

Online Personalisation of Human-Prosthetic Interfaces

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Abstract

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Upper-limb loss affects over 541,000 people in the US, and over 3,500 new amputations are reported each year in countries like Italy and the UK. The daily life of people living with upper-limb loss is severely impacted as the arm is a human's principal means of interaction with the environment. Moreover, the limitations of current human-prosthetic interfaces result in prosthesis users relying on compensatory motion to achieve activities of daily living, which may result in overuse injuries. This is due to prosthesis users only being able to control the degrees-of-freedom in the prosthesis sequentially. To address this challenge, the prosthetics community has looked into motion-based human prosthetic interfaces.

Novel motion-based human-prosthetic interfaces use the motion of the residual-limb to determine the motion of the prosthesis. Typically, this relationship between the residual-limb and prosthesis is established from the motion of able-bodied individuals. However, their application to prosthesis users has been a challenge due to individual differences in motor behaviour and amputation physiology. Therefore, it has been identified in the literature that kinematic synergy-based HPIs need to be personalised to their users.

The scope of the research presented in this thesis is to provide a framework for autonomously personalising human-prosthetic interfaces. The proposed framework is based on a data-driven optimisation approach. The contributions of this thesis surrounding the proposed data-driven-based framework are as follows. First, the feasibility of using online optimisation methods in motion-based human-prosthetic interfaces is demonstrated experimentally. Second, the features of motor preference and motor adaptation in human motor behaviour, which affect the performance of a task with a motion-based prosthesis, are experimentally observed and characterised in a grey-box model. Third, an online personalisation algorithm for human-prosthetic interfaces was developed based on the algorithm of Fast Extremum Seeking. The algorithm uses the grey-box model of human motor preference and adaptation to inform the design of the components of the algorithm.

An alternative model-based method for motion-based human-prosthesis interface personalisation is also proposed, where user-specific kinematic information is employed. This novel “task-space synergy” incorporates task information in the formulation of kinematic synergy-based human-prosthetic interfaces. The method uses desired hand path information, a kinematic model of the human-prosthesis arm, and the motion of the residual-limb to determine the motion of the prosthesis joints.

Declaration of Authorship

I, Ricardo Garcia-Rosas, declare that this thesis titled, “Online Personalisation of Human-Prosthetic Interfaces” and the work presented in it are my own. I confirm that:

- The thesis comprises only my original work towards the Doctor of Philosophy degree except where indicated in the preface;
- due acknowledgement has been made in the text to all other material used; and
- the thesis is fewer than the maximum word limit in length, exclusive of tables, maps, bibliographies and appendices as approved by the Research Higher Degrees Committee.

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Date:

Preface

- The following is the publication status of the chapters presented in this thesis;
 - The contents of Chapter 3 have been partially published in the IEEE Transactions on Cybernetics in 2019 and are in revision following peer review in the IEEE Transactions on Neural Systems and Rehabilitation Engineering.
 - The contents of Chapter 4 have been published in the Proceedings of the American Control Conference in 2018 and in the Proceedings of the Engineering in Medicine and Biology Conference in 2018.
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Abbreviations

HPI(s)	H uman- P rothetic I nterface(s)
sEMG	S urface E lectromyography
TMR	T argeted M uscle R einnervation
CNS	C entral N ervous S ystem
ADLs	A ctivities of D aily L iving
ANN(s)	A rtificial N eural N etwork(s)
ES	E xtremum S eeking
VR	V irtual R eality
HMD	H ead M ounted D isplay
VRE	V irtual R eality E nvironment
VR	V irtual R eality
DOF(s)	D egree(s) O f F reedom
FES	F ast E xtremum S eeking
PLS	P lain L anguage S tatement
LTI	L inear T ime I nvariant
MSE	M ean S quare E rror
I-SSO	I ntput to S tady S tate O utput
PE	P ersistency of E xcitation
IMU	I ntertial M easurement U nit
SA	S houlder A cromion
UA	U pper A rm
LA	L ower A rm
AB	A ble-bodied
EP	s EMG P roportional
TS	T ask-space S ynergy

JS	J oint-space S ynergy
PC	P rothetic C ase
SAL	S pectral A rc L ength

Symbols

Symbol	Name
rad	Radians
s	Seconds
N	Newtons
m	Meters
cm	Centimeters
$\mathbb{R}$	Real numbers
$\mathbb{R}_+$	Positive real numbers
$\mathbb{N}$	Natural numbers
$\mathbb{N}_+$	Positive natural numbers
$\mathbf{q}_r$	Residual limb joints pose
$\dot{\mathbf{q}}_r$	Residual limb joints angular velocity
$\ddot{\mathbf{q}}_r$	Residual limb joints angular acceleration
$\mathbf{q}_p$	Prosthetic joints pose
$\dot{\mathbf{q}}_p$	Prosthetic joints angular velocity
$\ddot{\mathbf{q}}_p$	Prosthetic joints angular acceleration
$\boldsymbol{\theta}$	Synergy parameter vector
Θ	Parameter set of interest for $\boldsymbol{\theta}$
J	Objective function
J_h	Human objective function
J_p	Prosthesis objective function
q_{abd}	Joint abduction/adduction angle
q_{fle}	Joint flexion/extension angle
q_{rot}	Joint rotation angle
q_{elb}	Elbow rotation angle

$\mathbf{M}_r$	Residual limb generalized inertia matrix
$\mathbf{C}_r$	Residual limb Coriolis and centrifugal matrix
$\mathbf{G}_r$	Residual limb gravity matrix
$\mathbf{Z}_r$	Residual limb and prosthesis interconnections matrix
$\boldsymbol{\tau}_r$	Torques at the residual limb joint
$\mathbf{M}_p$	Prosthesis generalized inertia matrix
$\mathbf{C}_p$	Prosthesis Coriolis and centrifugal matrix
$\mathbf{G}_p$	Prosthesis gravity matrix
$\mathbf{Z}_p$	Prosthesis and residual limb interconnections matrix
$\boldsymbol{\tau}_p$	Torques at the prosthetic joint
$\mathbf{p}$	Hand position in space
$\dot{\mathbf{p}}$	Hand velocity in space
$\ddot{\mathbf{p}}$	Hand acceleration in space
$\ddot{\mathbf{p}}$	Hand jerk
$\mathcal{J}$	Arm Jacobian
α	Objective function (J) weight
ψ	Non-linear mapping component of the objective function
t_o	Initial time/start time
t_f	Final time/end time
v_q	Human joint trajectory/position variation
v_t	Task completion time variation
v_p	Hand trajectory/position variation
$\Delta\boldsymbol{\tau}$	Motor behaviour variation in joint torques
u_θ	Synergy-performance static map
u'_θ	Gradient of the synergy-performance static map
u''_θ	Curvature (Hessian) of the synergy-performance static map
$\bar{\boldsymbol{\lambda}}$	Human motor performance parameter vector
y	Output of human motor adaptation LTI system
$\bar{v}$	Human motor variation scalar
$\bar{\Phi}$	Human motor adaptation LTI dynamics matrix
$\bar{\Gamma}$	Human motor adaptation LTI input matrix
$\bar{\Psi}$	Human motor adaptation LTI output matrix
I_n	Identity matrix in $\mathbb{R}^{n \times n}$

$\mathbf{w}$	Filter state vector
ω_o	Dither frequency
Φ_f	Filter dynamics matrix
Γ_f	Filter input matrix
Ψ_f	Filter output matrix
$\mathbf{z}$	Observer state vector
Φ_o	Observer dynamics matrix
Ψ_o	Observer output matrix
$\mathbf{L}$	Observer gain vector
$\mathcal{S}_n$	$\sin(n\omega_o i)$
$\mathcal{C}_n$	$\cos(n\omega_o i)$
k	Optimiser gain
ε	Gradient region threshold
Δ	Gradient ratio used in optimiser
a	Dither gain
$\mathbf{d}$	Dither generator output
x_t	Trunk forward displacement
$\bar{x}_t$	Desired trunk forward displacement
x_s	Shoulder forward displacement
$\bar{x}_s$	Desired shoulder forward displacement
$\boldsymbol{\theta}_{ss}$	Steady-state synergy parameter vector
r_{SH}	Vector from shoulder joint to hand
$\{R\}$	Reference frame of reference
$\{H\}$	Hand frame of reference
$\{E\}$	Elbow frame of reference
$\{D\}$	Direction of motion frame of reference
$\mathbf{v}$	Hand velocity in space
$\mathbf{q}_s$	Shoulder joint pose
$\dot{\mathbf{q}}_s$	Shoulder joint angular velocity
$\mathbf{q}_e$	Prosthetic elbow pose
$\dot{\mathbf{q}}_e$	Prosthetic elbow angular velocity
d_{SE}	Length from shoulder joint to elbow joint
d_{EH}	Length from elbow joint to the hand

${}^D_R\mathbf{R}$	Frame transformation from $\{R\}$ to $\{D\}$
$\mathbf{R}_y(\alpha)$	Rotation matrix along the y -axis of α angle
C_α	Cosine of angle α
$C_{\alpha\beta}$	Cosine of the sum of angles α and β
S_α	Sine of angle α
$S_{\alpha\beta}$	Sine of the sum of angles α and β
ℓ_u	Upper-arm length
ℓ_l	Lower-arm length
ϵ_q	Bound on angle q
t_f^μ	Median of population task completion time
δ^μ	Mean of population reach terminal error
η	Spectral Arc Length
σ_μ	Mean standard deviation of the hand and joint paths across
Δ_μ	Hand or joint path difference
$\mathbf{x}_{AB}$	Able-bodied hand or joint path
$\mathbf{x}_{PC}$	Prosthetic hand or joint path
ϕ^μ	Upper-body displacement

Notation

The following notation is used throughout the Thesis. The set of real numbers is denoted as $\mathbb{R}$, the set of positive real numbers is denoted as $\mathbb{R}_+$. The set of natural numbers is denoted as $\mathbb{N}$, the set of positive natural numbers is denoted as $\mathbb{N}_+$. The term “synergy” is used to describe the parametrization of the human-prosthesis interface. For a given static mapping $y_x = h(x) : \mathbb{R} \rightarrow \mathbb{R}$, its gradient is expressed as $y'_x = \partial h(x)/\partial x$, and curvature (Hessian) as $y''_x = \partial^2 h(x)/\partial x^2$. The subscript x_i is used to indicate the iteration domain, such that x_i indicates the i th iteration of x , where an iteration represents a repetition of the task. The “bar” notation on a variable, e.g. $\bar{\lambda}$, indicates that the variable is individual dependent. The measured performance of a given task is characterized by the performance $\hat{J}_i \in \mathbb{R}_+$. The synergy parameters are given by $\theta_i \in \Theta$, where Θ is a compact set in $\mathbb{R}$ representing the parameter set of interest. The left hand superscript ${}^R\mathbf{x}$ is used to indicate the frame of reference $\{R\}$ of the vector $\mathbf{x}$. $\|\cdot\|_2$ represents the Euclidean norm. $\mathbf{r} \times \mathbf{p}$ represents the cross product between vectors $\mathbf{r}$ and $\mathbf{p}$.

Chapter 1

Introduction

1.1 Motivation

The upper-limb allows humans to interact with the environment and perform many of the tasks encountered in day-to-day life. These tasks, while appearing simple, require complex coordinated motion of the multiple degrees of freedom in the human arm [1]. Upper-limb loss affects over 541,000 people in the US, and over 3,500 new amputations are reported each year in countries like Italy and the UK [2, 3]. The daily life of people living with upper-limb loss is severely impacted as the arm is a human's principal means of interaction with the environment [4], such that basic activities of daily living (ADLs) like eating, pouring water into a glass, and brushing teeth become arduous. This occurs as a result of people living with upper-limb loss resorting to compensatory movements and different strategies for interaction that utilise only their remaining able-bodied limb and the residual limb where the amputation occurred [3, 5].

Prosthetic devices are designed to return amputees capabilities reduced due to limb loss. In the case of upper-limb loss, these capabilities are related to the function of the human arm and hand, which include reaching and grasping [3, 6, 7]. Returning these capabilities to amputees becomes harder as the level of amputation increases. For instance, in the case of below-elbow (transradial) amputations, it is necessary to restore grasping capabilities, which include hand orientation, due to the loss of the hand and wrist joint. As such, a typical transradial prosthetic device is composed of a hand that can open and close, and a single degree-of-freedom (DOF) wrist that can orient the

hand. On the other hand, in the case of above-elbow (transhumeral) amputations, both reaching and grasping capabilities are lost due to the loss of the hand, and the wrist and elbow joints. As such, a typical transhumeral prosthetic device is composed of a hand that can open and close, a single DOF wrist, and an elbow joint. While transhumeral prostheses aim to replace the missing joints in above elbow amputations, achieving the same functionality as the human arm is a challenge due to the complex coordinated motion required by the tasks.

