached to the body, about which several participants complained. Moreover, the reduced humerus direction's range of motion resulted in an increased trunk torsion, especially when reaching contralateral targets. Due to the weight of the artificial limb, the participants compensated for the lack of shoulder mobility with larger trunk torsion's ranges of motion. However, the prosthesis weight did not impair the humerus elevation of the participants who could lift the arm with similar amplitudes to those measured with individuals without prosthesis.

Since the models' input signals described the shoulder motions, a consequence of restricted shoulder ranges of motion was an prosthetic elbow movement that did not match with the expected extension movements. Since most participants changed their own reaching strategy in order to use the prosthesis, the experiment failed in assessing the elbow control strategy in terms of intuitiveness and natural body behavior. Moreover, the performance of **Model 2**, **Model 3**, and **Model 4**, which took as input signals the time derivatives of the three shoulder angles, was biased by the fact that the participants had a restricted shoulder motion due to the prosthetic equipment.

IV.5 Conclusion

Healthy participants were equipped with a prosthesis prototype that included an externally-powered elbow driven by inter-joint coordination models from healthy individuals' data. The control strategy whereby prosthetic elbow motion is automatically-linked to the movements of the shoulder joints, presented in several studies of the literature, had never been tested on a device yet. The experiment showed that the participants could use the prosthesis and the presented control approach to reach the targets. The study did not conclude on a better model; however, the fact that **Model 2** performed as well as **Model 1** despite the limited shoulder ranges of motion, especially in terms of humerus elevation and rotation, suggested that good results could be expected with **Model 2** for tests with amputees.

Chapter V

Control of a prosthetic elbow using residual limb motion

In Chapter III, a group of healthy individuals were asked to reach several targets while their upper limb kinematics were recorded using IMUs (for shoulder angles), and a camera-based motion capture system (for the elbow angle). The data were combined to build a generic model of the shoulder/elbow coordination. Several regression methods were used to model the inter-joint relationship. It resulted in four different models that were tested in Chapter III with 10 healthy participants equipped with a prosthesis prototype. Even though the task was achieved, the participants shoulder kinematics were different from the values of the healthy baseline; especially, the range of motion of the humerus axial rotation was reduced. The participants developed trunk compensatory movements to adapt for the unnatural way of wearing the prosthesis in parallel to their own arm. Based on arguments from the literature and previous chapter's results, the RBFN-based regression algorithm was selected for implementation of the prosthesis prototype and the present chapter investigates the performance of 6 amputees in using an automatically-driven prosthetic elbow to reach targets.

Experiment overview

Six transhumeral amputees participated in the study: three had a conventional external socket, and three had an osseointegrated prosthetic implant. An RBFN-based regression model of healthy inter-joint coordinations was implemented on the prosthesis prototype, which could be attached to the participants' sockets. The protocol consisted in the same reaching task performed by the two groups of healthy individuals (without and with prosthesis, presented in the previous chapters). However, the task was performed twice: first with conventional dual-site myoelectric control, then with the generic model-based automatic control strategy. The outcomes of the automatic elbow control mode were assessed in terms of performance, joint kinematic analysis, and compensatory strategies.

V.1 Participants

Six transhumeral amputees participated in the study. The inclusion criteria were a good residual limb mobility, absence of pain, and no brachial plexus damage. the



Figure V.1 – Illustration of the residual limb mobility when fitted with the prosthesis prototype, despite wearing an external prosthesis socket and a harness. This subject exhibits a large mobility compared to the average transhumeral patients, thanks to an optimized design of the socket (which is not covering the shoulder as it is usually done).

participants had to be familiar with myoelectric control, in the sense that they were already equipped with at least one myoelectrically-controlled prosthetic element (elbow, wrist, and/or hand). The participants were split in two groups. The first group of participants (Group 1 - Conv) was recruited at the IRR of Nancy: their own prosthetic equipment included a conventional external socket maintained by a harness, as shown in Fig. I.3. The latter had to allow some residual limb mobility for inclusion in the study, as illustrated in Fig. V.1. A collaboration with the Biomechatronics and Neurorehabilitation Laboratory (Chalmers University, Göteborg, Sweden) directed by Dr. M. Ortiz-Catalán was developed to recruit the second group of subjects (Group 2 - Osseo), chosen among the participants of an ongoing experiment on osseointegrated prosthetic devices. The selected Swedish participants had undergone surgery to attach an abutment to their residual humerus bone (Jönsson et al., 2011). Any prosthesis device can be attached to the abutment's external end, like the prosthesis prototype for instance, as illustrated in Fig. V.2. One osseointegrated participant controlled his own prosthesis with surface electrodes, while the two others had been recently implanted with electrodes (less than two months prior the experiment) (Ortiz-Catalan et al., 2014a), as shown in Fig. V.2. Information on the participants is given in Table V.1; the symbols refer to the individual results representation in Appendix C.

V.2 Protocol

All participants performed twice the task consisting in reaching 18 targets (9 targets at 2 distances) with the prosthetic hand. As explained in Chapter II, the target positions were adjusted depending on each participant's height and healthy arm length. The length difference between the limb equipped with the prosthesis and the healthy limb was less than 5 cm. For every reaching movement, the subject started in the initial position (i.e. elbow flexed at 90 degrees), brought the hand to the target, and stayed immobile until told to come back. Since only reaching movements were modeled (from the initial position to the target position), the elbow returned automatically to



Figure V.2 – For osseointegrated prostheses, the residual limb’s bone is implanted with a metal bone rod on which the prosthesis can be plugged. The external abutment is depicted in the left figure (from Jönsson et al. (2011)). The middle picture shows a participant wearing the prosthesis prototype. Two osseointegrated participants had implanted electrodes that read the myoelectric signals within the muscular tissues (right picture, from Ortiz-Catalan et al. (2014a)).

	Gender	Age	Height	Amputation		Osseo. [†]	EMG
	M/F			Side	Date		
S1 ○	M	34 yo	1m80	Left	2014	No	Surface
S2 □	M	36 yo	1m68	Left	2017	No	Surface
S3 ▽	M	41 yo	1m87	Right	2015	No	Surface
S4 ◇	M	43 yo	1m85	Left	2011	Yes	Implanted
S5* ▷	M	28 yo	1m75	Left	2006	Yes	Surface
S6 ○	M	42 yo	1m87	Right	1997	Yes	Implanted

[†] Osseointegration.

* S6 had undergone bilateral transfemoral amputation, in addition to a left transhumeral amputation.

Table V.1 – Amputated participants’ general information

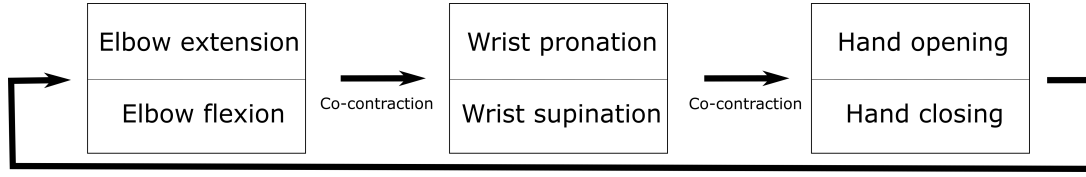


Figure V.3 – Illustration of the ME-mode.

90 degrees when the subject was indicated to go back to the initial position.

During the first trial (18 targets), a conventional dual-site myoelectric control strategy, referred to as the ME-mode, was implemented on the prosthesis controller. The signal corresponding to hand closing in the participants' own myoelectric strategy was used for elbow flexion, wrist pronation, and hand closing, and the signal used for hand opening extended the elbow, supinated the wrist, and opened the hand. A co-contraction of the biceps and triceps groups allowed the participants to switch between the joints (elbow, wrist, then hand), as illustrated in Fig. V.3. Except for Subject S1, whose control strategy differed greatly from the proposed ME-mode, none of the participants had a myoelectric elbow in their own prosthetic equipment.

During the second trial, the participants used the automatic elbow control strategy, referred to as the A-mode. The latter was run with a generic model of the shoulder/elbow coordination built with healthy individuals' data. In Chapter III), there was not any clear difference in between the participants' performance with the four models. However, in terms of online computation and spatial generalization property, it seemed that the RBFN-based model lead to better results. Hence the latter was chosen to drive the prosthesis prototype worn by the participants with a trans-humeral amputation; the input set was the time derivative of the three Euler angles describing the humerus orientation with respect to the trunk. The IMU-based residual limb's kinematic data were utilized by the prosthesis controller to estimate in real time the elbow angular velocity. As a result, the shoulder joint was driving automatically the elbow extension. Simultaneously, the participants' myoelectric signals were used to control the wrist rotation and the hand opening/closing.

In the initial protocol, performed with Subject S4 only, it was planned to ask the participants to reach the targets by bringing the finger around the circular targets, as it was shown in Fig. II.2, while they could freely rotate the wrist and close the fingers around the target. However, after following this protocol with Subject S4, who had high-quality myoelectric signals from implanted electrodes and a good control over his contractions, it appeared that voluntarily contracting muscles while moving the stump required a longer training period than the one we could propose within this experimental protocol. Most participants elicited contractions unwillingly when they moved their residual limb. A solution to avoid involuntary contractions or artifacts caused by pressure over the electrodes would have been to build a personalized socket with an optimal electrodes placement. However, designing a new socket is a long and expensive process requiring molding steps and fitting sessions with a prothesist, which was not compatible with the experiment's time schedule. Thus, the study was restricted to elbow control: myoelectric signals were only utilized with the ME-mode, and the participants were asked to use only the elbow joint to perform the task.

The participants were instructed to do the main reaching movement at one go, as would be the gesture with a sound limb. With the A-mode, if the target was not reached when the participants stopped the residual limb's motion, they had the opportunity to correct the end-effector's position: when residual limb's end of motion was detected by the prosthesis controller (threshold on the shoulder angular velocity), the elbow was locked such that the subject could move the residual limb without coupled prosthetic elbow motion. Before the beginning of each trial, the participants had 5 minutes to train with both control modes.

V.3 Data analysis

V.3.1 Data preparation

The participants performed 18 movements for each control mode (ME-mode, and A-mode). The recorded data (kinematic data from the motion capture cameras, forces from the force plate, and IMUs data) were synchronized: the participants were instructed to perform a synchronization signal by clicking the heels on the ground prior each recording, so that the movement was seen by the IMUs, the motion capture system, and the force plate. Unfortunately, the force plate could not be used in the experimental setup used with Group 2 (osseointegrated participants), and thus, force data were only measured with individuals in Group 1 (conventional socket). The data were cut in short segments, one for each movement towards a target. The data segmentation started when a change in the finger position was detected, and ended when the distance between the finger marker and the target was inferior to 2 cm.

V.3.2 Performance and movement analysis

The performance was assessed with the precision error and the task completion time. For both values, the data segments utilized for the calculation were measured at the end of motion of the residual limb (before that the elbow was locked and that the subject corrected eventually the end-effector's position). The analysis was focused on comparing the joint angular variations, and the body kinematics when using one mode or the other; the metric calculation was detailed in Chapter II. Also, the participants' reaching movements were compared to those performed by healthy participants using their physiological coordination (i.e. the control situation), which corresponded to the data set recorded in the model training data set acquisition experiment (see Chapter III). For each assessment metric, the results are presented subsequently under the form of a bar plot comparing the participants' performance with the ME-mode and the A-mode for each target. Each bar represents the mean value of the considered metric for one control condition, plus and minus the corresponding standard deviation. Individual graphs are shown in Appendix C, in which each participant's data is represented by a symbol (see Table V.1). In summary, the following values assessed the participants' performance:

Overall assessment:

- **Task completion time**
- **Precision error** before final readjustments

Assessment of trunk movements:

- Angular variation of the **anteroposterior bending angle**
- Angular variation of the **mediolateral bending angle**
- Angular variation of the **torsion angle**
- **Trunk mean speed**: trunk cumulative path over the completion time
- **Weight distribution variation** on the force plate

Assessment of shoulder and elbow movements:

- Angular variation of the **plane of elevation**
- Angular variation of the **elevation angle**
- Angular variation of the **humeral axial rotation**
- Angular variation of the **elbow flexion/extension angle**
- **Inter-coordination angle**.

V.3.3 Statistical analysis

Repeated measures ANOVAs were carried out in the participants with the Type (Harness: Group 1 - conventional external socket, or Osseo: Group2 - osseointegrated device) as between-subject factor, and the Mode (myoelectric or automatic) and the Target as within-subject factors. When there were significant interactions, two factors ANOVA (with Type as between-subject factor and Mode as within-subject factor) was performed separately for each target.

V.4 Results

All participants could reach the targets with both modes. An example of one trial performed by Subject S3 (Group 1 - conv) with the ME-mode is depicted in Fig. V.4. However, different reaching strategies could be observed, depending on the participants' residual limb capabilities, especially when they used the prosthesis with the elbow in ME-mode control. As detailed below, the A-mode, appreciated by all participants, lead to trunk and upper-limb movement strategies that appeared more "natural", i.e. more similar to the reaching movements made by healthy individuals.