1.2 State-of-the-Art and Scope

State-of-the-art prostheses employ active mechanisms to actuate their joints, while a form of human-prosthesis interface (HPI) is employed for the amputee to provide commands to the prosthetic device, and thus control its movement. The most common HPI for active prostheses to-date are based on surface electromyography (sEMG) [8, 9]. sEMG detects muscle activation through the voltage differentials generated by muscles, which can be measured through the skin [8]. In HPIs, sEMG sensors are placed on the muscles in the residual limbs; thus, the number of signals available for the HPI depends on the level of amputation. For instance, in a transhumeral case the residual muscles are the biceps and triceps; then, two signals can be obtained from sEMG sensors.

Two challenges have been identified with this type of HPI, the first due to its mode of operation and the second due to the dimensionality difference between the control signals required by the prosthesis and the available signals in the HPI [3, 7, 10, 11]. Regarding the mode of operation, the commands provided to the prosthesis are given by muscle activation, which has been deemed unintuitive as it is widely accepted that humans plan motion in task-space rather than muscles [12, 13]. Regarding the dimensionality difference, a prosthesis has multiple joints that need to be precisely coordinated to achieve a task; on the other hand, a traditional sEMG HPI is limited to the few signals that can be extracted from the residual limb. This difference between the control signals available and the joints that need to be controlled leads to amputees commanding their prosthesis joint-by-joint. While there are novel approaches that increase the number of independent sEMG signals an amputee can generate, such as targeted muscle reinnervation [14] and pattern recognition [15–18], these are not sufficient to allow the simultaneous and coordinated control of multi-articulated prosthetic devices. This is

due to the fact that users of these HPIs need to re-train their muscles to be able to voluntarily and independently activate them to provide commands to the prosthesis [8].

Restoring the reaching capabilities of above elbow amputees is a significant challenge as it requires coordinating the multiple joints in the prosthetic device with those of the user's residual limb. Unlike lower-limb prostheses where the motion is cyclical [19–21], and thus can often be estimated, the upper-limb has a wide range of different motions it can perform and the tasks performed with it are varied. Moreover, given its redundancy, there are infinite poses the upper-limb can take to perform a task. As such, the prosthetics research community has taken inspiration from the human motor theory of synergies. This theory suggests that the central nervous system (CNS), in order to control the large number of muscles that generate the motion of the human body, creates muscle groups whose movement is synchronously regulated through a few variables [22–24]. This grouping and coordination of muscles is known as muscle synergies [25]. This behaviour can also be observed between joints, such that the joints are grouped together to realise a coordinated motion. Synergies at the joint level are known as “kinematic synergies” [26–29].

Kinematic synergies have gathered interest in the prosthetics research community through their application to motion-based HPIs due to their inherent coordination capabilities. This type of interfaces relate the motion of the prosthetic device with the motion of the residual limb, through either their position or velocity depending on the synergy type [30–32]. The majority of the kinematic synergy-based HPIs presented in the literature have used regression or artificial neural-networks (ANNs) methods to realise the synergies. These methods use data gathered from able-bodied subjects to determine the able-bodied relationship between the shoulder and elbow joints. This relationship is then used to determine the motion of the prosthesis (elbow) as a function of the motion of the residual limb (shoulder). There are two challenges with this approach:

1. **People are different:** There is a wide variance in the motor behaviour of humans, particularly when comparing able-bodied and prosthesis-users groups. While similar motor patterns can be observed, the human-to-human variation in the performance of motor tasks is significant. Moreover, the motion of able-bodied people does not necessarily represent the ideal motion for prosthesis users. This is mostly

due to the physiological changes introduced by amputation and the changed dynamics introduced by the use of a prosthesis. As current synergy-based methods generate average synergies from data-sets of able-bodied individuals, these do not always perform as intended in prosthesis users.

2. **Humans adapt:** Second, humans change their motor behaviour with time as learning occurs. The able-bodied data gathered for algorithm training can be considered as the steady-state motor behaviour of the individuals, given that these individuals have been performing reaching tasks throughout their life. On the other hand, as amputees learn to use the prosthetic device, they will learn its dynamics and adapt their motor behaviour to make the best use of the device. This means that for a given trained kinematic synergy-based HPI, individuals will develop a strategy to make the best use of it. However, this does not mean that this is the best setting for that given individual.

As such, it has been identified in the literature that kinematic synergy-based HPIs need to be personalised to their users [11]. This is yet to be addressed. Personalised synergy-based HPIs have the potential to compliment EMG-based interfaces by enabling the accurate coordination of the residual-limb and prosthesis while freeing EMG-based interfaces for other volitional commands such as those necessary for grasping.

The scope of the research presented in this thesis is to provide a framework for autonomously personalising human-prosthetic interfaces. More specifically, the case of transhumeral prostheses is used for the studies presented herein. The following research aims are addressed:

1. To determine the feasibility of using data-driven optimisation methods in the personalisation of human prosthetic-interfaces.
2. To characterise the features of human motor behaviour observed in the use of upper-limb prostheses.
3. To develop a data-driven optimisation method for the personalisation of human prosthetic-interfaces.
4. To study the inclusion of task information in the formulation of kinematic synergies in human-prosthetic interfaces.

1.3 Thesis Structure

This thesis is laid out as follows. Chapter 2 presents a review of the state-of-the-art in upper-limb HPIs. The challenges with pattern recognition and regression-based sEMG HPI approaches are presented to motivate the use of synergistic HPIs. The analysis of current synergistic HPI approaches, along with the findings of studies in the field, identified the two major research opportunities: the need for personalisation of synergistic HPIs and the dependency of synergies on the task to be performed. These research opportunities are the motivation behind the contributions in this thesis. The chapter concludes by presenting background information relevant to the methodologies presented in this thesis and the research aims addressed herein.

Chapter 3 presents details on the experimental platform and methodology used throughout this thesis. The experimental platform was developed using virtual reality hardware with a focus on studying human motor behaviour during the use of prosthetic devices. The use of virtual reality enabled the studies to include both able-bodied subjects and subjects with limb differences.

Chapter 4 presents the experimental evaluation of human motor behaviour while using a synergistic prosthesis. Through these experiments is observed that individuals using synergistic HPIs present a “preference” for a particular synergy setting. This preferred synergy setting achieves the best performance as determined by a pre-defined measure of performance. Based on these observations, a black-box algorithm based on ES [33, 34] is proposed to achieve the online personalisation of a synergistic HPI. This algorithm, however, operates under the assumption that human motor adaptation has reached its steady-state; i.e. that the human has learned how to use the prosthetic device. Experimental results in VR show that under these conditions it is possible to use data gathered online to personalise synergistic HPIs. However, due to the human motor adaptation limitation, this method requires extensive previous training with the synergistic prosthesis.

Chapter 5 presents a formalisation of the observed human motor behaviour in individuals using a synergistic prosthesis through a mathematical model. The model characterises motor preference and motor adaptation. The structural information from this model is then used in a proposed grey-box algorithm, based on Fast ES [35, 36], for the online

personalisation of synergistic HPIs. This method averts the need for individual algorithm tuning and allows the personalisation process to occur concurrently to human learning. Experimental results in VR demonstrate the successful implementation of the algorithm on individuals with diverse motor preference and adaptation characteristics, with minimal time required for the personalisation process.

Chapter 6 extends the results from the previous chapter to a hardware application of the synergistic prosthesis and personalisation algorithm where compensation motion is used to measure performance. Experimental results demonstrate that the personalisation algorithm was successful in finding individual synergy settings that minimise compensation motion.

Chapter 7 presents a novel synergistic HPI which uses task information and a kinematic model of the human-prosthetic arm for the formulation of the synergy used in the HPI. Experimental results in VR show that, for a set of forward reaching tasks, the proposed method achieved better performance than conventional sEMG and comparable performance to state-of-the-art synergistic HPIs. This demonstrates the proposed method's potential to replace the need for personalisation and task calibration with a model-based approach requiring knowledge of the individual users arm kinematics, the anticipated hand motion during the task, and voluntary information from the prosthetic user.

Chapter 8 presents a summary of the contributions in this thesis and a discussion on potential avenues for future development.

Chapter 2

Literature Review

A review of the literature relevant to this thesis is presented in this Chapter. First, upper-limb human-prosthetic interfaces are detailed, discussing the different traditional and state-of-the-art methods which are mainly surface Electromyography-based (sEMG). This is followed by a review and discussion of more recent motion-based and synergistic human-prosthetic interfaces. A description of the types of kinematic synergies in motion-based human-prosthetic interfaces and their application to reaching tasks is revisited. The findings from these studies are discussed, most importantly the need of synergy personalisation in synergistic HPIs. Methods to address the personalisation of HPIs are discussed and the use of data-driven optimisation is motivated. Lastly, the research questions arising from the analysis of the literature which addressed in this thesis are presented.

2.1 Introduction

Upper-limb amputation affects the ability of individuals to perform ADLs. To restore these capabilities, amputees are fitted with prosthetic devices that partially restore the functionality of the lost limb. Depending on the level of amputation the number of functional joints that the prosthesis must provide can be determined. These prostheses can be active, body powered, or passive, where passive prostheses are mostly used for cosmetic purposes [3]. An example of a passive prosthesis is shown in Figure 2.1a [37]. Body powered prostheses use cable-driven mechanisms that are activated by the user's body-parts [3]. An example of a body powered prosthesis is shown in Figure 2.1b [37].

Active prostheses use powered mechanisms to drive the motion of the joints in the device, typically through an electric motor. An example of an active prosthesis is shown in Figure 2.1c [37]. The driving of the joints can be done sequentially, i.e., joint-by-joint; or synchronously, i.e., coordinating multiple joints [8]. HPIs allow prosthesis users to modulate the motion of active prosthetic devices through voluntary activation of the interface signals. These signals can be obtained through different media, with sEMG being the most widely used [8, 9]. The capabilities of the prosthesis and the HPI being used determine whether the prosthesis can be commanded in a sequential or synchronous manner. For example, the finger joints in a prosthetic hand are moved synchronously to perform specific grasp-types, where the user commands the closure of the hand [8, 38]. On the other hand, commanding different prosthetic devices, such as a prosthetic elbow, wrist, and hand, is done in a sequential manner [8, 38]. In this case, the user provides a command to select the device to be controlled, and then a different command to control the movement of the selected device. These different HPIs are discussed in detail next.

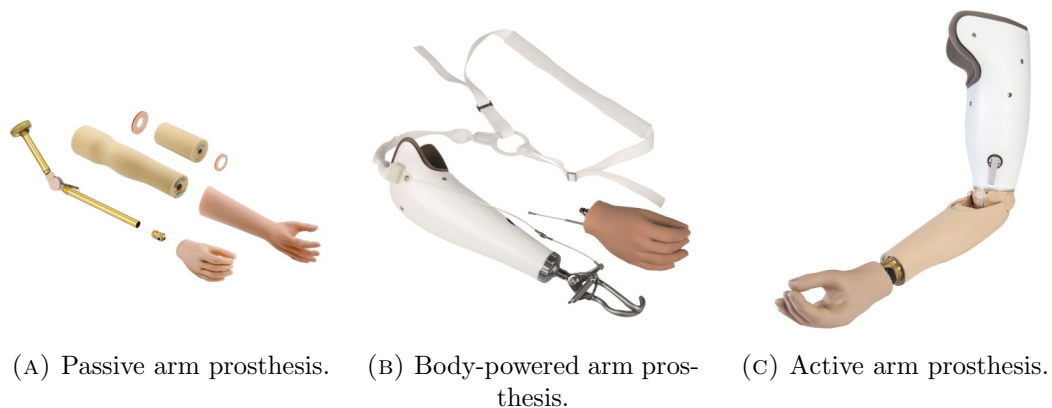


FIGURE 2.1: The different types of upper-limb prosthesis: passive, body-powered, and active. Images by Ottobock.

2.2 Surface Electromyography-based Human-Prosthetic Interfaces

sEMG-based HPIs have been in use in active upper-limb prosthetics for over 30 years with little change [8]. These HPIs use sensors that detect voltage differentials on the skin that arise from muscle activation. sEMG sensors are typically attached to residual muscles that are no longer functionally attached to a joint due to the amputation [8]. For example, in above elbow amputations, sEMG sensors are placed on top of the biceps

and triceps muscle groups. The voltage differential detected from these muscle groups is amplified, rectified, and thresholded, such that only voluntary muscle activation is detected. This voluntary muscle activation can be used as a continuous signal whose amplitude is dependent on the strength of the muscle activation, i.e., proportional to muscle tension [8]. These signals are then used to generate a command for the prosthesis, which can be either continuous or discrete. Depending on the number of available muscle sites, and thus the signal channels, different types of commands can be used by the prosthesis user. Typically, only one or two channels can be extracted using traditional sEMG-based HPIs. An example of a common sEMG-based HPI set-up for transradial amputees is shown in Figure 2.2 [37]. The following are the types of commands that are commonly used with single and dual-site sEMG interfaces.

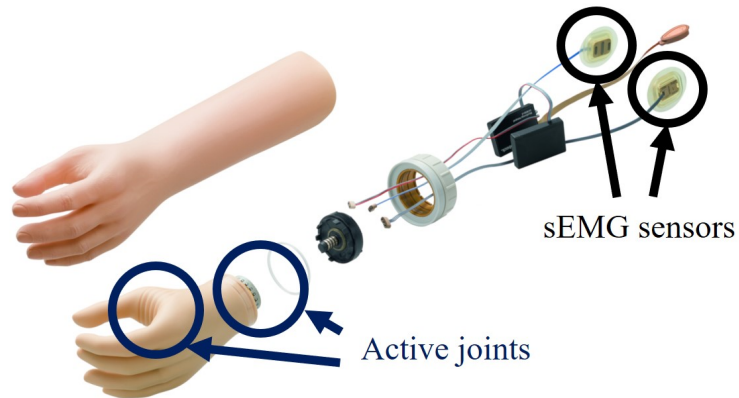


FIGURE 2.2: Typical sEMG-based HPI set-up for a transradial amputation. Two sEMG sensors are used to actuate a powered hand and wrist (2 DOF). Prosthesis image by Ottobock.

1. **Continuous Commands:** This type of commands use the continuous signals generated by the sEMG interface to determine a proportional function in the prosthesis. This is the most common type of traditional sEMG-based commands and is typically used to determine the motion of the prosthesis.

- **Single-site Proportional:** This type of command is typically employed when only a single sEMG sensor is available. In this case, the motion of the prosthesis is proportional to the amplitude of the provided sEMG signal. This signal is typically used to determine the position of the prosthetic joint or the closure of the prosthetic hand [8].
 - **Dual-site Differential:** This type of command is typically employed when two sEMG sensors are available. For this command, the difference in amplitude between the two sEMG channels is used to determine the motion of the prosthetic device. This continuous signal is typically used to regulate the velocity and direction of prosthetic device joints, or the closing/opening of a prosthetic hand [8].
2. **Discrete Commands:** This type of commands transform the continuous signals generated by the sEMG interface into a discrete signal. This type of sEMG-based commands is typically used in multi-actuated prostheses to change the function of the prosthesis.
- **Timed Peaks:** This command requires the user to generate two sEMG activation peaks in sequence above a threshold under a predefined time. When the user generates such timed peaks, the prosthesis performs a pre-programmed action. This type of command is generally reserved for switching commands, such as changing between one joint of the prosthesis to another (or between devices), or changing between grasp types in a prosthetic hand [8].
 - **Co-contractions:** The prosthesis user contracts both muscle groups for each sensor site to generate two concurrent sEMG peaks. This activation is typically done in opposing muscle groups, thus named co-contraction. Similarly to “Timed Peaks”, detection of this dual-channel peaks is used to command the prosthesis to perform a pre-programmed action. This type of command is generally reserved for switching commands, such as changing between one joint of the prosthesis to another (or between devices), or changing between grasp types in a prosthetic hand [8].

Given that the number of joints in prosthetic devices generally outnumbers the available HPI signals, sEMG-based interfaces are typically used in a sequential manner. This means that the user needs to provide switching commands to then be able to provide

motion commands to the different joints in the prosthesis. As the amputation level increases, fewer signals become available while more joints are replaced by prostheses, which required command signals. This is due to the fact that sEMG-based HPIs rely on the muscles in the residual-limb. Such difference between prosthesis joints and HPI signals is a major challenge with traditional sEMG-based HPIs, which are prevalent in commercial prosthesis, thus leading to device abandonment [6]. To address this dimensionality problem in prosthetics, the research community has taken multiple approaches with the major ones being pattern recognition-based and synergistic HPIs. These are ongoing research topics in upper-limb prosthetic control.

2.2.1 Machine Learning in sEMG-based HPIs

An approach to tackle the dimensionality problem between HPI signals and prosthetic device actuated joints is to extract more information from the muscles available. This can be done by placing an array of sEMG sensors around the muscle group and using a pattern recognition or regression algorithm to estimate the intention of the user [8, 39, 40]. An example of an sEMG sensor array used in this type of HPIs is shown in Figure 2.3 [37]. Pattern recognition and regression algorithms are referred to as “estimators” henceforth. Intention estimation is achieved by first training the estimator using data from a group of able-bodied individuals performing a set of actions related to the prosthesis function [38, 41, 42]. Then, the estimator is calibrated for the prosthesis user in a similar fashion. This has the advantage that it may be possible to extract functional information from the sensor readings instead of just the amplitude of muscle activation [39]. For instance, it has been shown to be possible to distinguish between grasp intention and wrist movement [18, 42]. As conscious human motor control is done at a functional level rather than muscle level, estimator-based sEMG HPIs are more intuitive and easier to use than their traditional counterparts; however, these methods have a few short-comings.

Pattern recognition and regression methods are limited by the quantity and quality of the signals available for estimation. Therefore, they are restricted by the available muscles that can generate activation signals, and thus the level of amputation. In order to be able to estimate different actions, the actions must each have unique muscle activation patterns. This means that estimation methods are restricted by the capability of the

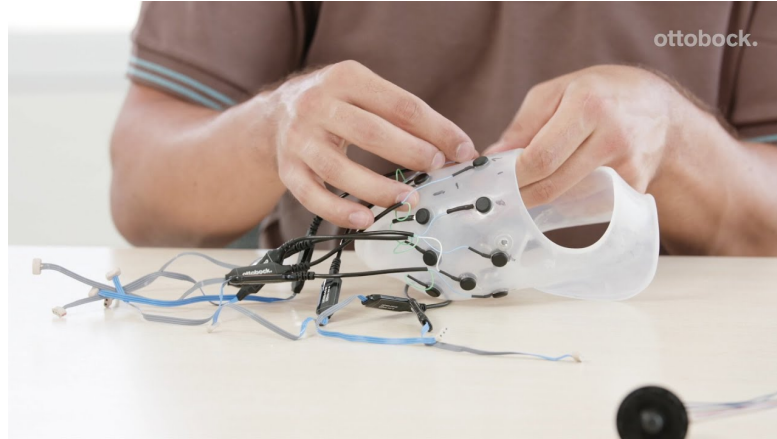


FIGURE 2.3: An example of an sEMG sensor array used in pattern-recognition-based sEMG HPIs by Ottobock. Image by Ottobock.

user to generate muscle activation patterns that are sufficiently different from each other such that the system can recognise them in a robust manner [43]. For example, in a transradial amputation close to the wrist where forearm muscles are still available, it may be possible to distinguish between multiple grasp types as these have different finger patterns [44, 45]. On the other hand, in a transhumeral amputation close to the elbow where only biceps and triceps muscles are still available, it may only be possible to distinguish between flexing or extending the arm [8, 46]. This is still dependent on the individual being able to perform these actions naturally and as able-bodied people do, which may not be the case due to the physiological changes introduced by amputation and the degradation of unused muscles over time [47–49].

In order to increase the number of signals that are available for pattern recognition based prosthetic interfaces, the research community has turned to surgical procedures. The main procedures to date are Targeted Muscle Reinnervation (TMR) [14, 42, 50, 51] and sensor implants [15]. In TMR, the nerve bundles in the residual limb that were routed to the lost part of the limb are re-routed and placed on other muscles such that the activation of the lost limb can be measured through the new muscle sites. This way multiple signals that are directly mapped to parts of the lost limb can be used for prosthesis control. However, these do not directly correspond to joint motion in the prosthetic device due to the changed dynamics, physiology, and loss of feedback. This occurs because of the loss of musculoskeletal connections after amputation, and the loss of the feedback mechanism used for muscle regulation and proprioception (loss of Golgi Organs and muscle spindles). Thus, the lack of human feedback results in a purely

open-loop control from the brain’s perspective. On the other hand, sensor implants aim at providing a cleaner and more consistent muscle activation signal by placing sEMG sensors closer to the nerves [15]. This has the advantage of reducing the external factors that affect sEMG signals, such as sensor placement change and sweat. These surgical procedures allow a larger number of high-quality signals to be used in estimator-based prosthetic interfaces.

In general, invasive procedures are restricted to the feasibility of the surgery on any particular individual, as not everyone is a suitable candidate for these procedures. While the procedure could be performed during the amputation surgery, people born with limb difference or who had the amputation surgery in the past may not be willing to go through the risk of a TMR surgery. While estimator-based sEMG HPIs have shown improvements over traditional methods in terms of their intuitiveness and ease of use, this has not been sufficient to lead to widespread adoption. Only a few commercial devices have recently implemented estimator-based sEMG HPIs; such as the Ottobock MyoPlus and the CoApt Gen2 [52]. However, due to the previously discussed limitations of estimator-based sEMG HPIs, these are mostly suited to transradial amputees or individuals with TMR sites. As such, the research community has actively developed non-invasive methods to complement sEMG interfaces with additional sensors, most commonly motion sensors. The use of motion sensors in prosthetics led to motion-based or synergistic HPIs.

2.3 Motion-based Human-Prosthetic Interfaces

Motion-based HPIs were proposed to address the need for the coordinated motion of multiple joints in the residual limb and prosthetic device in an intuitive way [53–55]. This type of interfaces augments traditional or estimation-based sEMG methods by using measurements of the motion of the residual limb to regulate the motion of the prosthetic device. Thus, inherently achieving coordinated motion between the residual limb and the prosthetic device. This type of interfaces have been explored mostly for reaching tasks with transhumeral prostheses, due to the increased number of joints that need to be coordinated to perform the task and the limited number of sEMG signals available [32, 55–57]. As such, the focus of discussion in this thesis is on above elbow amputations and the methods used in such cases.

The coordination of the joints in human-prosthesis arm is done by virtually coupling the movement of the prosthesis with the residual limb. For instance, in a transhumeral amputation case, the shoulder joint is the residual limb, and the elbow, wrist, and hand joints are the prosthesis. Then, the motion of the shoulder joint determines the motion of the prosthetic elbow and wrist, while sEMG signals can be left to determine closure of the prosthetic hand [58]. This joint coordination is inspired by the theory of motor synergies, where it is theorised that the Central Nervous System (CNS) recruits multiple joints, or muscle groups, to operate synchronously by being regulated by shared command signals [22, 27, 59, 60]. This way the CNS achieves dimensionality reduction from the actuation level (high dimensional) to the command level (low dimensional). In the prosthetics application, instead of muscles synergies, kinematic synergies are employed as these relate joint movement rather than muscle activation [61]. This is due to the fact that motion can be measured with Inertial Measurement Units (IMUs), which are widely available and commonly used in wearable devices. Kinematic synergies are discussed in detail next.