V.4.1 Functional assessment

Precision error before final readjustments All the participants could achieve the task with both modes. However, with the A-mode, several participants had to make additional corrections mostly because the prosthetic elbow over-extended: by using the elbow locking feature, they could adjust the end-effector position by moving the residual limb without evoking a supplementary elbow extension. These final corrections were not observed with the ME-mode since the whole reaching movement was an end-effector position adjustment. As explained in Chapter IV, there was an offset in the precision error values due to the marker placement. It was estimated at about 5.9 cm,



Figure V.4 – Example of a trial performed by Subject S3 (Group 1 - conv). The numbers correspond to the aimed target.

which corresponded to the mean precision error of the control situation. For a clearer reading, the offset value was subtracted from the precision error values calculated in the present chapter. The resulting precision errors, depicted in Fig. V.5A, larger for some targets in A-mode, confirmed that re-adjustments of the end-effector position were sometimes necessary to achieve the task. Especially, for Targets 8 and 9, Subject S5 (Group 2 - osseo, symbol $\triangleright$ in Fig. C.1) tended to first extend the elbow with A-mode without aiming at any target, then brought the hand around the target once the elbow was locked. Since the precision error calculation considered data segments before the elbow locking period, the resulting values were ranging between 25 and 40 cm for Targets 8 and 9 (performance by Subject 5 only). Thus they were considered as outliers, and they were removed from the analysis. The overall error values, averaged over all targets, distances and participants of each group, were reported in Table V.2 and Table V.3 after subtracting the baseline value: the overall precision error for Group 1's participants was $1.2 \text{ cm} \pm 0.8 \text{ cm}$ using the ME-mode, and $1.7 \text{ cm} \pm 1.2 \text{ cm}$ using the A-mode. For Group 2's participants, the precision error when using the ME-mode was $1.7 \text{ cm} \pm 1.6 \text{ cm}$, and it was $7.0 \text{ cm} \pm 7.2 \text{ cm}$ when using the A-mode. The statistical analysis showed that there the precision error varied with the Target ($F(17,51)=3.71$, $p<0.0001$), with a borderline effect of Type ($p=0.051$) and Mode ($p=0.06$). There were strong interactions between the effects of Target and Type ($F(17,51)=2.73$, $p<0.005$), Target and Mode ($F(17,51)=2.72$, $p<0.005$) and Target*Type*Mode interactions ($F(17,51)=2.21$, $p<0.05$). There were no significant result but borderline tendencies (between 0.05 and 0.08) for the effect of Type (Targets 1-3, 17), Mode (Targets 1, 3, 7) and interaction (Targets 1, 3, 5, 17).

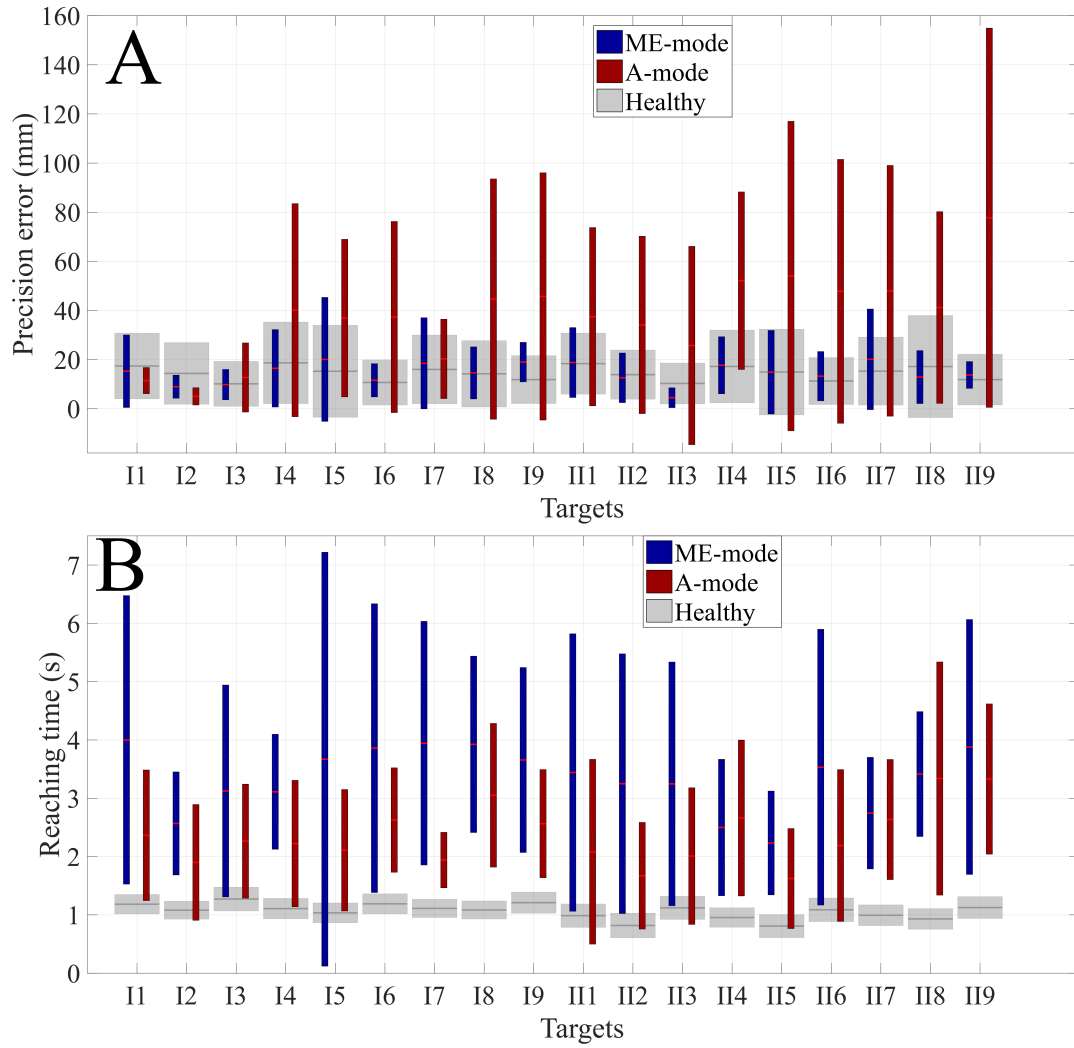


Figure V.5 – Precision errors (A) and task completion times (B) in ME-mode (blue bars) and A-mode (red bars) for all targets (distance I*i*, distance II*i*, where *i* represents the target number), computed before re-adjustments of the end-effector position. Blue (resp. red) bars represent the mean value (short red line) of the precision error (A) and the completion time (B) plus and minus the standard deviation with the ME-mode (resp. A-mode). Grey lines and shaded areas represent the average precision error and completion time ($\pm$ standard deviation) of the control situation.

	Group 1 - Conv		Group 2 - Osseo		Healthy
	ME-mode	A-mode	ME-mode	A-mode	
Precision (mm)	12.1 $\pm$ 8.4	16.8 $\pm$ 16.0	17.1 $\pm$ 15.7	69.7 $\pm$ 72.2	58.7 $\pm$ 19.8
Duration (s)	2.9 $\pm$ 1.3	2.2 $\pm$ 0.8	3.8 $\pm$ 2.2	2.5 $\pm$ 1.5	1.1 $\pm$ 0.2
Trunk speed (mm/s)	38.9 $\pm$ 20.7	35.7 $\pm$ 14.1	32.0 $\pm$ 31.3	20.9 $\pm$ 14.3	14.0 $\pm$ 11.1
S/E coord.* (deg)	27.7 $\pm$ 12.7	4.5 $\pm$ 2.8	41.7 $\pm$ 11.2	21.3 $\pm$ 5.8	x
T/S/E coord.** (deg)	35.0 $\pm$ 4.2	24.0 $\pm$ 8.7	51.9 $\pm$ 7.8	25.6 $\pm$ 11.7 deg	x

* Angle between the Shoulder/Elbow coordinations of healthy amputated participants.

** Angle between the Trunk/Shoulder/Elbow coordinations of healthy and amputated participants.

Table V.2 – Results of the experiment with amputated participants (global results).

Completion time The task completion times were computed on the same data segments as for the precision error calculations, i.e. without considering the end-effector re-adjustments that were eventually made by the subjects after the end of the main reaching gesture. The reaching gestures performed with a prosthesis (Group 1 and 2) were longer than healthy movements (1.1 s $\pm$ 0.2 s), as shown in Fig. V.5B. However, the movement duration was reduced when using the A-mode, as shown by the completion time values grouped in Table V.2 and Table V.3. For participants in Group 1 (conv), the average completion time was 2.9 s $\pm$ 1.3 s with ME-mode, and 2.2 s $\pm$ 0.8 s with A-mode. For Group 2's participants, the average movement duration when using ME-mode was 3.8 s $\pm$ 2.2 s, and 2.5 s $\pm$ 1.5 s when using A-mode. The statistical analysis showed that the movement duration did not vary significantly.

V.4.2 Movement strategy assessment

A typical reaching movement is illustrated in Fig. V.6. The pictures represent the initial and final postures taken by Subject S1 while he performed the reaching movement towards Target 5 of Distance I with the prosthetic elbow in ME-mode (ME1 and ME2), and in A-mode (A1 and A2). The prosthetic elbow's control mode influenced the participants' overall motor strategy. Indeed, differences in the trunk kinematics could be observed between the two trials. Like in Chapter IV, the results were compared to the reaching strategies of the healthy individuals recruited in the model training data acquisition experiment (see Chapter III).

Elbow joint utilization Depending on the elbow control mode, the participants had a different utilization of the prosthesis. Only the Subject S3 (the most recently amputated, symbol ∇ in the figures in Appendix C) used similarly the prosthesis in ME-mode and A-mode: he was able to extend easily the elbow as he moved the residual limb, which could not be performed by the other participants who were often disturbed by involuntary residual limb contractions. The elbow angle variation, i.e. the difference between the final and initial elbow angle values, were computed for each

		ME-mode	A-mode
Precision (mm)	S1	18.9 ± 8.1	28.1 ± 17.6
	S2	10.0 ± 7.4	14.8 ± 15.2
	S3	7.3 ± 4.9	7.6 ± 5.2
	S4	24.7 ± 15.9	43.1 ± 40.0
	S5	20.6 ± 17.2	104.7 ± 97.3
	S6	6.0 ± 4.0	61.3 ± 55.4
Duration (s)	S1	2.6 ± 1.5	1.8 ± 0.6
	S2	3.5 ± 1.6	3.0 ± 0.8
	S3	2.7 ± 0.5	1.9 ± 0.3
	S4	5.6 ± 2.1	2.1 ± 1.4
	S5	4.0 ± 1.6	3.2 ± 1.3
	S6	1.7 ± 0.4	2.2 ± 1.5
Trunk speed (mm/s)	S1	55.7 ± 24.1	33.0 ± 11.7
	S2	32.8 ± 14.9	39.5 ± 18.4
	S3	28.2 ± 9.0	34.5 ± 11.0
	S4	16.1 ± 5.8	27.1 ± 12.1
	S5	10.7 ± 4.4	9.1 ± 3.4
	S6	69.1 ± 28.5	26.6 ± 16.1
S/E coord.* (deg)	S1	39.0	1.4
	S2	30.2	6.8
	S3	13.9	5.3
	S4	51.4	14.7
	S5	44.2	25.7
	S6	29.5	23.6
T/S/E coord.** (deg)	S1	40.2	23.0
	S2	34.2	15.8
	S3	32.1	33.2
	S4	60.8	14.2
	S5	46.4	37.7
	S6	48.4	24.9

* Angle between the Shoulder/Elbow coordinations of healthy and amputated participants.

** Angle between the Trunk/Shoulder/Elbow coordinations of healthy and amputated participants.

Table V.3 – Results of the experiment with amputated participants (individual results).

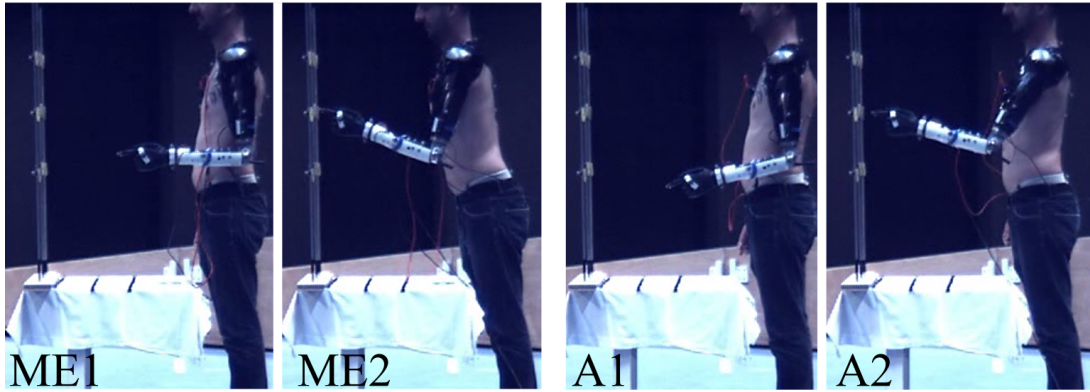


Figure V.6 – Reaching movements towards Target 5 (Distance I) are illustrated, with myoelectric control (ME1-ME2), and automatic control (A1-A2).

target, distance, and participant, and the values were depicted in Fig. V.7. When compared to the healthy elbow angle variations, the prosthetic utilization was more limited for participants in both groups when using a myoelectrically-control elbow.