2.3.1 Kinematic Synergies in Motion-based HPIs

A kinematic synergy describes a joint-space relationship, such that the movement of a particular set of joints becomes a function of another set of joints or signals. In the prosthetic case, movements of the joints in the residual limb correspond to movements of the joints in the prosthesis [31]. Let the residual limb joint pose be given by $\mathbf{q}_r \in \mathbb{R}^R$, where $R \in \mathbb{N}_+$ is the number of DOFs in the residual limb, and the residual limb joint angular velocity be given by $\dot{\mathbf{q}}_r \in \mathbb{R}^R$. Let the prosthetic joint pose be given by $\mathbf{q}_p \in \mathbb{R}^P$, where $P \in \mathbb{N}_+$ is the number of DOF in the prosthesis, and the prosthetic joint angular velocity be given by $\dot{\mathbf{q}}_p \in \mathbb{R}^P$. Let a set of parameters $\boldsymbol{\theta} \in \Theta$ characterise the kinematic synergy, where Θ is a compact set in $\mathbb{R}^S$ representing the parameter set of interest, and $S \in \mathbb{N}_+$ is the number of parameters. Then, in general, a kinematic synergy is given by

$$\begin{bmatrix} \mathbf{q}_p \\ \dot{\mathbf{q}}_p \end{bmatrix} = \mathbf{f}(\boldsymbol{\theta}, \mathbf{q}_r, \dot{\mathbf{q}}_r), \quad (2.1)$$

where $\mathbf{f} : \Theta \times \mathbb{R}^R \times \mathbb{R}^R \rightarrow \mathbb{R}^P \times \mathbb{R}^P$. So far, two approaches to realise joint-space kinematic synergies have been reported in the transhumeral prostheses literature: postural [55, 62]

and differential synergies [31, 32, 58, 63]. Postural synergies define the human-prosthesis joint relationship in terms of joint displacements; such that for a given task and combination of joint displacements in the residual limb, there will be a resultant prosthesis joint displacement. On the other hand, differential synergies define the human-prosthesis joint relationship in terms of joint velocities; such that the pose of the prosthesis is a function of the initial position and the residual limb joint velocity trajectory. As such, at any given position, the movement of the prosthesis is a function of only the movement of the residual limb in both cases of kinematic synergies. These two types of kinematics synergies are presented in detail next, followed by the contributions in the literature where they are studied.

2.3.1.1 Postural Kinematic Synergies

In the prosthetics case, a postural kinematic synergy defines the human-prosthesis arm motion coordination in terms of the residual limb and prosthesis joint angles. In general, this can be described as follows

$$\mathbf{q}_p = \mathbf{f}_{ps}(\boldsymbol{\theta}, \mathbf{q}_r). \quad (2.2)$$

Here, $\mathbf{f}_{ps}(\cdot)$ defines the type of relationship, which can be linear or non-linear, while the parameter vector $\boldsymbol{\theta}$ determines a particular synergy for a task. The synergy parameters ($\boldsymbol{\theta}$) are identified for a fixed starting position and a set of tasks, where the number of tasks that can be distinguished is dependent on the DOF of the residual limb (R) that are used for the synergy [28, 64]. This means that in order for the postural synergy to perform the correct task intended by the human, there must be a unique relationship between the residual limb and prosthetic limb joint angles. Hence, for a given task, the prosthesis will always be driven to the position that matches the current residual limb pose. This is a shortcoming of this type of HPIs, as the human arm is redundant and thus there are multiple poses that can achieve a task. This is due to redundancy being a strategy employed in ADLs to overcome workspace or task constraints. Therefore, for a postural synergy to be successfully employed in HPIs, the human would need to learn unique postures for each task that the postural synergy can achieve.

2.3.1.2 Differential Kinematic Synergies

In the prosthetics case, a differential kinematic synergy defines the human-prosthesis arm motion coordination in terms of the residual limb and prosthesis joint angular velocities. In general, this can be described as follows

$$\dot{\mathbf{q}}_p = \mathbf{f}_{ds}(\boldsymbol{\theta}, \dot{\mathbf{q}}_r). \quad (2.3)$$

Similarly to postural synergies, $\mathbf{f}_{ds}(\cdot)$ defines the type of relationship, which can be linear or non-linear, while the parameter vector $\boldsymbol{\theta}$ determines a particular synergy for a task. Again, the number of tasks that can be identified depends on the DOF of the residual limb (R) that are used for the synergy and the uniqueness of the motions. The synergy parameters ($\boldsymbol{\theta}$) are identified for a fixed starting position and a set of tasks; however, given that the relationship is in terms of velocities, the movement always needs to be initiated from the same starting position for it to successfully perform the desired task. Therefore, kinematic synergies are typically obtained for predetermined tasks.

2.3.2 Kinematic Synergies in the Transhumeral Prosthetics Literature

There are multiple approaches to the application of kinematic synergies in the prosthetic literature, with postural synergies preferred for hand prosthesis [65–67], and differential synergies preferred for above elbow amputations [31, 58, 63]. Given that the focus of this thesis is on above elbow amputations, the methods used in such cases will be discussed. Regardless of the type of synergy, the following steps are common among the works presented in the literature to identify the synergies for a given prosthetic task.

1. Define a fixed initial position and task, e.g., arm resting on the side and reaching to a range of targets in front of the person.
2. Gather motion data from able-bodied subjects performing the task while measuring all joint angles involved in the synergy/task, e.g., measure shoulder, elbow, and wrist joint position and angular velocity.
3. Identify the able-bodied joint relationship that corresponds to the desired residual limb-to-prosthetic device synergy, e.g., using linear regression for a linear synergy.

4. Implement the identified synergy in the prosthetic device.

Most studies reported in the literature have considered forward reaching tasks for studying synergies in above elbow prosthetics due to their generality and use in daily life, e.g., [1, 31, 58]. As show in the typical steps to determine the kinematic synergy, current methods in the literature use ANNs, or other regression methods, and supervised learning to identify kinematic synergies from the data gathered from able-bodied subjects [32, 55, 57, 62]. These methods are discussed in detail next.

The first application of synergies in transhumeral active prostheses was by Kaliki et.al. in 2008 [53–55], who proposed a synergy composed of a two-layer perceptron ANN. The inputs to the ANN were the shoulder angular pose (shoulder flexion, shoulder abduction, and humeral rotation) and shoulder displacement on the sagittal plane (2 DOF). The hidden perceptrons in the ANN used a hyperbolic tangent activation function while the output perceptrons used a sigmoid activation function. The number of perceptrons in the hidden layer were determined through a cascade learning algorithm that increases the layer size until no improvement in performance is achieved [68]. Here the authors utilised three different ANNs with different synergy relationships, where the first ANN determined the shoulder-to-elbow flexion relationship, the second ANN determined the shoulder-to-wrist rotation relationship, and the last related a specific shoulder movement to proportional grasp closure. Given that the synergies were created from able-bodied behaviour, the focus of the study in [55] was to determine whether amputees can learn to use such synergies. The main challenge with this approach was the generalisation of such ANNs. While the ANNs showed desirable performance with the subjects they were trained with, these did not achieve the desired performance with subjects outside of the training set, leading subjects to use undesirable compensation motion. This is a common issue with ANNs, which require large training data-sets to achieve desirable performance in previously unseen scenarios. However, the training algorithms aim to minimise the prediction error for the given data-set, thus the identified synergy is not necessarily the best synergy for all subjects in the data-set, but the average synergy of the population used for training. This means that for some individuals, this synergy will not perform as desired and thus require them to compensate with their upper body.

An example of the different motor behaviour of individuals, in the form of upper-arm flexion velocity, is shown in Figure 2.4. This shows how motor behaviour varies across

individuals, and that the average behaviour of these individuals may not be suitable for all. Given individual physiological characteristics, preferences in motor behaviour, and the uniqueness of each amputation, the generalisation of ANN based methods for kinematic synergy identification is a challenge.

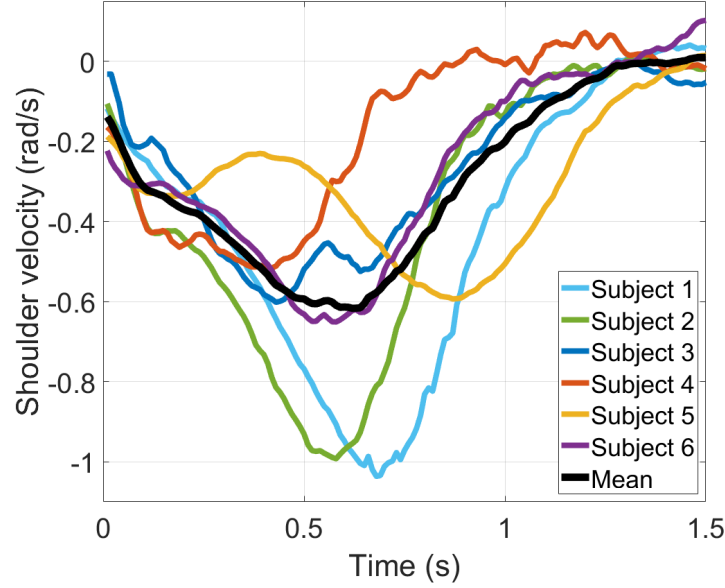


FIGURE 2.4: An example of the upper-arm flexion velocity for six different subjects (coloured lines) and their average behaviour (black line). This highlights individual variation and the difference between average synergies and individual synergies. Data gathered from able-bodied subjects performing a reaching task.

In order to increase the data available to determine the synergy and predict prosthesis motion, Blana et.al. [32] proposed combining sEMG and IMU data. This approach utilises two time-delayed ANNs which related shoulder joint position from an IMU and shoulder muscle activation from sEMG sensors to elbow flexion and forearm rotation angles. Both ANNs consisted of two layers, with the hidden layer using a sigmoid activation function and the output layer a linear activation function. The first ANN was trained to estimate elbow flexion while the second ANN to estimate forearm rotation. Able-bodied data was gathered to train the ANNs, and the training required the estimation error to be below 4° for ANN1 and below 8° for ANN2. Similarly to [55], the proposed method showed larger prediction errors than the training set when implemented on the test population, with the mean prediction errors for the population being 13.7° and 23.3° for elbow flexion and forearm rotation, respectively. Again, this highlights the issue of using synergies generated from a population in specific individuals,

which have their unique characteristics. While the subjects can learn to compensate for these errors, compensation motion is widely regarded as undesirable [5, 6, 69].

In an attempt to overcome the training shortcomings of ANNs in prosthetics, Akhtar et.al. [62] proposed using mirrored bilateral reaching motion for training data gathering. This means that amputee subjects performed reaching tasks simultaneously with both their able-bodied limb and amputate limb, such that data from both could be used in ANN training. Similar to [32], both sEMG and IMU data were used; however, in [62] TMR subjects were included, such that sEMG data from the amputated limb can be gathered during the bilateral motion used for training. Here, two different estimation methods were used to estimate elbow flexion and forearm rotation. Locally weighted projection regression and a two-layer time-delayed adaptive neural network were chosen as these fit the large input space in the approach, which consisted of three shoulder angle signals and 55 sEMG signals. The best results obtained from these approaches rendered mean prediction errors of 10.65° and 21.35° for elbow flexion and forearm rotation, respectively. Even though this approach used a larger number of signals for prediction, and data from the same subject for training and prediction, the results obtained were comparable to previous studies. Interestingly, the best result for forearm rotation estimation was obtained when sEMG was not involved in estimation, with a prediction error of 11.38° , which shows that more data is not necessarily always the best solution.

The work of Merad et.al. [11, 31, 57, 70, 71] and Legrand et.al. [63] took a different approach to the development and evaluation of synergistic prosthetic elbow interfaces, focusing on developing an understanding of the human-prosthesis synergy and its effects on human motor behaviour. Their initial studies [31, 57] presented a differential kinematic synergy based on Radial Basis Function Networks (a type of ANN) where a two DOF joint angular velocity representation of shoulder motion is used to predict prosthetic elbow angular velocity. Their results on able-bodied subjects showed similar prediction errors as in the studies previously discussed, where in this case the elbow extension angle error from the desired position was of 28.53%. However, a reduction in the duration of the movement and upper body compensation motion when subjects used the estimator-based method in comparison to traditional sEMG methods. Lastly, the study involved multiple cases of training and estimation data-sets, and the results from these tests suggested that human motor variability (both inter and intra-subject) is a

significant contributor to the performance results of estimator-based synergistic HPIs. This is due to the large number of possible coordination patterns that arise in natural human motion.

Further studies by Merad et.al. on amputee subjects focused on the motor behaviour aspects of synergistic prosthetic reaching [11]. Here, it was found that the use of synergies for reaching tasks with prosthetic elbows significantly reduces undesirable compensation motion, regardless of elbow motion prediction errors. Lastly, in [63], different regression techniques were performed in a bid to obtain a common synergy for a group of able-bodied people, including Radial Basis Function Networks, Locally Weighted Regression, and Principal Component Analysis. The identified synergies were then used on individual able-bodied subjects wearing a supernumerary prosthetic elbow. This study concluded that the choice of regression technique did not significantly improve the performance of the synergistic prosthetic interface. The results, however, demonstrated that while general common motor features can be observed (a general trend in limb trajectory), there is also a significant amount of inter-subject motor variability. The conclusion from the work of Merad et.al. and Legrand et.al. was that the type of algorithm used to generate human-prosthesis synergies does not significantly improve estimation performance, but the individualisation of these synergies may prove a better approach to the application of synergies in upper-limb prosthetics. As stated by Merad et.al.: *“It shows the need for novel modelling methods and mapping designs that bring the user back to the center of the control development process in order to achieve a more natural prosthetic motion”* [11].

A different approach to address the shortcomings of using estimator-based synergistic HPIs was taken by Alshammary et.al. [56, 58], where a single DOF shoulder extension to elbow extension synergy was linearly combined with traditional sEMG to drive a prosthetic elbow. Here, the traditional sEMG component of the HPI was used to allow the user to adjust the elbow position due to synergy inaccuracies. Moreover, a motion-based joint switching mechanism was employed, where the prosthetic device automatically switches to enable the combined synergy and sEMG control of the elbow upon detection of shoulder motion. The switching mechanism reduced the time needed to change between the different joints in the prosthesis, which is a major difficulty with the use of upper-limb prosthetic devices [6]. While the results in [58] showed a reduction in task time when using the proposed synergy+sEMG method, it was not possible to

determine whether this was due to the motion-based switching mechanism or the synergy itself. Moreover, the compensation motion results were contradictory with other results in the field as no significant change in upper body compensation motion was observed. However, qualitative feedback from participants in the study indicated a preference towards the synergistic approach over a traditional sEMG interface, highlighting its intuitiveness.

2.3.3 The Challenges of using Kinematic Synergies in Prosthetics

The analysis of the state-of-the-art in transhumeral synergistic HPIs revealed two major challenges regarding the use of synergies for prosthetic reaching. The first challenge is the need for personalisation of synergies due to individual differences in motor behaviour and the physiological and motor changes due to amputation. The second challenge is the dependency of synergies on the task and initial condition.

The personalisation of HPIs is required to accommodate human-to-human physiological and motor behaviour variations, and the numerous variations in the nature of amputation [6]. This need for personalisation has been explicitly identified for synergistic HPIs [11]. With the current methods in the literature, personalisation of the human-prosthesis synergy is a challenge as able-bodied motion data is required to identify the synergy; however, this data is not available from amputee subjects. Because of the physiological changes due to amputation, the use of mirrored bilateral motions for training failed to render any improvement in performance [62]. Moreover, this would only be possible for unilateral amputees. Alternatively, it could be possible to gather sensor data while the prosthesis user performs a task with the prosthetic device, i.e., online, and use it in an explore-exploit algorithm to find the best synergy setting for the user. Ideally, this personalisation process for HPIs should be unobtrusive and short so it can be performed during consultation with prosthetists or at home. As the personalisation procedure is expected to be performed by either clinicians or prosthesis users, it should be designed so it is easy to use and requires little involvement.

The task dependency of kinematic synergies means that a library of task-specific and individually personalised synergies would be needed to provide the arbitrary range of movements required by ADLs. Generating and personalising these synergies could be a long and time-consuming process, which is undesirable for the successful deployment

of synergistic HPIs. Current methods do not utilise explicit task information, such as the location of the target, in the formulation of the synergy as it is challenging to obtain it in a prosthetic setting. However, using this information may be beneficial in improving the robustness and performance of synergistic interfaces, and avert the need of generating a library of task specific synergies. While obtaining this information may be a challenge with current methods, this may be overcome with future technologies or interface modalities that assist with determining reaching intention and direction [72].

2.4 Synergistic HPI Personalisation as an Optimisation Problem

Current synergistic HPIs in the literature use supervised learning methods to train the prosthesis motion estimation algorithms with able-bodied data. This has proven to be a challenge in the prosthetic setting as the able-bodied synergy may not be the best for a given prosthesis user. This challenge, however, motivates the study of whether there exists a “best” synergy configuration in synergistic HPIs for a given individual and whether this synergy can be found. This type of problem is well suited for optimisation techniques, though human involvement introduces unique challenges. The formulation of the personalisation of synergistic HPIs as an optimisation problem is presented next. Without loss of generality, optimisation is considered to be maximisation here.

The personalisation of a synergistic HPI for a given individual is defined as finding the “optimal synergy” for the individual with respect to a pre-determined task-relevant measure of performance. Let the synergy be parameterised by the vector $\boldsymbol{\theta}$ and the pre-determined measure of performance be given by an objective function $J(\boldsymbol{\theta})$. In order to find the optimal synergy $\boldsymbol{\theta}^*$, the following assumptions need to be satisfied by the human-prosthetic system.

Assumption 2.1. *Given an objective function $J(\boldsymbol{\theta}) : \Theta \rightarrow \mathbb{R}_+$, there exists a unique $\boldsymbol{\theta}^* \in \Theta \subset \mathbb{R}$ such that $J(\boldsymbol{\theta}^*) > J(\boldsymbol{\theta})$.* ◦

Current methods that use regression with ANNs and supervised learning for training synergistic HPIs can be formulated using the notation above. In these cases, the objective function $J(\boldsymbol{\theta})$ is defined as the average prediction error over all the training data, where

θ are the weights and biases of the ANN. Through the ANN training process, the ANN parameters are iterated such that the prediction error is minimised across the training data-set [53]. Therefore, the synergy obtained from this process can be considered as the average synergy for the training population. To obtain the optimal synergy θ^* for a given individual, the training process would need to be performed with reaching data from the individual; however, this data may not be available for individuals with limb differences or amputations.

From a general optimisation perspective, under Assumption 2.1, it may be possible to determine the optimal synergy θ^* from its relationship to the objective function. However, an explicit mathematical relationship between J and θ is unknown and may be unfeasible to obtain as it is given by human behaviour. Therefore, model-based optimisation methods, which require explicit information on the $J(\theta)$ map, are not suitable to this application.

A possibility to address the unknown explicit relationship between the synergy (θ) and the objective function (J) is to use a data-driven approach. Data-driven methods utilise data gathered online to improve the performance of the system based on a predefined measure of performance. Such problems where the exact relationship between a parameter and the performance of a system is unknown appear in the online optimisation [73] and parameter identification [33] literature. These methods operate under the assumption that information on the $J(\theta)$ map, e.g., its gradient, can be estimated through measurements of its output [33, 74]. Out of the data-driven methods available for optimisation, the framework of Extremum Seeking (ES) provides a unified set of techniques for gradient estimation and optimisation that are guaranteed to operate under certain system conditions [75, 76]. The two main conditions are summarised as follows:

Condition 2.2 (Convexity of Map). *Let $J(\theta)$ be an input-output map that satisfies Assumption 2.1. $J(\cdot)$ is sufficiently continuously differentiable such that*

$$\frac{\partial J}{\partial \theta}(\theta) = 0, \quad \text{iff } \theta = \theta^*, \forall \theta \in \Theta \quad (2.4a)$$

$$\frac{\partial^2 J}{\partial \theta^2}(\theta) < 0, \quad \forall \theta \in \Theta. \quad (2.4b)$$

◦

Condition 2.3 (Existence and Properties of Manifold). *Let $u = J(\boldsymbol{\theta})$ be a static map that satisfies Assumption 2.1 and Condition 2.2. Let a dynamic system be given by $\dot{\mathbf{x}} = g(\mathbf{x}, \boldsymbol{\theta})$ and $y = h(\mathbf{x})$, where $\mathbf{x} \in \mathbb{R}^D$, and a function $\mathbf{l} : \Theta \rightarrow \mathbb{R}^D$. For any constant $\boldsymbol{\theta} \in \Theta$, the system $\dot{\mathbf{x}} = g(\mathbf{x}, \boldsymbol{\theta})$ is globally asymptotically stable, uniformly in $\boldsymbol{\theta}$, and $\mathbf{l}$ satisfies the following conditions:*

$$g(\mathbf{x}, \boldsymbol{\theta}) = 0, \quad \text{iff } \mathbf{x} = \mathbf{l}(\boldsymbol{\theta}), \quad (2.5a)$$

$$J(\boldsymbol{\theta}) = h \circ \mathbf{l}(\boldsymbol{\theta}). \quad (2.5b)$$

◻

In terms of the synergy personalisation problem, Condition 2.2 refers to the existence of a unique optimal synergy vector $\boldsymbol{\theta}^*$ within the range of interest Θ , and the existence of gradient and Hessian of the map. Condition 2.3 refers to the existence of a static mapping between a dynamic system $g(\mathbf{x}, \boldsymbol{\theta})$ and the objective function J , such that the $J(\boldsymbol{\theta})$ map is static at the steady-state of the dynamic system. The ES framework has been applied to a wide range of engineering problems as it was developed for autonomous systems [33, 34]. However, the ES framework is yet to be considered in upper-limb prosthetics applications, so its applicability to these applications is unknown.

The applicability of the framework for a given system of interest depends on whether the system satisfies Conditions 2.2 and 2.3. In the case of the human-prosthesis system, it is unknown whether the relationship between the synergy parameters and a given measure of performance satisfies these conditions. However, studies in the field suggest that optimal synergies for individuals exist [11]. Therefore, research opportunities arise from the potential application of the ES framework to the personalisation of synergistic HPs. The research opportunities relevant to this thesis are presented next.

2.5 Research Aims

The following research aims were identified from the formulation of the synergy personalisation problem as an online optimisation problem and the application of the ES framework to it.

1. To determine the feasibility of using online optimisation methods in the personalisation of human-prosthetic interfaces.
2. To determine the characteristics of human motor behaviour related to motor preference and learning in the use of upper-limb prosthetics.
3. To develop a minimally invasive and autonomous method for the personalisation of human-prosthetic interfaces.
4. To investigate methods to incorporate task information in kinematic synergies for human-prosthetic interfaces.

This thesis addresses these aims in the following chapters.

Chapter 3

A Virtual Reality-based Experimental Protocol for Evaluating Human Motor Behaviour in Upper-limb Prosthetic Applications

In this chapter the experimental platform and protocol used throughout the thesis is presented¹. The general structure of the experiments is detailed herein, while specific details about the experiments performed to evaluate the methods proposed in this thesis are presented in the relevant chapters for each method. The experimental platform was developed to study the motor behaviour of individuals using an upper-limb prosthetic device. Immersive virtual reality technology was employed to allow able-bodied subjects to participate in the studies, thus increasing the number of subjects available for the experiments. The platform was also used with amputee subjects; however, due to the limited number of amputee subjects available, these were limited to case studies. The development of the platform followed the recommended best practices for VR development [80], studies on VR tracking capabilities [81], and other VR-based experimental platforms for prosthesis evaluation and neurorehabilitation [82–86]. The use of the platform for human trials

¹Part of the content presented in this chapter has been published or submitted for publication in [77], [78], and [79].

was approved by the University of Melbourne Human Research Ethics Committee, project number 1750711.

3.1 Introduction

Immersive virtual reality has seen significant growth in recent years due to the introduction of consumer level devices such as the Oculus Rift and the HTC Vive [87, 88]. Immersive VR is characterised for utilising head mounted displays (HMD) that restrict the field of view of the user to only the virtual reality environment (VRE) being displayed by the VR device. Moreover, these devices allow users to interact with the virtual environment through hand-held controllers. Because of these characteristics, the senses of the users are focused on the virtual environment producing a sense of “immersion” which improves the cognitive effects of the simulation [89]. While the prosthetics and neuro-rehabilitation literature makes liberal use of the term “virtual reality” to refer to computer-game-based experimental and clinical platforms [89], these are not considered to be VR by current standards. Therefore, only HMD-based VR platforms are discussed herein.

The earliest appearance of VR in a prosthetic setting was done by Hauschild, Davoodi, and Loeb in 2007 [84]. There, a VR-based platform for designing and fitting upper-limb prostheses was detailed, emphasising the measurement of performance information to evaluate prosthesis use and physical realism in the simulation. While realism is highly debated in VR applications due to the aversive effects of the uncanny valley [89], the data acquisition and evaluation potentials of VR in clinical settings is widely accepted [83, 86, 89, 90]. Moreover, VR allows able-bodied individuals to experience prosthesis use as it is possible to “virtually amputate” a limb through the placement of motion sensors at the desired amputation level. Regardless, recently developed VR platforms that utilise consumer level HMD-based VR devices focus on the functional aspects of prosthesis use and are limited to below elbow prostheses [86, 91, 92]. The experimental platforms that have been used to evaluate the motor behaviour of prosthesis users, which include above-elbow prostheses, are not publicly available and limited information on them is available [32, 56, 58]. Therefore, the development of a VR-based experimental platform for the study of motor behaviour of prosthesis users and the evaluation of prosthetic devices and HPIs was required. The

characteristics of the developed platform are presented next. A video description of the VR platform can be accessed from <https://youtu.be/vvq4tjShdB4>. The platform software application has been made publicly available on Github and can be accessed from <https://github.com/Rigaro/VRProEP>.