Trunk movements Except for the Subject S3 with the ME-mode who could simultaneously evoke myoelectric signals to control the elbow extension, and move his residual limb to position the end-effector, the prosthetic elbow was mostly used with the ME-mode to position the forearm prior to do the actual reaching motion. The end-effector was then brought to the targets by elevating the humerus, and in some cases by leaning over the table, yielding large body displacements. The thorax center's cumulative trajectory normalized by the completion time, referred to as the trunk mean speed, was larger for movements performed with the ME-mode, as depicted in Fig. V.8. Specifically, the trunk displacements of participants in both groups were largely reduced when the residual limb motion was coupled to the prosthetic elbow extension (A-mode), as shown by the overall trunk mean speed values in Tables V.2 and V.3. For Group 1, the average trunk mean speed was $38.9 \text{ mm/s} \pm 20.7 \text{ mm/s}$ when using the ME-mode, and $35.7 \text{ mm/s} \pm 14.1 \text{ mm/s}$ with the A-mode. For Group 2, the values were $32.0 \text{ mm/s} \pm 31.4$ with the ME-mode, and $20.9 \text{ mm/s} \pm 14.3 \text{ mm/s}$ with the A-mode. The trunk mean speeds for participants in Group 2 (osseo) were close to healthy values ($14.0 \text{ mm/s} \pm 11.1$ in average). The trunk mean speed varied significantly with the Target ($F(17,51)=4.4$, $p<0.0001$) without significant interactions.

The analysis of trunk movements showed large differences within the participants' reaching strategies, especially in terms of trunk involvement in the movement, as shown in Fig. V.9. Automatic coupling of residual limb motion and elbow extension evoked an important trunk backward bending reaction for high-located targets (Targets 7, 8, and 9): it was mostly due to an elbow over-extension with the A-mode that participants corrected by leaning their trunk backwards in order to reach the targets. The trunk was more involved in Group 1's participants' reaching motions (see Fig. C.4), especially since the prosthesis attachment to the body limited their residual limb movements. Trunk mediolateral bending and trunk torsion towards the contralateral side were reduced for participants in both groups.

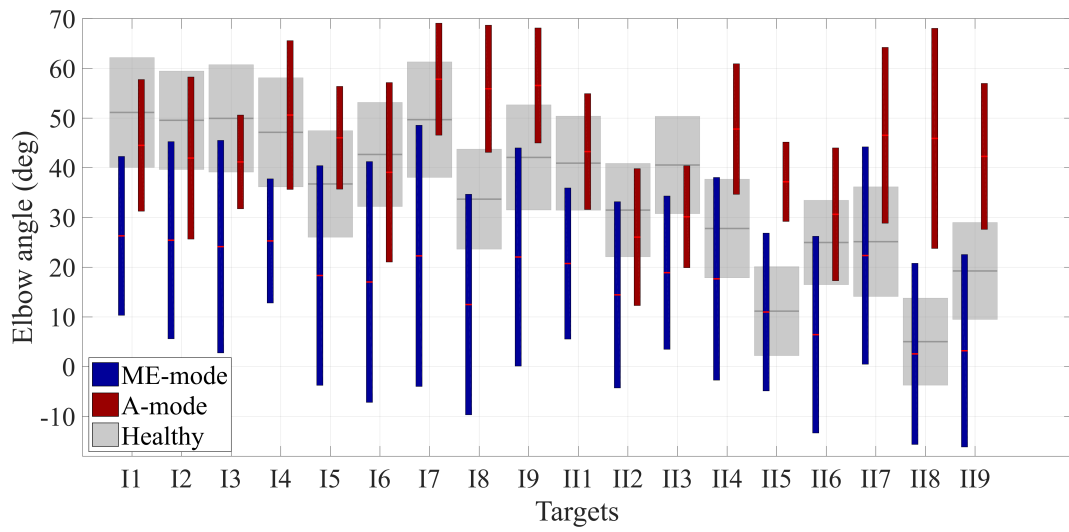


Figure V.7 – The difference between the final and initial elbow angle values, defined as the elbow angle variation, is depicted for each target and each participant. The elbow prosthesis was used differently depending on the control strategy (myoelectric in blue, and automatic in red).

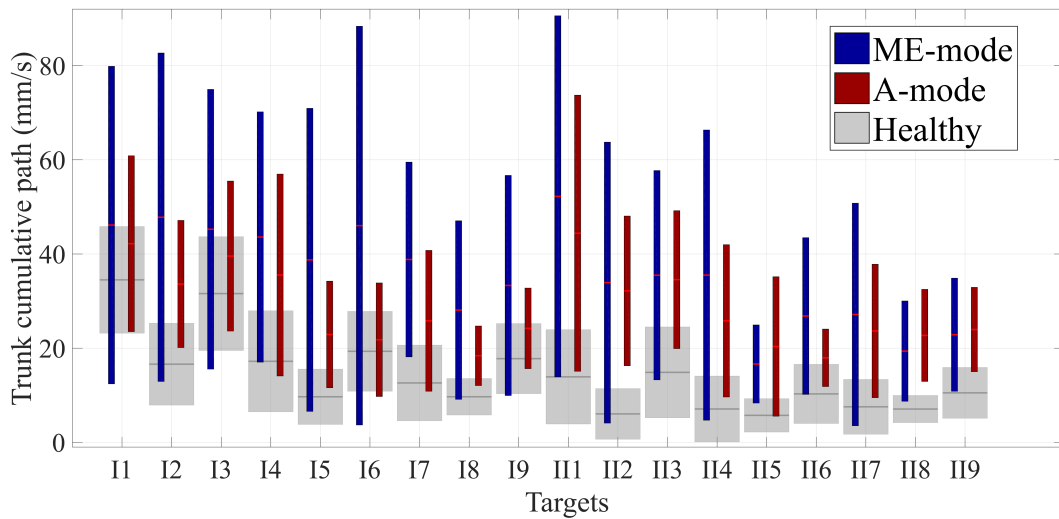


Figure V.8 – Analysis of trunk compensatory movements. The cumulative trajectory of the thorax center quantified the trunk's displacements during each reaching movement; for each movement, it was normalized with the completion time, leading to the trunk mean speed value.

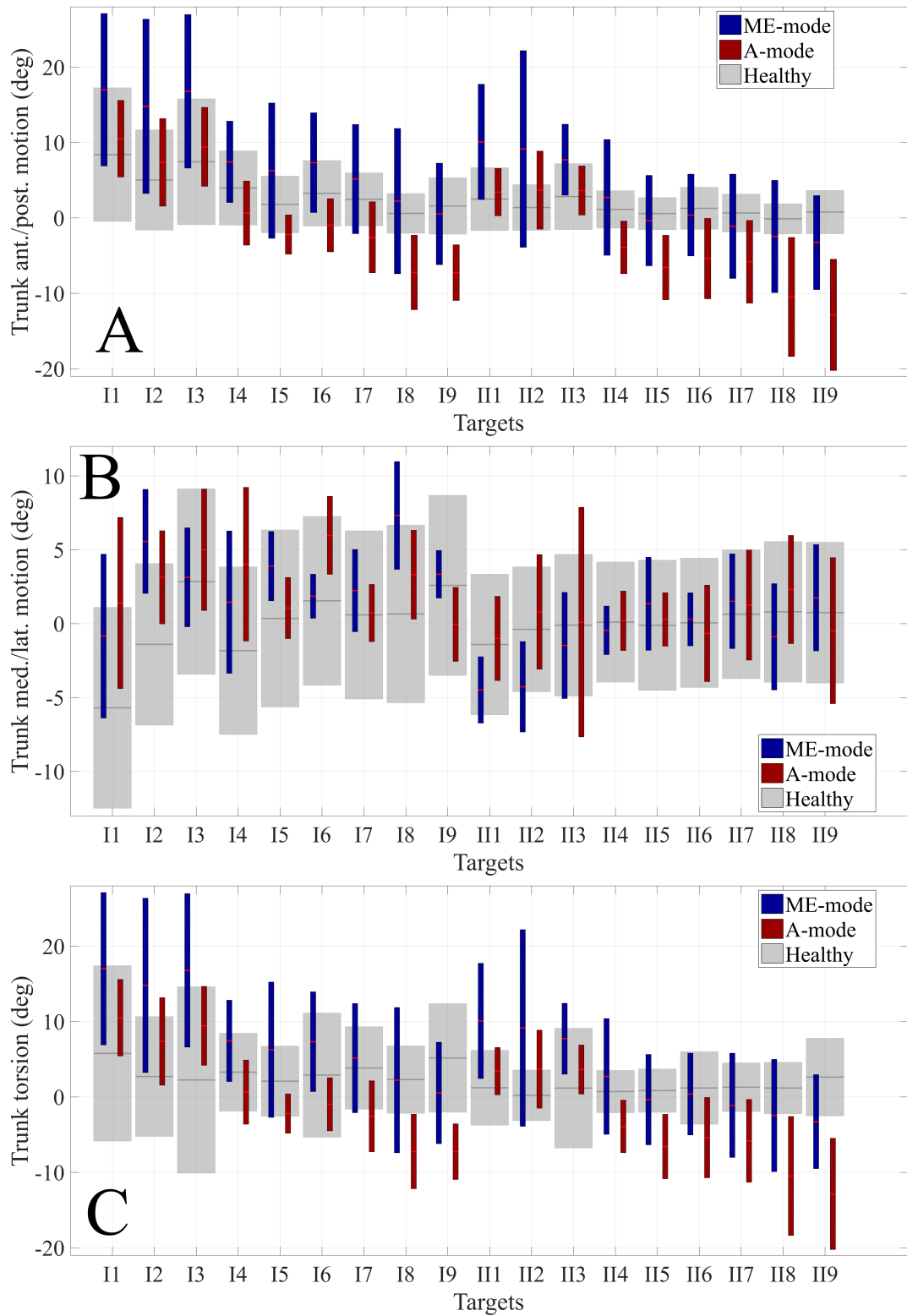


Figure V.9 – Variations of the three angles describing the trunk motions for each targets. A: Trunk anteroposterior bending. B: Trunk mediolateral bending. C: Trunk torsion.

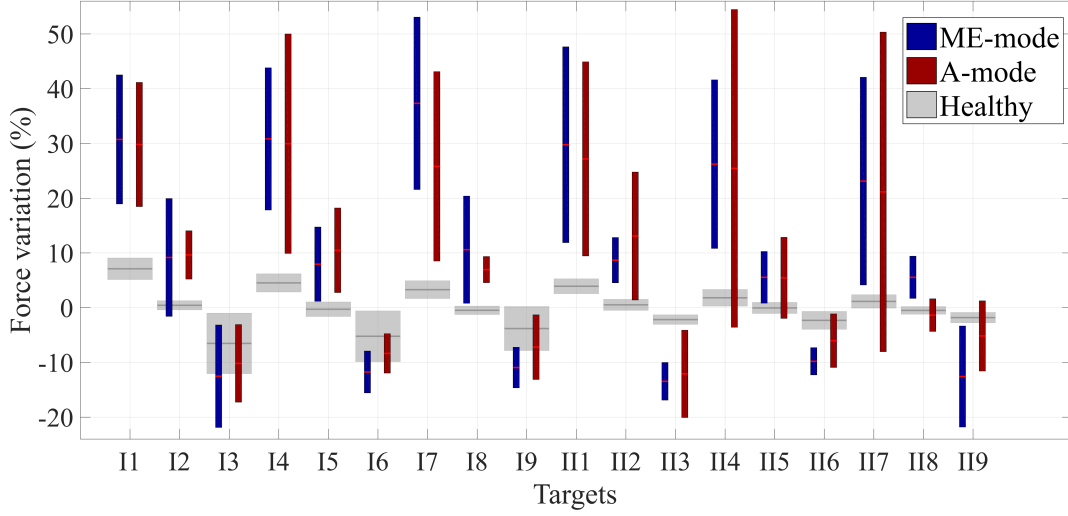


Figure V.10 – Variation of the amount of force applied by the ipsilateral foot with respect to the total force between the beginning and the end of each reaching movement. Only values with participants in Group 1 could be measured.

Changes in movement strategies could also be observed with the analysis of the reaction force with the floor. The values depicted in Fig. V.10 represent the variation of the amount of force exerted by the ipsilateral foot with respect to the total force. When the movements were performed with the ME-mode, the participants' weight shifted more towards the foot located on the same side as the target (e.g. left foot for targets located on the subjects' left). The force variation values confirmed that the trunk was more involved during reaching movements with the ME-mode.

Residual limb movements Humerus motion was assessed with three parameters: humerus direction, elevation, and rotation. The residual limb motion was different depending on the elbow control strategy, as illustrated in Fig. V.11. The participants were required to use their residual limb with the A-mode control strategy in order to achieve the task, whereas movements with the ME-mode could be performed with the trunk after setting the prosthetic forearm into the adequate position.

As explained in Chapter II, the shoulder/elbow coordination for each participant was compared to a coordination of reference, which was built using the data measured with 20 healthy individuals for the training data set acquisition experiment (see Chapter III). The difference between two coordinations was assessed numerically with the angle between the first PCs (quantifying the differences between inter-joint coordinations) of the two data set (amputated participant's upper limb kinematics versus the healthy upper limb kinematics). The values were grouped in Tables V.2 and V.3. For both groups of participants, using the A-mode reduced the difference between the amputated participants and a healthy coordination pattern. For participants of Group 1, an average angle of $27.7 \text{ deg} \pm 12.7 \text{ deg}$ was calculated with the ME-mode, whereas the value was $4.5 \text{ deg} \pm 2.8 \text{ deg}$ with the A-mode. For Group 2, the average angle value was $41.7 \text{ deg} \pm 11.2 \text{ deg}$ with the ME-mode, and $21.3 \text{ deg} \pm 5.8 \text{ deg}$ with the

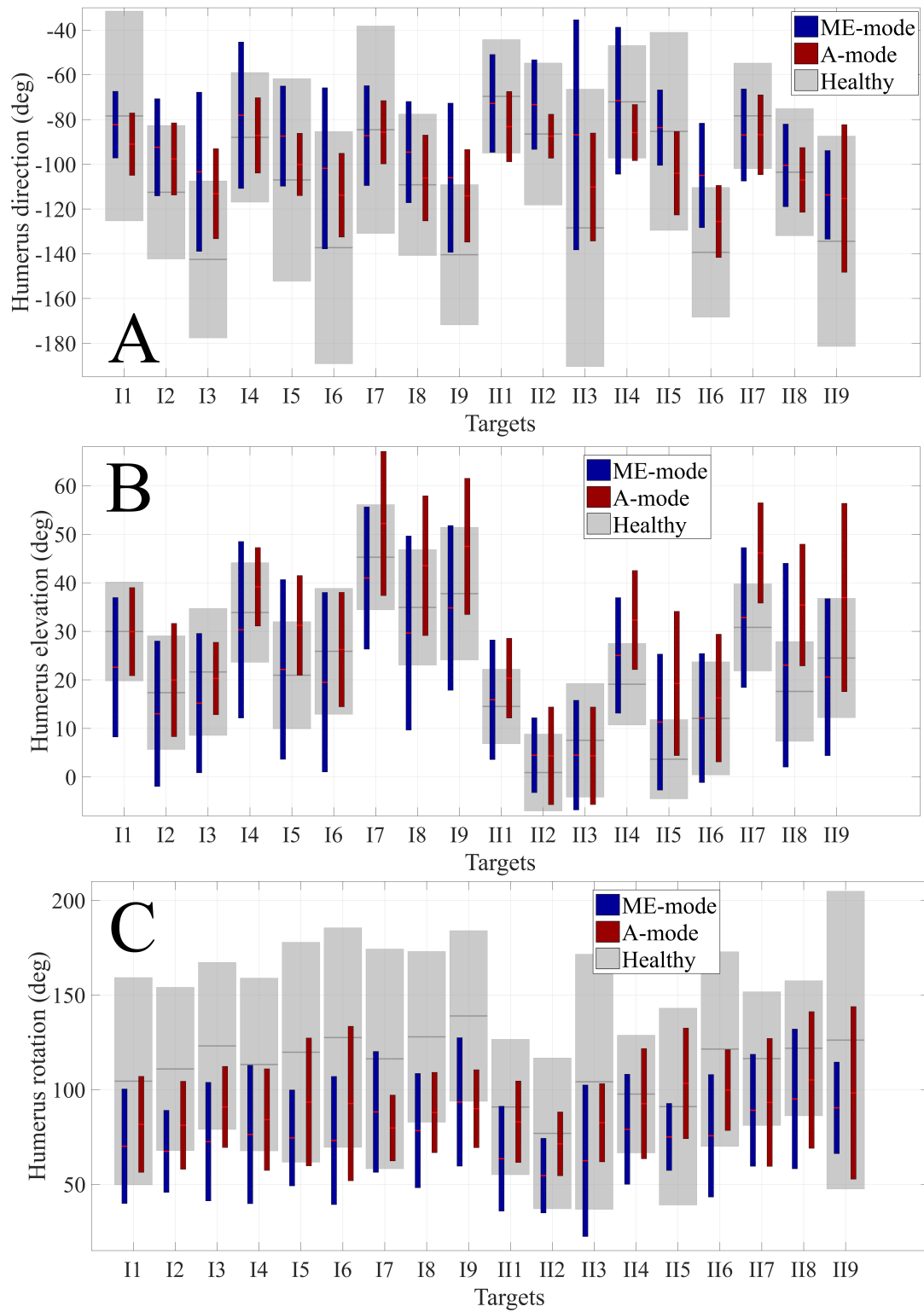


Figure V.11 – Variations of the three angles describing the residual limb motions for each targets. A: Humerus direction. B: Humerus elevation. C: Humerus rotation.

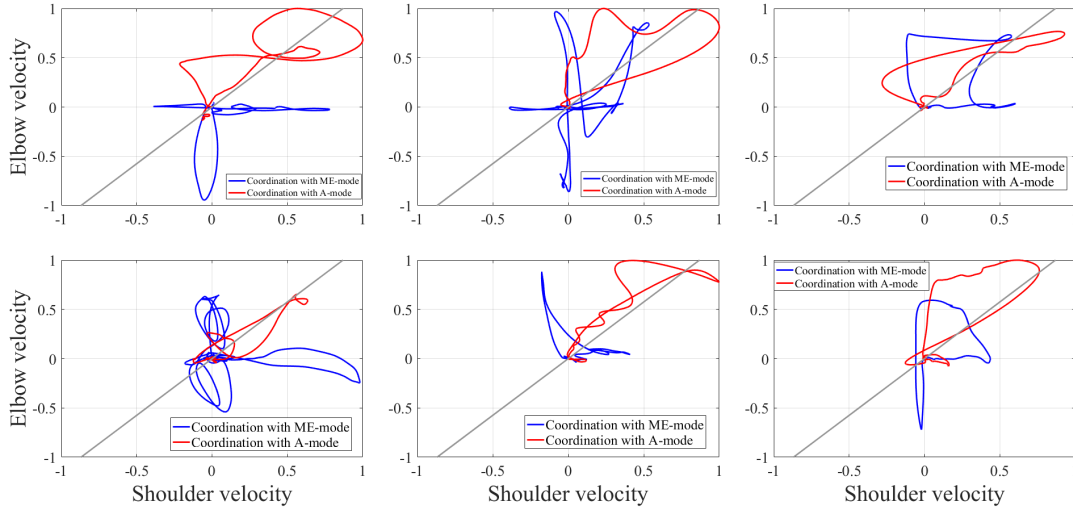


Figure V.12 – Illustration of the coordination between the residual limb motion and elbow extension for the 6 participants: the 6 cyclograms represent the elbow angular velocity values with respect to the humerus elevation angular velocity for one reaching movement performed by each individual. The grey line represents the first PC of the healthy coordination (derived from the data set measured in Chapter III).

A-mode. Similarly, the coordination between the trunk, the shoulder, and the elbow was assessed for the participants in the two groups. As shown in Tables V.2 and V.3, the angles between Group 1's participants' coordination and a healthy coordination pattern increased when the trunk motion was included in the analysis. For participants equipped with an external socket (Group 1), the angle was in average $35.5 \text{ deg} \pm 4.2 \text{ deg}$ with the ME-mode, and $24.8 \text{ deg} \pm 8.7 \text{ deg}$ with the A-mode. For Group 2, the average angle value was $51.9 \text{ deg} \pm 7.8 \text{ deg}$ for the ME-mode, and it was $25.6 \text{ deg} \pm 11.7 \text{ deg}$ with the A-mode. For the shoulder/elbow coordination, there were significant Target*Mode and Target*Type interactions ($F(17,51)=1.91$, $p<0.05$, and $F(17,51)=2.55$, $p<0.01$ respectively). There were borderline tendencies for the effect of Type (Targets 2-4, 10), Mode (Targets 2, 16). The coordination between the trunk, shoulder and elbow movements varied significantly with the Mode ($F(17,51)=10.35$, $p<0.05$) with significant Mode*Target*Type interactions ($F(17,51)=2.2$, $p<0.01$). There was a significant Mode*Type interaction for Targets 8 and 15, and borderline tendencies for the effects of Type (Targets 1-4, 11, 16, 17), Mode (Targets 11, 13, 16) and Mode*Type interactions (Targets 4, 7, 13, 17).

V.5 Discussion

Six transhumeral amputated individuals were asked to reach 18 targets distributed over two distances. The participants were split in two groups depending on their prosthesis attachment to the body: Group 1's participants had a conventional external socket attached to the body via a looped under the contralateral shoulder, and

Group 2's participants had undergone surgery to receive an osseointegrated implant to attach the prosthesis. The subjects performed the task with a prosthesis prototype comprising a motorized elbow controlled either by a dual-site myoelectric control strategy (ME-mode, biceps contractions controlling elbow flexion, and triceps contractions controlling elbow extension), or by a generic model of healthy inter-joint coordinations coupling the residual limb motions to the prosthetic elbow movements (A-mode).

The results showed that all participants were able to perform the task with both elbow control modes. None of them was familiar with the imposed myoelectric strategy for the elbow joint - most of them used to have only a myoelectric hand - and thus, they were all untrained to both elbow control strategies (ME-mode and A-mode). Although they could only test the A-mode in a restrictive reaching task, the participants approved the concept by describing it as natural and intuitive; all of them asked to be included in future tests to see the prosthesis development.

V.5.1 Precision error before final adjustments

The task precision metric was not adapted to the reaching strategy used by several participants. Even though the participants achieved successfully the task with both modes, the error value was larger (before final adjustments) when the task was performed with an automatically-driven elbow. It was explained by the fact that the calculation did not account for the final corrections of the end-effector position that were made after the main reaching movement, and that allowed the participants to reach the targets. Specifically, Group 1's participants performed the task with healthy-like precision (see Fig. C.1). In Group 2, the participants used more the elbow locking feature, yielding a larger precision error before that the subject corrected the end effector position.

Targets located at Distance II were difficult to reach, and some of them could not be reached without flexing the elbow (Target 7, 8, and 9). The prosthetic elbow could not be flexed: since most of the recorded healthy movements in the model training data acquisition experiment were extension movement, a threshold was applied to the elbow angular velocity predicted by the RBFN-based regression model such that the prosthetic elbow could only extend (flexion threshold set at 10 deg/s).

V.5.2 Completion time

The participants achieved the task with a high precision using the ME-mode (inferior to 5 cm). However, most of them did not adjust the forearm position during the reaching movement itself, but prior to the movement, making the overall reaching strategy unnatural. As a result, the completion time for movements with the ME-mode, which included the forearm pre-positioning phase (i.e. the elbow positioning that some participants performed prior the reaching movement), was increased. The participants in the study of [Hussaini et al. \(2016\)](#) and [Metzger et al. \(2012\)](#) had a similar behavior before starting the actual tasks: the elbow angle or the objects themselves were pre-positioned before the movements such that it was easier to achieve the task. Nonetheless, pre-positioning the prosthesis did not reduce the compensatory behavior, and neither reduced the movement duration.

The recruited participants were familiar with myoelectric control, but they were not used to have a prosthetic elbow with motorized flexion and extension; the only subject who had motorized elbow had a significantly different myoelectric control strategy (only the flexion was motorized). Moreover, the task required simultaneous motion of the shoulder and the elbow, which the participants were not accustomed to (mainly because the reaching task was not part of their daily prosthetic gestures). Several participants (Subjects S1, S2, S5, and S6) struggled in using the ME-mode concurrently with moving the residual limb. Seeing that the prosthesis was not responding well to their myoelectric signal inputs, they used alternative body parts to compensate for the lack of mobility of the prosthesis.

The task completion times with the A-mode were reduced in comparison with the ME-mode. It can be explained by the simplicity of the control strategy which consisted in projecting the residual limb towards the target, as done by an healthy limb, while the elbow automatically extended. Neither anticipation nor cognitive efforts were needed when extending the elbow before starting the reaching movement. However, reaching gestures performed with the A-mode were still longer than the healthy baseline values, maybe due to the lack of training with the A-mode.