3.2 Experimental Set-up

The experimental platform was developed using the HTC Vive Pro HMD with the software application developed in Unity3D. For the duration of the studies included in this thesis, the experimental platform ran on an Intel Core i7-8700K processor at 3.7GHz, with 32GB RAM, and a Gigabyte GeForce GTX 1080Ti video card with 11GB GDDR5. HTC Vive Trackers were used for motion tracking, except for hand motion tracking where the HTC Vive Controller was used. The motion tracking capabilities of the HTC Vive system can be found in [81]. Motion tracking sensors are attached directly to the subject's body using medical tape. For the case of able-bodied subjects, a mechanical brace for the upper-arm is used to attach the motion tracking sensors. For the case of amputee subjects, Vive Tracker straps are used to attach motion tracking sensors to the residual-limb, or through a custom socket. Data gathering and VR update are performed at 90Hz. Myoware sensors with Ag-AgCl electrodes and the Myoband sensor were integrated for sEMG data gathering.

The platform allows for able-bodied and prosthetic experiment modalities. The able-bodied modality (AB) allows the use of the subject's able-bodied arm and hand in the VR environment. Thus, it is suitable for subjects with an able-bodied arm, such as able-bodied subjects and subjects with unilateral amputations. This modality is akin to normal VR applications. The AB modality can be used to determine the benchmark motor behaviour and task performance for the subjects. The prosthetic (PR) modalities allow the emulation of amputation in able-bodied subjects and the use of a virtual prosthesis for both able-bodied and amputee subjects. Different amputation levels and HPis can be used in this case.

Figure 3.1 presents an example of an experiment set-up on able-bodied and amputee subjects, which was used to evaluate upper-body motor behaviour in above-elbow prosthesis users. The virtual environment and task objects in third person and subject

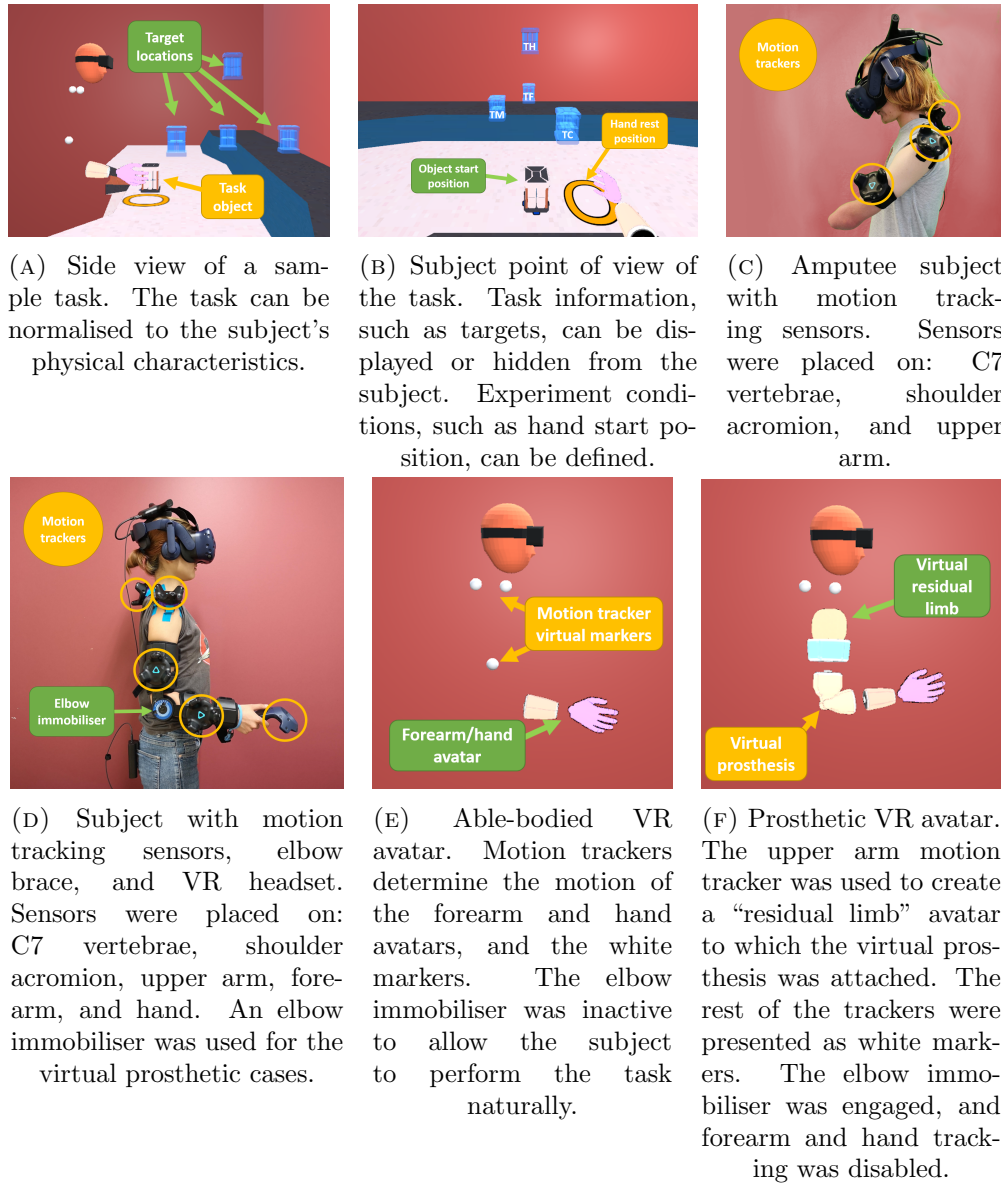


FIGURE 3.1: Experimental platform and task set-up. (a) presents the side view of the task and (b) the subject point of view in VR. (c) shows the motion tracking sensor placement, and (d) and (e) the VR avatars for the able-bodied and prosthetic cases.

views are shown in Figures 3.1a and 3.1b, respectively. For the purpose of this thesis, the tasks considered for the experiment will be reaching tasks as the analysis of the motor behaviour of users of above elbow prosthesis is the purpose of the VR platform. Because of the virtual environment, all aspects of the task can be customised. For instance, it is possible to automate object grasping to simplify the HPI or to control it through additional inputs such as sEMG. Moreover, it is possible to measure the time taken to perform tasks, body posture, and motion trajectories which are important in the evaluation of upper-limb prosthesis use.

Figures 3.1c and 3.1d show the sensor set-up for an amputee subject and an able-bodied subject respectively. For the AB modality, subjects are fitted with an elbow orthosis with two motion tracking sensors attached to it, one for the lower-arm and one for the upper-arm. Two additional motion tracking sensors are placed on the C7 vertebrae (trunk motion), the shoulder acromion (shoulder motion), and the hand (see Figure 3.1d). The elbow orthosis immobilises the subject's elbow in the PR modalities to better represent muscle conditions in amputees. Amputee subjects are fitted as able-bodied on their able arm for the AB modality, while for the PR modalities the upper-arm sensor is strapped to their residual-limb as shown in Figure 3.1c.

In the AB modality, motion of the upper-body, the whole arm and hand is directly mapped to the virtual environment through a virtual avatar as shown in Figure 3.1e. In the PR modalities, transhumeral amputation is emulated in able-bodied subjects in VR by using the data from the upper-arm motion tracker to determine the motion of the virtual residual limb. A virtual prosthetic elbow, forearm, and hand are attached to the virtual residual limb as seen in Figure 3.1f. Additional sensors, such as sEMG sensor, can be placed on the subjects depending on the application that is being evaluated. Moreover, additional inputs can be obtained from the Vive controller held in the subject's able-bodied side.

3.3 Experimental Protocol

This section describes the experimental protocol framework followed throughout the experiments presented in this thesis. A summary of the experimental protocol framework is presented in Table 3.1. The protocol is organised in three blocks which are detailed next.

3.3.1 Pre-experiment Protocol

The first step of all experiments was to provide subjects with an introduction to the experiment. The introduction was done both verbally and written, and included a description of the tasks in the experiment, the protocol followed throughout the experiment, and the safety procedures of the experiment and laboratory. The written introduction was done through the approved ethics documentation, which include a plain language

TABLE 3.1: Summary of experimental protocol framework.

Step	Time (minutes)	In-VR/No-VR
Pre-experiment protocol		
Introduction	5-10	No-VR
Sensor placement	15	No-VR
VR fitting	2	No-VR
Experiment protocol		
AB case	< 80	In-VR
Break	5-10	No-VR
PR case	< 80	In-VR
Post-experiment debriefing		
Debriefing	5	No-VR
Equipment sanitation	5	No-VR

statement (PLS) and a consent form. These documents are included in the Appendix A sections A.3 and A.4 respectively. The consent form was used to obtain informed consent from the subjects. The introduction was followed by sensor placement as presented in Section 3.2. Then, the subject was fitted with the VR headset, ensuring subject comfort and correct display of the VRE; proceeding to the experiment tasks which were performed in VR.

3.3.2 Experiment Protocol

The experiment section was separated into two blocks with a 5 to 10 minute break outside VR in-between as shown in Table 3.1. Each of these blocks was designated to test a specific modality (AB or PR). The experiment protocol framework for these blocks of modality testing is summarised in Table 3.2.

TABLE 3.2: Modality testing protocol framework.

Step	Time (minutes)	In-VR/No-VR
Introduction	5	In-VR
Training	5	In-VR
Practice	5	In-VR
Task set #1	< 20	In-VR
Break	1-2	In-VR
Task set #2	< 20	In-VR
Break	1-2	In-VR
Task set #3	< 20	In-VR

This protocol was used for both modality test cases (AB and PR). These experiment blocks were limited to a maximum of 80 minutes in VR to reduce any discomfort induced by wearing an HMD (such as eye fatigue). In the first step, subjects received further detailed instructions in the VRE and were reminded of the VR safety procedures. The second step consisted of a training session where the VRE guided subjects through how to use the prosthesis, the HPI, and how to perform the task. In the third step, subjects were allowed to practice performing the task and to familiarise themselves with the prosthesis, the task, and the VRE. No data was collected from the practice block. The last step consisted of the experiment tasks, which were split into multiple task blocks. Since the experiments required subjects to perform a task repeatedly for a set number of iterations, the number of iterations in each task blocks was set such that the time subjects were required to continuously repeat the task for was limited to 20 minutes. A maximum of three tasks blocks were allowed per modality to keep the time in VR to a maximum of 80 minutes. Rest time was given between the task blocks to reduce the effects of muscle fatigue on the results.

3.3.3 Post-experiment Debriefing

To develop anecdotal feedback, the subjects were engaged in informal conversation post-experiments. The conversation was centered around their experience in the VRE, and their point of view on the different PR modalities tested. Lastly, the experiment equipment was thoroughly sanitised using disposable alcohol swabs.

3.4 Data Gathering

Gathering of task data was performed using the tools available through Unity3D which are integrated into the platform. Motion data was gathered using the following frames of reference:

1. Virtual world frame of reference. This frame of reference is defined such that for the task the z-axis represents the forward direction, the y-axis the upwards direction, and the x-axis the lateral direction. The origin is placed on the floor under the position where the subjects stand to perform the task.

2. Sensor frame of reference. This frame of reference is determined by the sensor's yaw, pitch, and roll.

The virtual world frame of reference is mostly used for translation data, while the sensor frame of reference for orientation data. An example of data that can be gathered with the platform is presented in Table 3.3. Upper arm orientation was measured in the sensor frame of reference. The sensor placement was such that upper arm flexion/extension was represented by sensor roll, abduction/adduction by pitch, and humeral rotation by yaw. Upper arm angular velocity was measured in the sensor frame of reference. Upper arm angular velocity was represented with the same reference as upper arm orientation. The virtual hand absolute position in the virtual space was measured in the virtual world frame of reference. The absolute angular position of the virtual prosthetic elbow was measured with full elbow extension as the origin.

TABLE 3.3: Example of data gathered from experiments.