V.5.3 Analysis of body kinematics

Elbow extension The analysis of the elbow joint's range of motion showed that the utilization was different from one control mode to another. Compared to the healthy baseline for the elbow utilization, amputated participants under-used the prosthetic elbow with the ME-mode. Interestingly, several participants, and S1 in particular, chose to flex the elbow to reach numerous targets with the ME-mode, although no instruction was given on the reaching strategy. The A-mode restored a healthy utilization, especially for participants in Group 2.

Trunk displacements The reaching strategy chosen by the participants with a myoelectrically-driven elbow was the costliest in terms of trunk compensatory movements. Indeed, elbow extension was performed in anticipation of the reaching movement, and thus it was often prematurely interrupted, yielding large trunk and acromion displacements to compensate for the lack of elbow mobility. Participants like S1 and S6 minimally used the prosthetic elbow with the ME-mode, and mostly reached the targets by leaning the trunk over the table. As a result, participants in both groups had a significantly larger involvement of their trunk than healthy individuals in the control situation, and in particular during movements with the ME-mode. The case of Subject S5 should be discussed individually: since he had a bilateral transfemoral amputation in addition to a left transhumeral amputation, this participant tended to reduced trunk movement to avoid to lose balance. This can be seen on the low trunk mean speed values and trunk forward bending motion in Fig. C.3. This participant compensated the lack of trunk mobility by extensively protracting the scapula (forward motion of the scapula). Elbow impairment, and even full locking as it is the case for most transhumeral amputees wearing a prosthesis, evokes trunk movements of large amplitude (de Groot et al., 2011; Deijs et al., 2016; Metzger et al., 2012). Metzger et al. (2012) measured trunk displacements of 35 cm in the anteroposterior and medi-

olateral directions, and shoulder cumulative path of 50 cm during reaching movements of transhumeral amputees. Such important modifications of the natural behavior can lead to severe musculoskeletal disorders.

The over-compensating behavior was reduced for participants in both groups when the elbow was automatically-driven by the residual limb movements. However, the elbow over-extension for high-located targets of Distance II (Targets 7, 8, and 9, that were difficult to reach without elbow flexion) had an opposing result: instead of trunk forward bending, large backward bending angle variations were measured for all the participants. Moreover, the weight distribution analysis of Group 1's data showed an important shift towards the foot located on the same side as the target, no matter which control mode was used. The whole body was involved into the reaching movement, and it can be justified by the fact that the prosthesis attachment to the body with a conventional external socket is greatly different from the natural attachment of a limb, thus leading to changes in the weight distribution which impacts the whole body biomechanical organization. The fact that the participants' center of pressure was moving more than for healthy movements showed that the reaching task is difficult for a transhumeral amputated individual and that they may lose balance more easily during ADLs.

V.5.4 Inter-joint coordination-based control

The results showed that body and trunk compensation were reduced when using the A-mode control strategy, especially for targets located at the maximal distance (Distance I). Movements with an automatically-driven elbow were more natural, with synchronous shoulder and elbow motions. Residual limb's ranges of motion for the direction angle and the elevation angle were comparable to those of healthy individuals, despite the cumbersome attachment of the prosthesis to the body for Group 1's individuals. The humerus rotation was limited for individuals with an external socket, and surprisingly also for individuals with a bone-anchored prosthesis, who should not have a limited residual limb mobility. The A-mode control strategy seemed to restore the coordination between upper body joints, which was nonexistent with the ME-mode. The shoulder/elbow coordination analysis showed that using an automatically-driven elbow enabled a more natural body behavior. Group 1's participants had a coordinated residual limb/prosthetic elbow movements that were the closest to a healthy shoulder/elbow coordination.

The inter-joint coordination model was implemented on the prosthesis with the assumption that residual limb kinematics were similar to the healthy kinematics included in the generic model training data set. Unfortunately, the residual limb motion analysis showed that it was not the case although the values were close for participants in Group 2 (osseo). The external socket of Group 1's participants limited the residual limb movements, which was not the case for Group 2's participants who had a bone-anchored prosthesis. More generally, the loss of a limb affected the residual limb kinematics by altering the whole sensorimotor loop. The participants, who were used to have a missing limb and a prosthesis, did not have time to get familiarized with a more natural way of moving the prosthetic limb. As a result, persistent strategies in the residual limb movements that corresponded to an acquired post-amputation motor

control strategy could be observed. Also, the weight distribution of the prosthesis is fundamentally different from the one of a healthy limb, which generates different dynamical effects such as reaction forces on the prosthesis users' body. Hence, mobilizing the residual limb with a prosthesis attached to it requires training.

V.5.5 Inter-individual variability

Although the recruited participants were all familiar with myoelectric control, they did not have the same experience with it: the equipment with a myoelectric prosthesis ranged between one month and 10 years ago. Thus, their performance with the ME-mode was influenced by the level of expertise of myoelectric prosthesis control. Moreover, they did not have the same prosthesis equipment: most of them had only a myoelectric hand, while several participants were equipped with a hand and wrist myoelectric system, to which was added a myoelectric elbow for one subject. There is no predefined myoelectric strategy: the latter is defined with the amputated individual and the prosthesist during several training and fitting sessions. As a result, some participants were more successful in achieving the task with the ME-mode, maybe because the imposed control strategy was close to their own myoelectric control strategy, while some participants struggled using the prosthetic elbow in ME-mode. For instance, the Subject S6, who struggled in producing strong and stable myoelectric signals and found that the ME-mode was too much time-consuming, often preferred to bend the trunk instead of extending the elbow. On the contrary, the Subject S3 was as good with the ME-mode and the A-mode: he could simultaneously move the residual limb and produce stable and strong myoelectric signal, yielding a similar overall body behavior with synchronized trunk, shoulder and elbow movements between the ME-mode and the A-mode.

The prosthesis attachment to the body had an important influence on the participants' performance with the ME-mode. For the Subject S4 who had implanted electrodes and was able to produce strong EMG signals, using the ME-mode was easy, and he was even given the possibility to actuate all the prosthetic joints. Since he was the first to be recruited, he misled our judgment on the actual difficulty of the task. Hence, for the participants recruited after him, who all struggled to perform the task with the ME-mode, the control strategy was restricted to only elbow control. Participants for whom the prosthesis socket was not stable, and did not maintain a good tight contact between the electrodes and the residual limb skin, encountered difficulty when moving the residual limb: configuration changes inside the socket or vibrations caused by the elbow actuation evoked signals artifacts or involuntary contractions that lead to undesired elbow extension or flexion.

The concept of the automatic elbow control mode (A-mode) was well received by the participants who understood quickly how to use it. No instruction was given on which was the proper way to use the A-mode. Most participants accepted the fact that the elbow motion was automatically driven by the residual limb motion. When the end of the main reaching movement was detected by the prosthesis, the prosthetic elbow was locked to allow the participant to adjust the end-effector position without extending further the elbow. However, several participants (Subjects S5 and S6) overused this elbow-locking feature. For some targets, especially high-located targets that

required full elbow extension, these participants first extended the elbow by elevating the residual limb without aiming at any particular targets, and once the elbow was locked, they brought the end-effector to the target by moving the residual limb. This unconventional utilization of the A-mode, that was supposed to mimic a physiological upper limb extension movement, showed that for these participants the prosthesis was seen as a tool during the experiment and not as an extension of the residual limb.

V.5.6 Study limitations

The transhumeral amputated individuals recruited in the study were familiar with myoelectric control from their own experience with a prosthesis, however they had received no prior training with the A-mode. Hence, the participants were not completely new with the two control modes, which could have biased the results in terms of intuitiveness of the control strategy. However, even though they knew how to control myoelectrically a prosthetic element, the participants were unfamiliar with ADLs performed with a motorized elbow. Before starting the recording, they had 5 minutes to explore the two control strategies. Combining residual limb motion and myoelectric control evoked eventually involuntary muscle contractions. As a result, the participants limited some of their residual limb movements, yielding increased trunk compensations. The inter-joint coordination-based control strategy reduced some of the compensatory movements and reduced the task completion time, but above all, participants were satisfied with the intuitiveness of the tested control method that restored a natural body behavior with synchronized trunk, shoulder, and elbow movements. Better results in terms of precision could be expected with more training.

The A-mode control strategy enabled simultaneous elbow and end-effector control since the residual limb motion drove solely elbow extension, and myoelectric signals were directed towards the prosthetic wrist and hand controllers. As explained in the paragraph V.2, the initial protocol planned to let the participants rotate the wrist and open/close the hand fingers on the targets via their myoelectric signals. However, only the subject S4 was able without training to produce high-quality myoelectric signals while moving the residual limb, which lead to a simplification in the protocol, restricting the study to solely elbow control. The last recruited participant, S3, had also a very good control over his myoelectric signals, which he could synchronize with residual limb motions: his shoulder/elbow coordination pattern during the reaching movements with a myoelectrically-controlled elbow were close to the one of healthy participants. Hence, he was given the opportunity at the end of the session to test the simultaneous control feature combining end-effector and elbow control.

The approach tested synthesized different inter-joint coordinations obtained with 10 able-bodied individuals into one generic coordination model used by the patients to control automatically the prosthesis elbow. By combining healthy individuals' data sets, the generic model assimilates inter-individual variability, but remains different from the prosthesis user's own pointing strategy. Thus, the paradigm whereby the shoulder/elbow coordinations from healthy individuals are driving an elbow prosthesis may not be adapted to prosthesis users, and the present results, although encouraging in terms of compensatory movements reduction, justify for the need of a model tailored to the user's residual movements.

Chapter VI

Conclusion and Perspectives

This dissertation presents a novel prosthetic control strategy whereby the residual limb motion of a transhumeral amputee could drive the motion of a prosthetic elbow based on an inter-joint coordination model. This preliminary work comes within the development of a global intuitive prosthesis control strategy for transhumeral amputees. Most of them are capable of using myoelectric control well, and have a residual limb mobility currently limited by a tightly-strapped harness. Amputation of distal joints alters the behavior of the proximal joints, and ultimately of the entire body, often leading to the development of compensatory strategies that are not reduced by current prostheses, due to complex control strategies, lack of feedback, device weight, etc. Assuming that future developments in the prosthesis industry will improve the prosthesis socket and interface with the wearer's body, the presented work, that is focusing on the reaching gesture, aims at demonstrating that an active prosthetic elbow can be used intuitively, and that it offers great advantages to the prosthesis users.

The research community has approved the coordinated aspect of the human motor control, yielding intuitive command of a limb with redundant kinematic capabilities. Building on literature results, it was shown that kinematic data from 10 healthy individuals could be combined to build a generic model of the shoulder/elbow coordination for the reaching task. IMUs were used to measure the shoulder angles. The concept had been presented in several studies of the literature, however it had never been implemented and tested with transhumeral prosthesis users, mainly due to the use of camera-based motion capture systems to provide inputs to the inter-joint coordination model.

Several modeling approaches were tested to approximate the shoulder/elbow relationship. Their capacity to predict accurately the elbow angular velocity was first tested offline with healthy individuals data recordings. Then, 10 healthy individuals were equipped with the prosthesis prototype that included an externally-powered prosthetic elbow, and they were asked to performed the reaching task with the prosthesis driven by different models of the inter-joint coordination. RBFN-based regression was chosen as the modeling method since it presented the most advantages for the development on an embedded controller.

Six transhumeral amputated individuals achieved a reaching task with the prosthetic prototype driven by a generic model of the inter-joint coordination built from a combination of healthy individuals' data. For comparison, the participants performed the reaching task with a conventional dual-site myoelectric elbow control mode,

and with the automatic elbow control mode. The results showed that in addition to reach the targets with both control modes, the trunk movements were reduced and the shoulder/elbow synchronization was restored with the A-mode. If only few participants were particularly good with a myoelectrically-controlled elbow, they were all able to use an automatically-driven elbow with a good performance. The participants appreciated the intuitiveness of the proposed control method that enabled for two participants simultaneous control of the elbow (via the A-mode) and the end-effector (with the myoelectric signals that were no longer necessary for the control of other joints). Hence, this study showed that reaching targets with an automatically-driven elbow was possible, and that it was beneficial to the users: the compensatory strategies and the required cognitive load were reduced, and simultaneous elbow and end-effector control was enabled.

Despite mitigated results in terms of performance, the overall feeling of all amputated participants is satisfying: not controlling the prosthetic elbow motion explicitly provides faster and more fluid movements than with a myoelectric control strategy. By automating the elbow motion, participants could focus and hand motion, and ultimately to the task. Participants could only test the automatic control strategy on a reaching task. However, reaching for an object, along with manipulating an object, returning the hand to the body, and bringing the hand to the face, are the most performed movements in ADLs of healthy individuals. Most of these movements cannot be performed by a transhumeral amputated person equipped with a commercial prosthesis: wearers bring the objects to the prosthetic hand with their contralateral limb and only actuate the prosthetic hand to hold the objects. An automated elbow control strategy could increase the catalog of ADLs that can be performed with the prosthesis, for instance with tasks performed away from the body. This work could be replicated to other tasks, hence adding more gestures to the catalog of automated elbow movements. Thus, one could imagine a global control framework that switches between the different modeled shoulder/elbow coordination models, depending on the task to be performed. Moreover, as residual limb motion drives the elbow motion, myoelectric signals can always be in charge of the hand control. Even though the experimental results showed that moving the residual limb as contracting the residual muscles voluntarily requires training, simultaneous control is a sought feature for prosthesis wearers and two of the recruited participants achieved to extend the elbow and flex the hand simultaneously without training.

Through the experimental sessions with the amputated participants, it could be observed that each wearer had a different use of the prosthetic device, especially in terms of residual limb mobility, and myoelectric capabilities. The residual limb's amplitudes were in some cases limited, especially for participants with an externally-attached prosthesis. Because of the socket-related impairments and post-amputation sensorimotor modifications, the residual limb movements showed dissimilarities with the expected inputs of the inter-joint coordination model. Therefore, the study also illustrated that the utilization of a model of healthy inter-joint coordinations to control prosthetic joints was limited by the residual limb movements that can be kinematically different from healthy upper limb movements. It shows the need for novel modeling methods and mapping designs that bring the user back to the center of the control development process in order to achieve a more natural and personal prosthetic motion.

Appendix A: Ethical approval

This work was carried out in accordance with the recommendations of the Université Paris Descartes ethic committee CERES, which had approved the protocol covering experiments at ISIR with healthy participants and at IRR of Nancy with patients in April 2016. In addition, a collaboration was developed with Chalmers University to test the developed elbow control strategy with osseointegrated transhumeral amputees. The protocol was approved by the local ethic committee of Göteborg, Sweden in February 2017.

Comité d'éthique de la recherche en santé (CERES)

Président : Denis Berthiau

N° 2016/30

PROTOCOLE : Évaluation de nouvelles stratégies de commande de prothèse du membre supérieur.

Noms du/ des chercheur(s) : Manelle Mérad, Nathanaël Jarrassé.

**Email pour la correspondance :
merad@isir.upmc.fr**

Labo/ Service: ISIR

Évalué à la séance du : 12 Avril 2016

AVIS : Favorable

Ce protocole ne pose pas de problème d'éthique particulier.

N°IRB : 20163000001072



Skelettförankrade amputationsproteser på övre extremiteterna- behandlingsmetodik, kirurgi, protetik och rehabilitering.

INKOM

2017 -02- 22

Etikprövningsnämnden i
Göteborg

Regionala Etikprövningsnämnden i Göteborg
Box 401, 405 30 Göteborg

Dnr

.....T 164-17.....

Göteborg, den 17 februari 2017

Ad

.....626-10.....

Granskad och godkänd som sekreterarärende
Göteborg 27/2-17

Betalit

.....2017-03-09.....

Gunnar Göthberg, docent, vetenskapl sekr
Med avd 1
Regionala Etikprövningsnämnden i Göteborg

Exp

.....2017-03-13.....

Komplettering till ansökan: *Skelettförankrade amputationsproteser på övre extremiteterna- behandlingsmetodik, kirurgi, protetik och rehabilitering. Diarienummer 626-10 Exp. 2010-12-07*

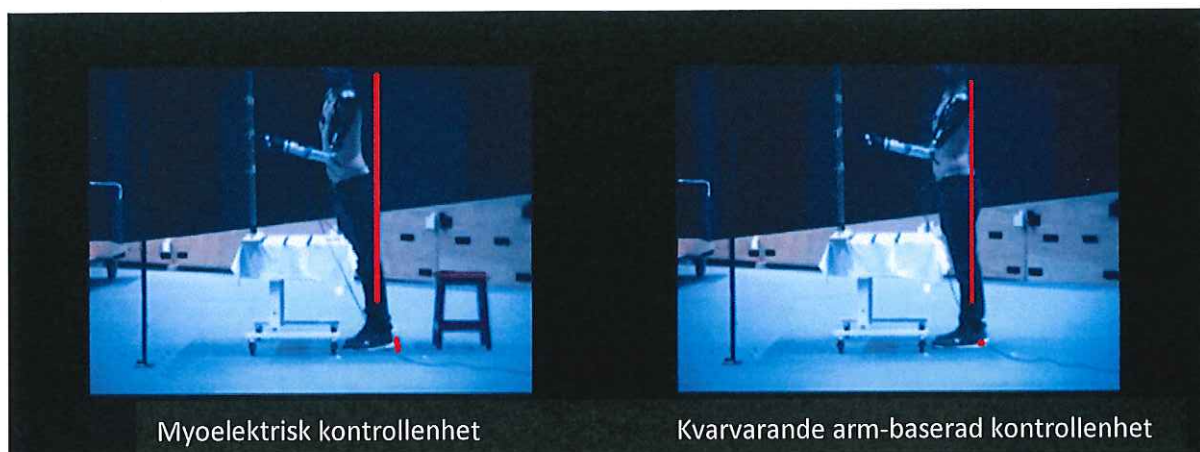
Vi önskar göra ett tillägg till ovanstående ansökan. Detta delprojekt ämnar att jämföra två olika kontrollstrategier/kontrollenheter av armbågen och dess påverkan på kompensationsrörelser och uppgiftsutförande.

Sex stycken överarmsamputerade som använder myoelektriska OI-proteser kommer att delta. En protes kommer att fästas på forskningspersonens stump. Denna protes har en motordriven armbåge (modifierad Hosmer E-Two) och en motordriven handled (Ottobock 10s17 handled rotator). Man kan koppla vilken hand som helst till protesen. Protesens styrenhet läser data från två tröghetsmätningenheter (Inertial Measurement Unit; IMU) och data från de myoelektriska elektroderna.

Testet består av två delar där forskningspersonen 1) utför funktionalitetstester med protesen med en icke-modifierad styrenhet (full myoelektrisk kontroll); 2) utför samma tester med protesen med en modifierad styrning för armbågen. I del två styrs armbågen av axelledsrörelser.

Under testerna kommer försökspersonens kroppsrörelser spelas in med ett "motion capture-system". Inspelningarna kommer användas till att analysera i vilken utsträckning forskningspersonen använder kompensatoriska rörelser för att fullborda uppgifterna, samt hur väl uppgifterna utförs. Hela testet kommer att ta ungefär tre timmar.

Studien kommer att genomföras i anslutning med att forskningspersonerna kommer till kliniken och forskningspersonen behöver därmed inte kallas in en extra gång enbart för mätningen. Data som behandlas kommer att sammanställas och alla register kommer kodas och avidentifieras. Kodlista/kodnyckel kommer att förvaras i utrymme skilt från databas.



Exempel på kroppskompensatoriska rörelser vid två armbåges kontrollenheter.

Skelettförankrade amputationsproteser på övre extremiteterna- behandlingsmetodik, kirurgi, protetik och rehabilitering.

Utförande

1. Forskningspersonen informeras om hur studien kommer utföras.
2. Protesen kommer förberedas och sedan fästas på forskningspersonens stump, motion capture-systemet kommer att monteras på kroppen.
3. Forskningspersonen blir ombedd att utföra specifika övningar med de två olika typerna av armbågsstyrning beskrivna ovan.
4. Protesen och motion capture-systemet avlägsnas och testet är klart.

Med vänlig hälsning,

Mölnadal 170220

Ort och datum

Kerstin Caine-Winterberger

Kerstin Caine-Winterberger,
Huvudansvarig forskare

Appendix B: Prototype

B.1 Structure

A picture of the prototype is presented in Fig. B.1A. The structure has been printed with ABS and reinforced with metal parts. Most of the electronics are located in the forearm part, in between the elbow and the wrist joints. The structure's main characteristics are described in Table B.1. Fig. B.1B depicts a bottom view of the prototype with power and USB inputs; a switch button enables the use of a stabilized power source or batteries.

B.2 Actuators

There are two actuators in the system: the wrist and the elbow. Both are modified commercialized products.

The wrist, Fig. B.2A, is a conventional electrical wrist rotator (model 10S17, Ottobock©) on which can be plug a myoelectric prosthetic hand. The connector has 4 pins that allows the transmission of EMG signals to the prosthetic hand. Also, the cylinder/cylinder junction enables infinite rotation in both directions (pronation and supination). All embedded electronics dedicated to the control has been removed from the original component that is left as a simple geared motor device.

The elbow is a commercialized Hosmer elbow© B.2B. A 2048-point magnetic encoder (Faulhaber 2232U006S R IEH2-2048©) has been added to control the 6V-motor (Faulhaber 2232.D0633©). Moreover, in order to ensure precise closed-loop motor

Weight	with batteries	880 g
	without batteries	810 g
Length	full extension	313 mm
	elbow center to wrist	250 mm
Diameter (elbow side)	external	73 mm
	internal	65 mm
Diameter (wrist side)	external	58.36 mm
	internal	50.3 mm
Maximum current when running		3200 mA
Voltage		7.0 V - 8.3 V

Table B.1 – General characteristics of prosthetic forearm prototype.

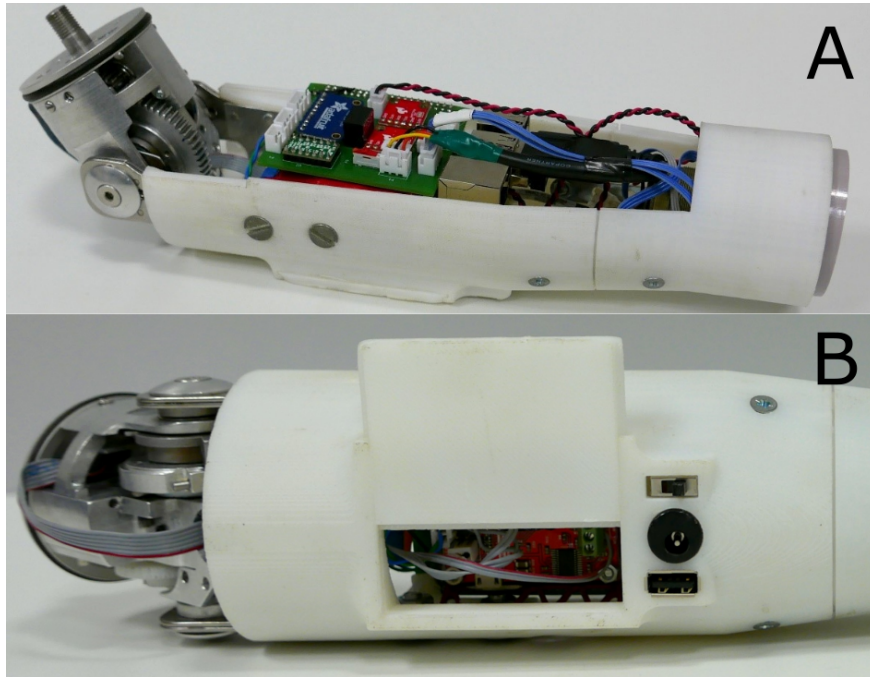


Figure B.1 – A: Prosthetic forearm prototype composed of a motorized elbow and a wrist rotator. B: Bottom view of the prototype.

control, the sliding transmission part has been modified such that it only have geared motor transmission.

The bandwidth of the elbow prototype (with its PID velocity control loop) has been experimentally characterized. To this end, sinusoidal velocity signals (with different frequencies) were sent to the prototype's controller, while the absolute velocity output of the prototype was measured with a camera-based motion capture system (Codamotion). The identified bandwidth of the prototype is [0-6 Hz]; the bode phase diagram, depicted in Fig. B.3, indicates a 90-deg phase shift for frequencies over 6 Hz.

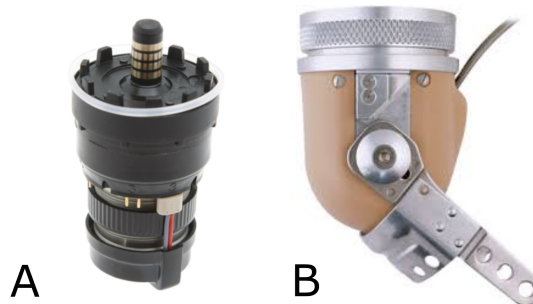


Figure B.2 – A: Electrical wrist rotator, Ottobock©. B: Hosmer elbow©.