Data	Frame of reference	x/yaw	y/pitch	z/roll	Accuracy
Upper/lower arm orientation	Sensor	rotation	abduction	flexion	0.012°
Upper/lower arm angular velocity	Sensor	rotation	abduction	flexion	0.012°
Virtual hand position	Virtual world	lateral	upwards	forward	0.008cm
Virtual elbow orientation	Sensor	flexion	N/A	N/A	< 0.0001°

3.5 VR Platform Strengths and Limitations

The use of a VR-based platform for experiments in upper-limb prosthesis use has its strengths and limitations. In terms of the strengths, it allows to tightly control the experimental environment and task. Moreover, it can help simplify certain aspects of prosthetic use that may not be relevant to the studies of human motor behaviour, such as joint switching mechanisms and grasping tasks. It also allows able-bodied subjects to visually and functionally experience prosthesis use as their limb can be replaced with a virtual prosthesis; rather than relying on a supernumerary joint as it is done with hardware applications.

Regarding limitations, a significant limitation is the subject's lack of physical interaction with both the prosthesis and the environment. In terms of physical interaction with the prosthesis, factors such as prosthesis weight and socket fit can significantly impact motor capabilities, as is commonly seen by above elbow sockets restricting upper-arm motion. On the other hand, there is no physical interaction with the environment as it is virtual. However, it is possible to minimise the need for physical interaction with the environment by the careful selection of tasks which do not require physical interaction, such as pointing and reaching target areas. Lastly, use of an elbow brace for sensor placement can affect the natural motion of the subjects due to the restrictive nature of the brace. This can introduce motion artifacts for the able-bodied cases; however, in the prosthetic case this may not be as significant as subjects only use their upper-arm, which is not restricted.

While these limitations can impact the subject's motor behaviour, other methods such as using supernumerary devices on able-bodied subjects also impact subject's behaviour due to the introduction of an external device. With this in mind, the strengths provided in terms of closer visual and functional representation for both able-bodied and amputee subjects outweigh the limitations.

3.6 Summary

An immersive virtual reality-based experimental platform was developed for the evaluation of task and motor behaviour in upper-limb prosthesis users. The platform allows the emulation of prosthesis use in a virtual environment in both able-bodied and amputee subjects. Multiple HPis and external hardware can be integrated to the platform, while VR hardware is used for motion tracking. Different levels of amputation and upper-limb prosthesis types can be emulated. The platform has been made publicly available on Github and was used to perform the human experiments presented in this thesis. An experimental protocol framework used for the experiments in this thesis was developed and is the basis of results in the next chapters. Finally, the strengths and limitations of the VR platform were discussed. The next chapters focus on the main contribution of this thesis regarding the online personalisation of human-prosthetic interfaces.

Chapter 4

Online Kinematic Synergy Identification in Personalised Human-Prosthetic Interfaces

This chapter presents a feasibility study of using online optimisation for the personalisation of HPIs and a study on the properties of human-prosthesis systems in terms of human motor behaviour. The feasibility study is performed to determine whether online optimisation methods are applicable to human-in-the-loop applications and what challenges may arise from such application. The study of the human-prosthesis system properties is performed to determine the applicability of ES-based methods in human-prosthetic applications, particularly whether a human-prosthesis system satisfies Conditions 2.2 and 2.3. The chapter is presented as follows. First, the mathematical formulation of the human-prosthetic system and the assumptions placed on the system are presented, followed by the means used to satisfy the assumptions placed on the system in a proof-of-concept human-in-the-loop experiment. A framework for the personalisation of HPIs based on ES is presented and demonstrated experimentally. Lastly, an experimental study to determine the shape of the synergy-performance map is presented which demonstrates that Condition 2.2 is satisfied.¹

¹The contents of this chapter have been published in [93] and [77].

4.1 System Description

This sections presents the mathematical formulation for a human-prosthetic system. This formulation is used in the study of the feasibility of applying online optimisation methods for the personalisation of prosthetic devices. For ease of presentation, the case for an elbow prosthesis is presented, where the residual limb consists of the shoulder joint.

4.1.1 Model of a Human-Prosthetic Arm

In the case of upper limb amputation, an amputee is left with the residual limb which is capable of motion. For instance, in transhumeral amputations (above one's elbow) [8], the residual limb is composed of the shoulder joints and residual parts of the humerus, biceps and triceps. The motion of the residual limb (r) is represented by the joint angles $\mathbf{q}_r \in \mathbb{R}^R$, where $R > 0$ is the residual limb's DOF.

The motion of the prosthetic device (p) is represented by the joint angles $\mathbf{q}_p \in \mathbb{R}^P$, where $P > 0$. Then, the joints for the whole human-prosthesis arm can be represented by the following vector:

$$\mathbf{q} = \begin{bmatrix} \mathbf{q}_r & \mathbf{q}_p \end{bmatrix}^T, \quad (4.1)$$

where $\mathbf{q} \in \mathbb{R}^{R+P}$.

The dynamics of the residual limb can be described by the generalised equation of motion of a manipulator as

$$\mathbf{M}_r(\mathbf{q}_r)\ddot{\mathbf{q}}_r + \mathbf{C}_r(\mathbf{q}_r, \dot{\mathbf{q}}_r)\dot{\mathbf{q}}_r + \mathbf{G}_r(\mathbf{q}) + \mathbf{Z}_r(\mathbf{q}, \dot{\mathbf{q}}) = \boldsymbol{\tau}_r, \quad (4.2)$$

where $\mathbf{M}_r \in \mathbb{R}_+^{R \times R}$ is the generalised inertia matrix, which is positive definite and symmetric. The matrix $\mathbf{C}_r \in \mathbb{R}^{R \times R}$ is the Coriolis and centrifugal matrix. The gravity matrix $\mathbf{G}_r$ is in $\mathbb{R}^R$. The matrix $\mathbf{Z}_r \in \mathbb{R}^R$ represents interconnections between the residual limb and prosthesis [94]. The torque vector $\boldsymbol{\tau}_r \in \mathbb{R}^R$ represents the torques at the residual limb joints, which are produced by muscle forces.

Prosthesis dynamics can be described by the equation of motion:

$$\mathbf{M}_p(\mathbf{q}_p)\ddot{\mathbf{q}}_p + \mathbf{C}_p(\mathbf{q}_p, \dot{\mathbf{q}}_p)\dot{\mathbf{q}}_p + \mathbf{G}_p(\mathbf{q}) + \mathbf{Z}_p(\mathbf{q}, \dot{\mathbf{q}}) = \boldsymbol{\tau}_p, \quad (4.3)$$

where $\mathbf{M}_p \in \mathbb{R}_+^{P \times P}$, $\mathbf{C}_p \in \mathbb{R}^{P \times P}$, $\mathbf{G}_p \in \mathbb{R}^P$, $\mathbf{Z}_p \in \mathbb{R}^P$ represent the respective matrices as in (4.2), and $\boldsymbol{\tau}_p \in \mathbb{R}^P$ the torque vector representing actuator torque. It is important to note that the matrices in (4.2), (4.3) satisfy desirable properties, such as uniform boundedness, as pointed out in [94, 95].

The position of the hand is represented as

$$\mathbf{p} = \begin{bmatrix} p_x & p_y & p_z \end{bmatrix}^T = \mathbf{h}(\mathbf{q}), \quad (4.4)$$

where the nonlinear mapping $\mathbf{h} : \mathbb{R}^{R+P} \rightarrow \mathbb{R}^3$ represents forward kinematics. Hand velocity is represented by:

$$\dot{\mathbf{p}} = \begin{bmatrix} \dot{p}_x & \dot{p}_y & \dot{p}_z \end{bmatrix}^T = \mathcal{J}(\mathbf{q})\dot{\mathbf{q}}, \quad (4.5)$$

where $\mathcal{J}(\mathbf{q}) \in \mathbb{R}^{3 \times (R+P)}$ is the human-prosthetic arm Jacobian.

The focus of this thesis is the case of transhumeral prostheses, where the residual limb is composed of the shoulder joint while the prosthetic limb is composed of the elbow joint, forearm and hand [8]. For the sake of ease of presentation, only the elbow is considered herein. Figure 4.1 shows a planar representation of the prosthetic elbow case.

In this case, the residual and prosthetic limbs are represented by

$$\mathbf{q}_r = \begin{bmatrix} q_{abd} & q_{fle} & q_{rot} \end{bmatrix}^T, \quad (4.6a)$$

$$\mathbf{q}_p = q_{elb}, \quad (4.6b)$$

respectively. $q_{abd} \in \mathbb{R}$ represents shoulder abduction/adduction, $q_{fle} \in \mathbb{R}$ shoulder flexion/extension, and $q_{rot} \in \mathbb{R}$ humeral rotation. $q_{elb} \in \mathbb{R}$ represents the prosthetic elbow flexion/extension. Then, the joint angles of the whole human-prosthetic arm for the transhumeral case are represented by

$$\mathbf{q} = \begin{bmatrix} \mathbf{q}_r & \mathbf{q}_p \end{bmatrix}^T = \begin{bmatrix} q_{abd} & q_{fle} & q_{rot} & q_{elb} \end{bmatrix}^T. \quad (4.7)$$

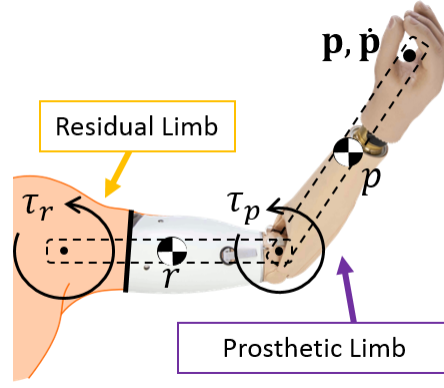


FIGURE 4.1: Human-prosthetic arm diagram.

4.1.2 Human Motor Control Model

Human motor control of the upper limb has properties that allow for the hand to track a reference trajectory in space. That is, for a given hand position, it can track it in steady-state even with unstable interaction forces [96], making it robust to bounded disturbances [97],[98].

Based on [99], a model of human motor control for the residual limb is presented as a summation of three terms:

$$\boldsymbol{\tau}_r = \boldsymbol{\tau}_{idm} + \boldsymbol{\tau}_{fb} + \Delta\boldsymbol{\tau} \quad (4.8)$$

$$\begin{aligned} \boldsymbol{\tau}_{idm} = & \hat{\mathbf{M}}_r(\mathbf{q}_r^*)\ddot{\mathbf{q}}_r^* + \hat{\mathbf{C}}_r(\mathbf{q}_r^*, \dot{\mathbf{q}}_r^*)\dot{\mathbf{q}}_r^* + \hat{\mathbf{G}}_r(\mathbf{q}^*) \\ & + \hat{\mathbf{Z}}_r(\mathbf{q}^*, \dot{\mathbf{q}}^*, \ddot{\mathbf{q}}^*) \end{aligned} \quad (4.9)$$

$$\boldsymbol{\tau}_{fb} = -\mathbf{K}_{r,p}(\tilde{\mathbf{q}}_r + r_{sd}\dot{\tilde{\mathbf{q}}}_r). \quad (4.10)$$

$\tilde{\mathbf{q}}_r = \mathbf{q}_r - \mathbf{q}_r^*$, $\dot{\tilde{\mathbf{q}}}_r = \dot{\mathbf{q}}_r - \dot{\mathbf{q}}_r^*$. The $\mathbf{q}^*$ notation represents the desired $\mathbf{q}$. $\boldsymbol{\tau}_r$ is the total joint torques given by a feed-forward term $\boldsymbol{\tau}_{idm}$, a feedback term $\boldsymbol{\tau}_{fb}$, and a perturbation term $\Delta\boldsymbol{\tau}$. $\boldsymbol{\tau}_{idm} \in \mathbb{R}^R$ is given by the brain's learned inverse dynamic model of the arm, which includes the learned disturbances related to the prosthetic device. Matrices $\hat{\mathbf{M}}_r$, $\hat{\mathbf{C}}_r$, $\hat{\mathbf{G}}_r$, and $\hat{\mathbf{Z}}_r$ represent the learned dynamics. $\boldsymbol{\tau}_{fb} \in \mathbb{R}^R$ represents muscle stiffness and reflex feedback, and $\Delta\boldsymbol{\tau}$ motor behaviour variability. $r_{sd} > 0$ is the joint's stiffness-to-damping ratio, and $\mathbf{K}_{r,p}$ is the positive definite joint stiffness matrix given by reciprocal muscle activation and voluntary co-activation [99]. Performance variability is assumed to be

bounded by a non-zero positive constant c_v such that

$$\|\Delta\tau\| < c_v. \quad (4.11)$$

First, it is assumed that after learning, humans are able to estimate the matrices in (4.9) well enough. When the inverse dynamic model of the residual limb with attached prosthesis has been learned by the CNS, it can be stated that $\hat{\mathbf{M}}_r = \mathbf{M}_r$, $\hat{\mathbf{C}}_r = \mathbf{C}_r$, $\hat{\mathbf{G}}_r = \mathbf{G}_r$, and $\hat{\mathbf{Z}}_r = \mathbf{Z}_r$; such that the closed loop dynamics of the residual limb, from equations (4.2), (4.8), can be simplified to

$$\ddot{\tilde{\mathbf{q}}}_r = -\mathbf{K}_{r,p}(\tilde{\mathbf{q}}_r + r_{sd}\dot{\tilde{\mathbf{q}}}_r) + \Delta\tau. \quad (4.12)$$

This can be ensured by providing the user with sufficient training time with the prosthesis, as it has been shown that the CNS can learn and compensate for disturbances [99]. Furthermore, it is clear that, after learning, the dynamics of the residual limb are dominated by the feedback term τ_{fb} . This follows experimental observations with regards to the behavior of the human arm [96].