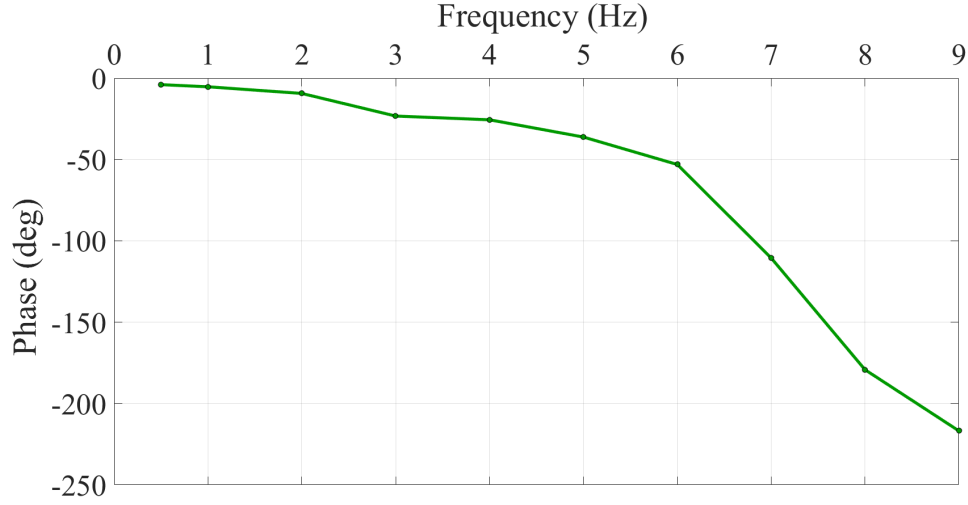


Figure B.3 – Bode phase diagram of the prosthesis prototype.

B.3 Electronics

All the electronics are controlled by a Raspberry Pi 3 using the Jessie OS from Debian (Linux). The overall control scheme is summarized in Fig. B.4.

- The Raspberry Pi 3 (Fig. B.5) has a 1.2 GHz 64-bits quad-core ARMv8 CPU, and a 1-GB RAM. Its computing speed enables to run the program at 100 Hz.
- TouchScreen User Interface: a RoboPeak 2.8" USB TFT touchscreen can be used as user interface during experiments. It is plugged to the Raspberry.
- Two x-IMUs (x-io Technologies) are providing the coordination-based algorithm's input data. Connected through USB ports to the Raspberry, they send quaternions values, and inertial values at 128 Hz or 256 Hz.
- An ADC (ADS1115 16-bits ADC) is used to read EMG signals from the patients' myoelectric electrodes. These signals are used for wrist or hand control. Hand prosthesis has a built-in controller, and needs only the EMG signals as inputs, which is provided by two DAC (MCP4725 Breakout Board 12-bits DAC) through the 4-pin connector of the wrist rotator. Both SAC and ADC use I2C connection with the Raspberry.
- The two motors are controlled by a RoboClaw 2x7A Motor Controller from Ion Motion Control, which is itself controlled by the Raspberry through UART connection. The elbow motor is closed-loop controlled easily by the RoboClaw which integrates dual quadrature decoders, whereas the wrist is open-loop controlled.

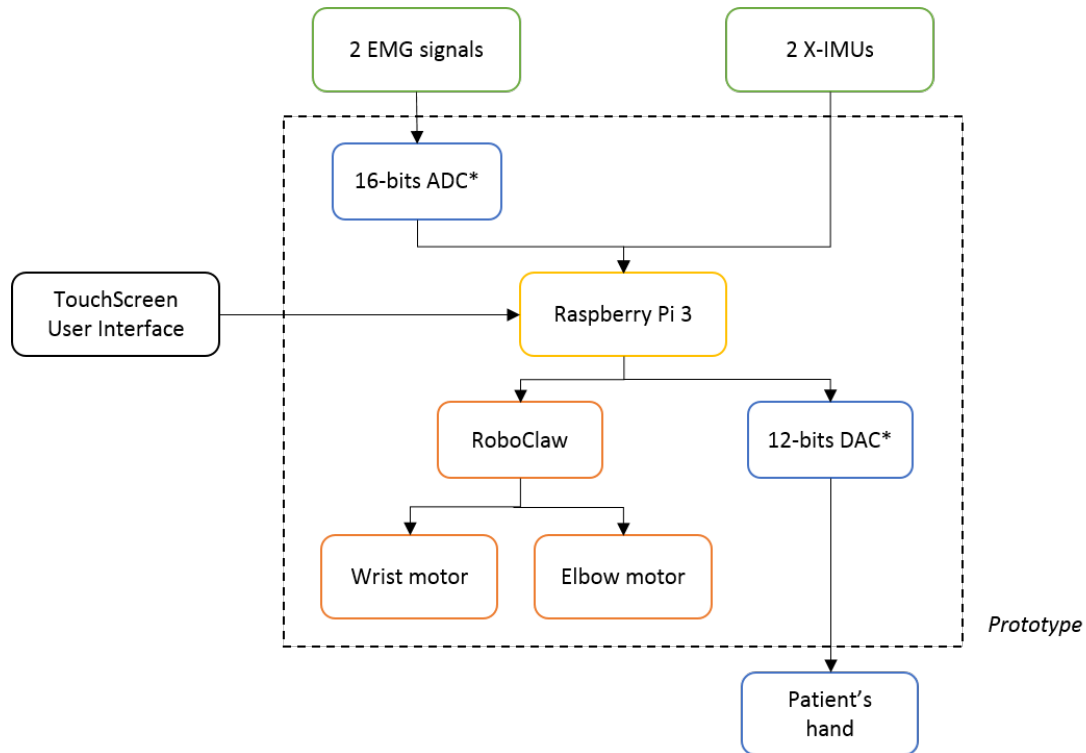


Figure B.4 – Control scheme of the prototype electronics. ADC: Analog to Digital Converter, DAC: Digital to Analog Converter.

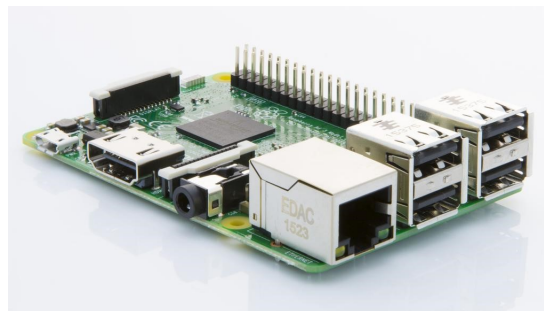


Figure B.5 – A Raspberry Pi 3 controls the prototype electronics.

B.4 Power

The electronics and the motors are powered either by a stabilized power supply, or by two Lithium ion polymer batteries (3.7 V - 2000 mAh). Motors are directly powered from the main source, while the electronics require 5 V: a TracoPower TSR 1-2450© is subsequently used to convert the voltage.

Appendix C: Individual results

Each of the following plots represents the values of the performance and the body kinematics assessment metrics for amputated participants' data. General information about the participants is grouped in Table C.1. The task was performed with the control strategies: the ME-mode (represented in dark/light blue), and the A-mode (represented in dark/light red). For each target, two values are depicted for each of the 6 subjects: the first value (dark blue for Group 1, and light blue for Group 2) represents the metrics values for gestures performed with the ME-mode, the second value (dark red for Group 1, and light red for Group 2) represents the values for gestures performed with the A-mode. The results are compared to a healthy baseline, corresponding to the control situation; it represent by grey bars with a central line corresponding to the average metric value for individuals in the control situation.

	Gender M/F	Age	Height	Amputation		Osseo. [†]	EMG
S1 ◯	M	34 yo	1m80	Left	2014	No	Surface
S2 ◻	M	36 yo	1m68	Left	2017	No	Surface
S3 ▽	M	41 yo	1m87	Right	2015	No	Surface
S4 ◇	M	43 yo	1m85	Left	2011	Yes	Implanted
S5* ▷	M	28 yo	1m75	Left	2006	Yes	Surface
S6 ◯	M	42 yo	1m87	Right	1997	Yes	Implanted

[†] Osseointegration.

* S6 had undergone bilateral transfemoral amputation, in addition to a left transhumeral amputation.

Table C.1 – Amputated participants' general information

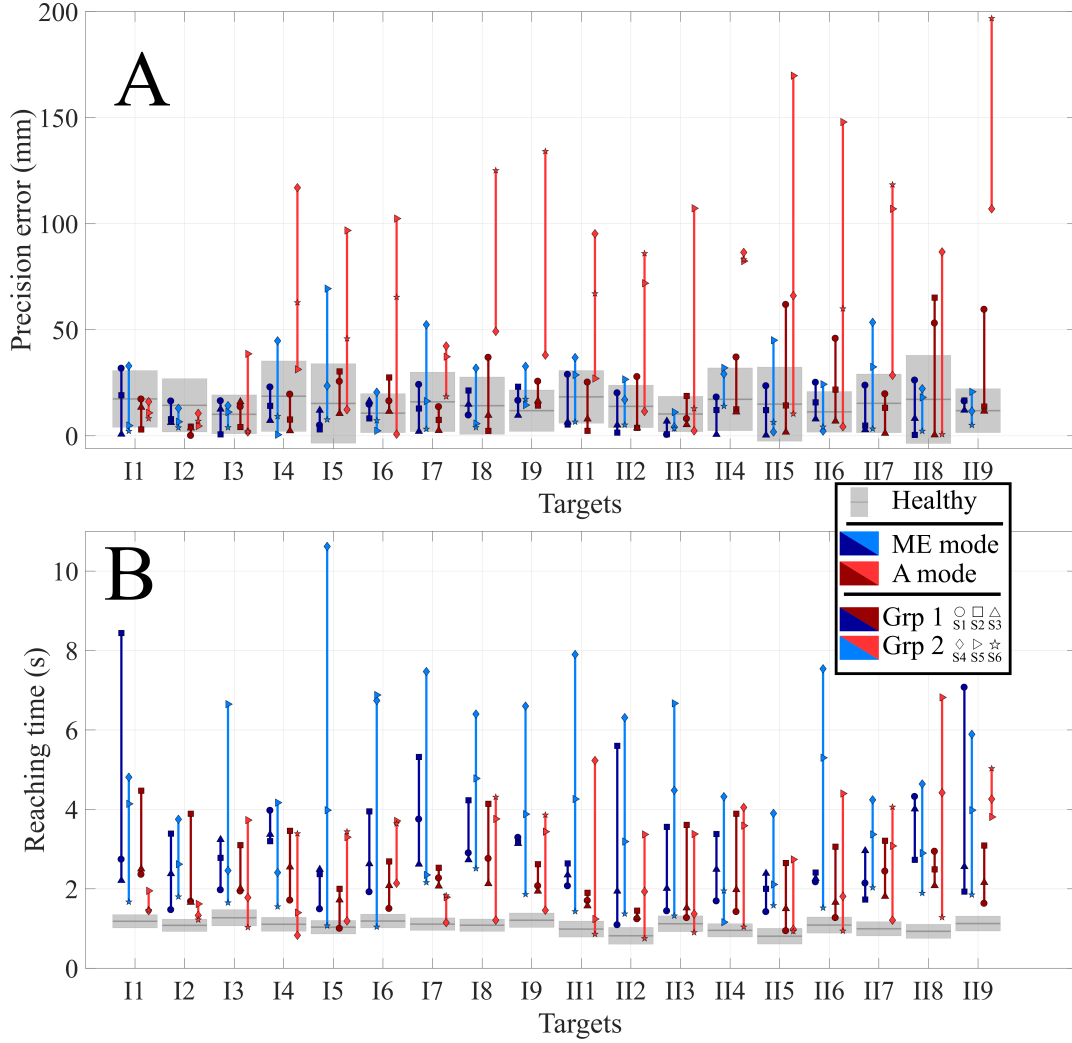


Figure C.1 – Precision errors (A) and task completion times (B) in ME-mode (dark/light blue) and A-mode (dark/light red) for all targets, computed before re-adjustments of the end-effector position. Each marker represents the metric for one participant; data of participants with a conventional external socket (Group 1 - Conv) are represented with dark colors, and data of osseointegrated participants (Group 2 - Osseo) are represented with light colors. Grey lines and shaded areas represent the average precision error ($\pm$ standard deviation error) for healthy individuals recruited in the model training data acquisition experiment. Precision errors (A) and task completion times (B) in ME-mode (blue bars) and A-mode (red bars) for all targets (distance Ii, distance Iii, where i represents the target number), computed before re-adjustments of the end-effector position. Blue (resp. red) bars represent the mean value (short red line) of the precision error (A) and the completion time (B) plus and minus the standard deviation with the ME-mode (resp. A-mode). Grey lines and shaded areas represent the average precision error and completion time ($\pm$ standard deviation) of the control situation.

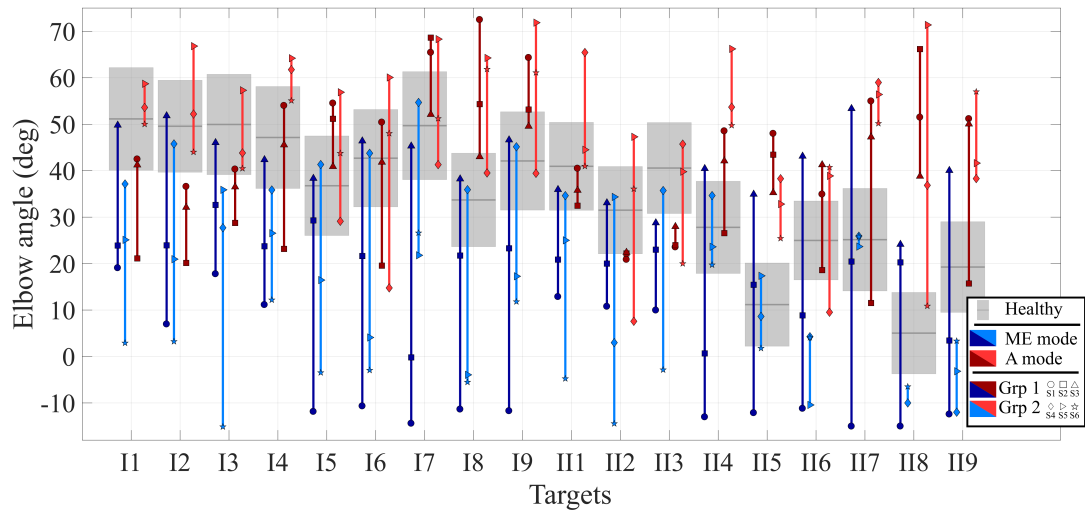


Figure C.2 – The difference between the final and initial elbow angle values, defined as the elbow angle variation, is depicted for each target and each participant. The elbow prosthesis was used differently depending on the control strategy (myoelectric in dark/light blue, and automatic in dark/light red).

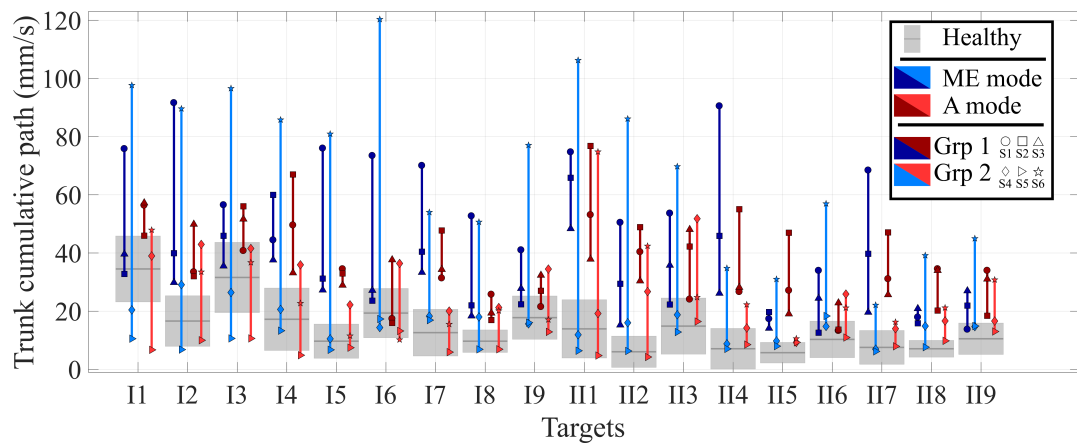


Figure C.3 – Analysis of trunk compensatory movements. The cumulative trajectory of the thorax center quantified the trunk's displacements during each reaching movement; for each movement, it was normalized with the completion time, leading to the trunk mean speed value.

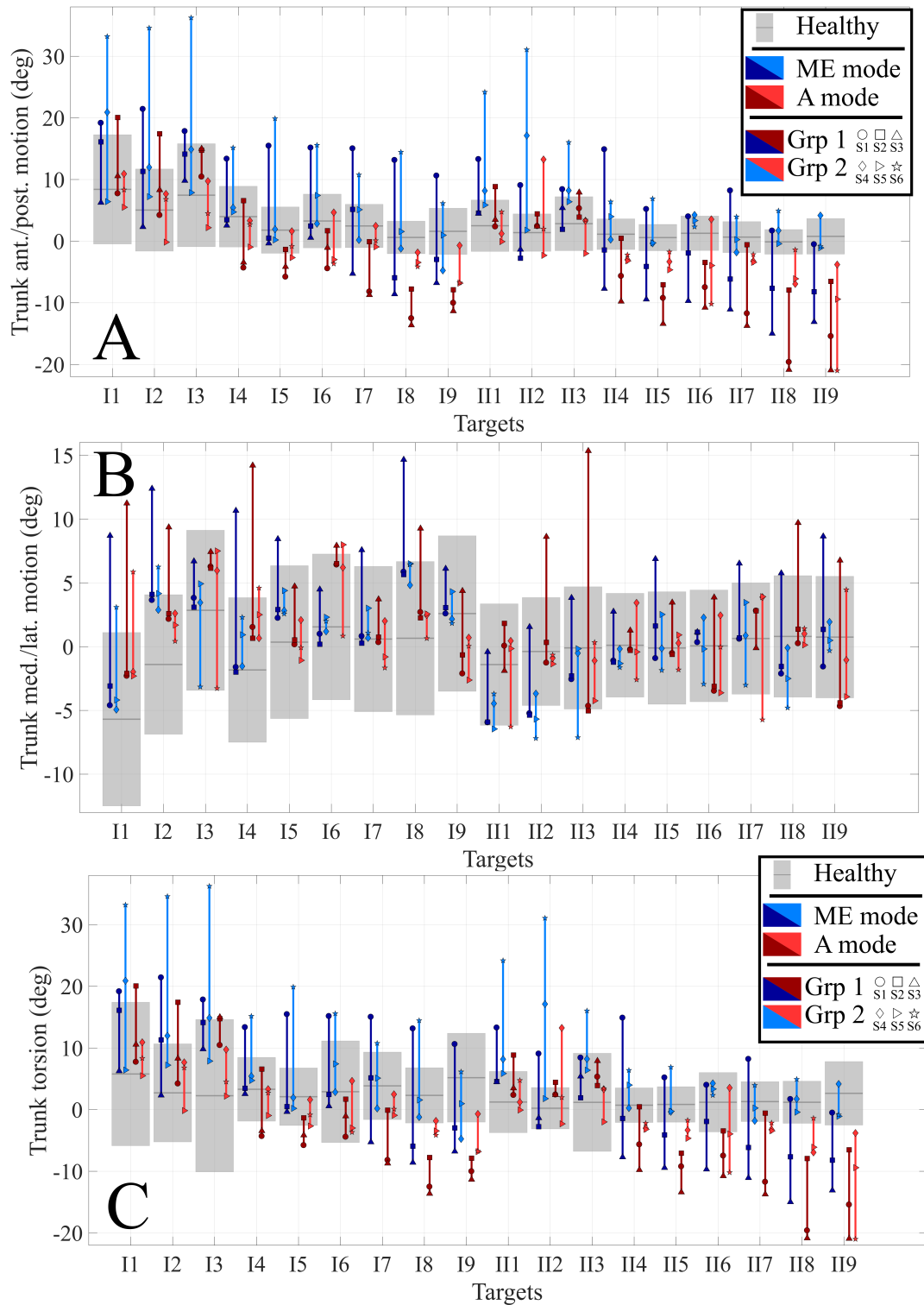


Figure C.4 – Variations of the three angles describing the trunk motions for each targets. A: Trunk anteroposterior bending. B: Trunk mediolateral bending. C: Trunk torsion.

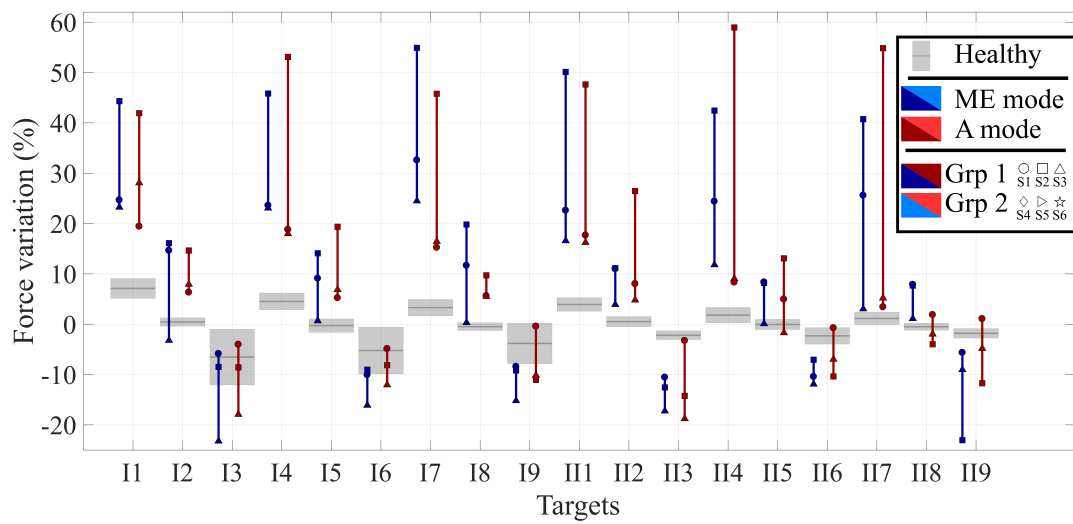


Figure C.5 – Variation of the amount of force applied by the ipsilateral foot with respect to the total force between the beginning and the end of each reaching movement. Only values with participants in Group 1 could be measured.

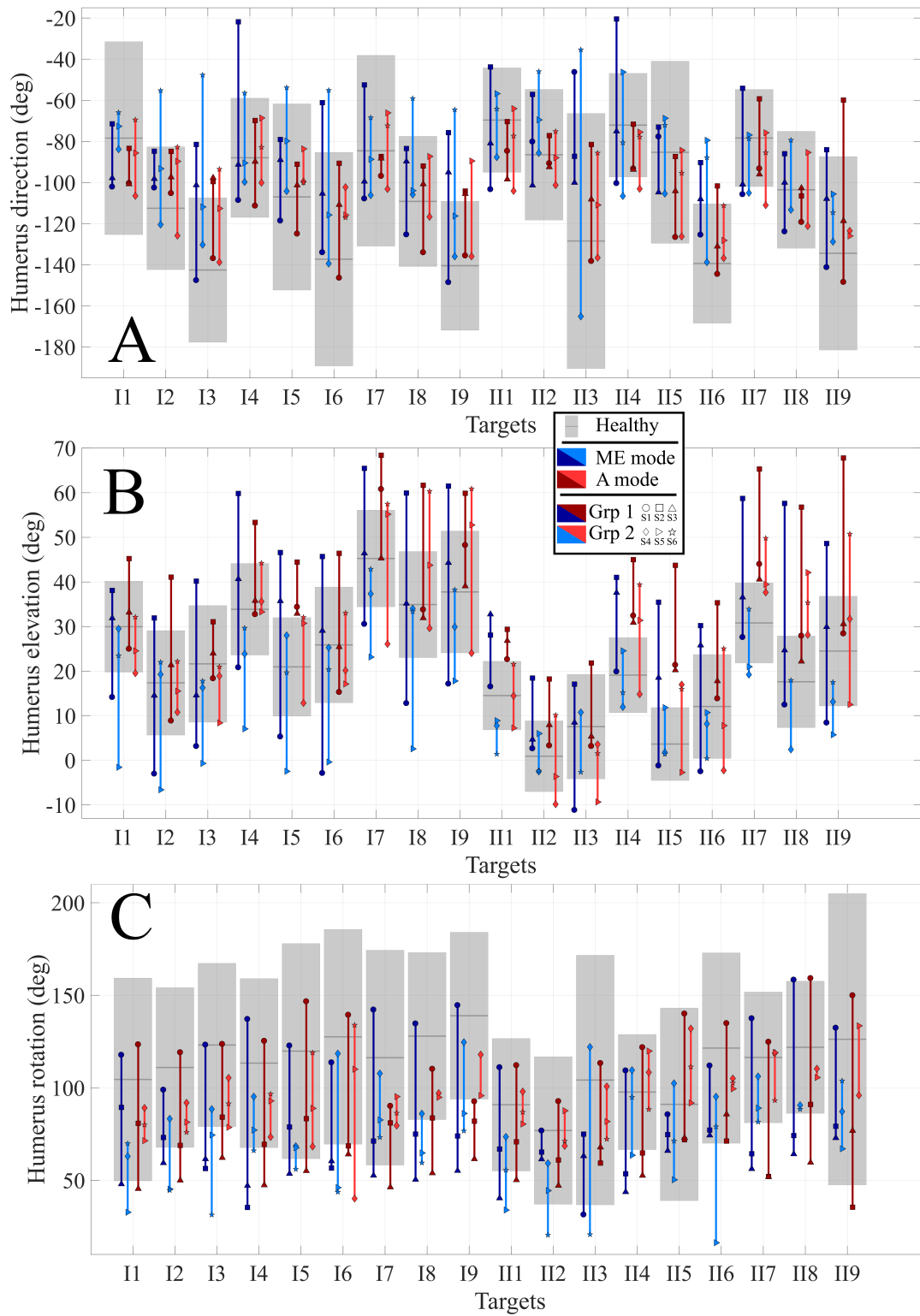


Figure C.6 – Variations of the three angles describing the residual limb motions for each targets. A: Humerus direction. B: Humerus elevation. C: Humerus rotation.

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