4.1.3 Prosthesis Control

Control of the joints in the prosthesis is usually given by a feedback controller, such as a PD controller with gravity compensation [95].

$$\tau_p = -\mathbf{K}_{p,p}\tilde{\mathbf{q}}_p - \mathbf{K}_{p,d}\dot{\tilde{\mathbf{q}}}_p + \hat{\mathbf{G}}_p(\mathbf{q}), \quad (4.13)$$

where $\mathbf{K}_{p,p}$, $\mathbf{K}_{p,d}$ are diagonal positive definite stabilizing gains, $\tilde{\mathbf{q}}_p = \mathbf{q}_p - \mathbf{q}_p^*$, and $\mathbf{q}_p^* \in \mathbb{R}^P$ is the desired prosthetic joint angle. Current prosthetic devices use the signals from an EMG interface to provide the desired joint angle reference; however, for the kinematic synergies approach, the desired angle reference is provided by the kinematic shoulder-elbow synergy. When the gravity compensation term is completely learned, $\hat{\mathbf{G}}_p = \mathbf{G}_p$. Moreover, if the feedback gains $\mathbf{K}_{p,p}$ and $\mathbf{K}_{p,d}$ are sufficiently large such that there exist positive definite diagonal matrices Γ_1 and Γ_2 , the prosthesis closed loop dynamics, from equations (4.3), (4.13), is simplified to

$$\ddot{\tilde{\mathbf{q}}}_p = -\Gamma_1\tilde{\mathbf{q}}_p - \Gamma_2\dot{\tilde{\mathbf{q}}}_p. \quad (4.14)$$

4.1.4 Kinematic Synergies Model

Kinematic synergies, in the context of prosthetics, characterise the motion of the prosthetic limb $\dot{\mathbf{q}}_p$ by that of the residual limb $\dot{\mathbf{q}}_r$. This, in general, can be represented by a function parameterised by a family of parameters. These parameters determine a specific kinematic synergy. A general form of kinematic synergies is:

$$\dot{\mathbf{q}}_p^* = \mathbf{f}(\boldsymbol{\theta}, \dot{\mathbf{q}}_r), \quad (4.15)$$

where $\boldsymbol{\theta} \in \Theta$ are the parameters that determine a specific synergy, Θ is a compact set in $\mathbb{R}^S$, S the number of synergy parameters, and $\mathbf{f} : \mathbb{R}^R \times \Theta \rightarrow \mathbb{R}^P$ is the known continuously differentiable general synergy function. It is important to note that f also depends on the initial condition and task used to train the synergy; however, for ease of presentation these terms are not included in the notation. A shoulder-elbow linear synergy can be parameterised as follows:

$$\dot{q}_{elb}^* = \mathbf{f}(\boldsymbol{\theta}, \dot{\mathbf{q}}_r) = \theta_a \dot{q}_{abd} + \theta_f \dot{q}_{fle} + \theta_r \dot{q}_{rot}. \quad (4.16)$$

The parameters for a given synergy parameterisation are then dependent on the characteristics of the task, desired motion, and the residual limb trajectory. While similarities exist in the motion and synergies of individuals, variations exist as these are affected by a wide range of factors such as preference [24]. Hence, finding a general model that can fit each individual is difficult, even though a large number of data can be collected. Furthermore, synergies in amputees are affected due to the limitations of the device and residual limb compensatory movements that arise from these limitations [11]. Thus a data driven online optimisation method to iteratively seek the optimal parameter set for a given parameterisation, a given task, and an individual subject is proposed herein.

4.1.5 Problem Formulation

The proposed synergistic human-prosthesis arm dynamic system is presented as a block diagram in Figure 4.2. The dynamic system can be represented in state space form as composed by three subsystems, the residual limb dynamics represented by Σ_1 , the synergy dynamics by Σ_2 , and the prosthesis dynamics by Σ_3 .

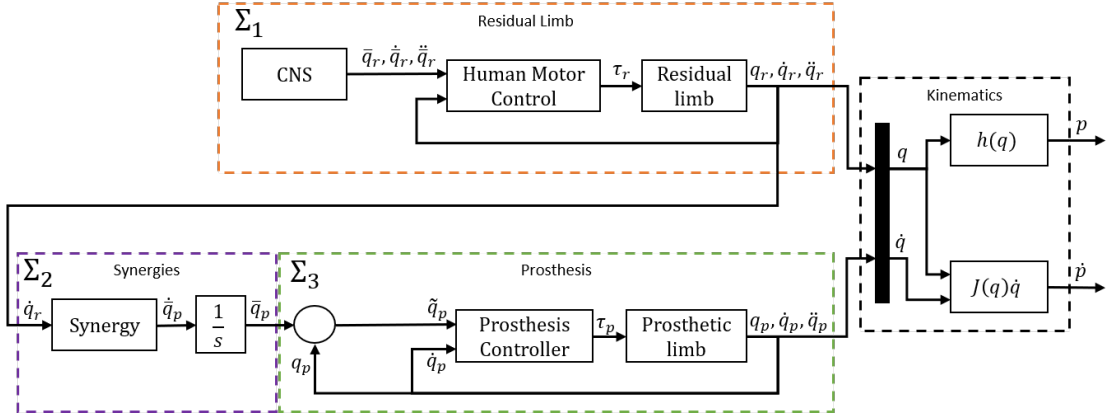


FIGURE 4.2: Synergistic human-prosthesis arm block diagram.

Consider the residual limb state signals $\xi_1 = \tilde{\mathbf{q}}_r$ and $\xi_2 = \dot{\tilde{\mathbf{q}}}_r$, such that the subsystem representing residual limb closed loop dynamics, from equation (4.12), Σ_1 , is given by

$$\Sigma_1 \left\{ \begin{bmatrix} \dot{\xi}_1 \\ \dot{\xi}_2 \end{bmatrix} = \begin{bmatrix} \xi_2 \\ -\mathbf{K}_{r,p}(\xi_1 + r_{sd}\xi_2) + \Delta\tau \end{bmatrix} \right. \quad (4.17)$$

Due to the boundedness of human variability (4.11), the trajectories of the system Σ_1 are globally uniformly bounded.

The synergy state is defined as $\zeta = \mathbf{q}_p^*$, such that the subsystem representing synergy dynamics, Σ_2 , is given by

$$\Sigma_2 : \dot{\zeta} = \mathbf{f}(\theta, \xi_2), \quad (4.18)$$

where θ is the synergy parameter vector to learn. This system Σ_2 depends on the state ξ_2 . From the physical meaning of this system, it is natural to assume that ζ is uniformly bounded for any $\theta \in \Theta$ and any ξ_2 from a predefined compact set. Moreover, the rate of change of the reference provided to the prosthesis controller, $\dot{\zeta}$, is sufficiently slow as it depends on the residual limb. It is assumed that the set for the unknown parameter is defined as $\Theta = \{\theta \mid \theta_{\min} \leq \theta \leq \theta_{\max}\}$, where $\theta_{\min}$ and $\theta_{\max}$ are the lower and upper bounds of θ , respectively. Thus enforcing that the reference provided to the prosthesis controller remains within the set of interest.

Finally, let the prosthesis state be $\eta_1(\zeta) = \tilde{\mathbf{q}}_p(\zeta)$ and $\eta_2 = \dot{\tilde{\mathbf{q}}}_p$, such that the subsystem representing prosthesis closed loop dynamics, from equation (4.14), Σ_3 , is approximated

by

$$\Sigma_3 : \left\{ \begin{bmatrix} \dot{\boldsymbol{\eta}}_1 \\ \dot{\boldsymbol{\eta}}_2 \end{bmatrix} = \begin{bmatrix} \boldsymbol{\eta}_2 \\ -\Gamma_1 \boldsymbol{\eta}_1 - \Gamma_2 \boldsymbol{\eta}_2 \end{bmatrix} \right. . \quad (4.19)$$

Moreover, it is assumed that the stability properties of Σ_3 are uniform with respect to any $\boldsymbol{\zeta}$ that is within a compact set of interest.

It is noted that the focus of this formulation is not the stability of the overall system as boundedness of the three systems has already been achieved. This can be concluded from the properties of the physical system (human-prosthesis), which cannot generate unbounded trajectories. Human joints have limited range of motion and angular velocity they can produce and the HPI is a bounded function of these bounded trajectories, hence the resultant trajectories are also bounded. The focus is finding an optimal set of parameters ($\boldsymbol{\theta}$) for a given parameterisation for each individual repeating the same task many times. Even though the proposed parameterisation might not be the best for this setting, with the proposed online parameter identification technique, the best parameter set can still be identified using the input-output measurements of the relationship between the parameters and the task. This is provided that the optimal parameter set is iteration invariant or slowly changing over iterations. In order to do online parameter identification, an appropriate measure of performance (cost function) is needed. Next, the problem is formulated as an optimisation problem.

When a point-to-point tracking task is considered, the cost is related to tracking performance. That is, finding an optimal set of parameters if a human subject repeats the task many times. More precisely, arm motion with hand target $\mathbf{p}_f^*$, initial conditions $\boldsymbol{\xi}_1(T_o)$, $\boldsymbol{\eta}_1(T_o)$, and residual limb trajectory $\boldsymbol{\xi}_1(t) \forall t \in [T_o, T_f]$ is considered. The objective is to determine the optimal synergy parameters $\boldsymbol{\theta}^*$ over iterations (or by repeating the same task over the iteration domain) such that the hand reaches a small neighbourhood of the desired target by the end of motion, i.e. $\mathbf{p}^{(i)}(T_f) \rightarrow \mathbf{p}_f^*$ as the iteration number i goes to infinity.

4.2 Task Characterisation and Online Kinematic Synergy Identification

In order to simplify the presentation, a reaching task is considered. A similar idea can be applied to more complex tasks with appropriate modifications. Furthermore, most Activities of Daily Living (ADLs) require some sort of reaching motions. Many others, such as eating, consist of repetitive reaching motions.

4.2.1 Reaching Task Characterisation

A point-to-point reaching task can be described by the desired hand start and end positions $\mathbf{p}_o^* \in \mathbb{R}^3$, $\mathbf{p}_f^* \in \mathbb{R}^3$, respectively. Other than tracking accuracy, the quality of the motion, typically represented by hand jerk $\ddot{\mathbf{p}}(t)$, is also considered, where $t \in [t_o, t_f]$, $t_f \leq t_{f,\max}$ for a given $t_{f,\max}$.

The number of iterations is represented by the superscript i . For example, the hand trajectory at the i^{th} iteration is denoted as $\mathbf{p}^i(t)$. It is assumed that $\mathbf{p}_o^*$ and $\mathbf{p}_f^*$ can be determined through an initialisation or teaching phase where the user manually moves the prosthesis to the desired start and end positions, such as is the case with training environments.

In general, this set of motion characteristics can be represented as a cost function that linearly combines the motion objectives [13]. Let the task cost function be given by

$$J(\boldsymbol{\theta}) = \sum_{j=1}^n \alpha_j \psi_j, \quad (4.20)$$

where $n > 0$ is the number of motion characteristics considered, and $\alpha_j > 0$ the weight given to each characteristic. The non-linear mapping $\psi_j : \mathbb{R}^{M_j} \rightarrow \mathbb{R}_+$ represents a desired motion characteristic, where M_j is the dimension of the arguments of ψ_j . It is assumed that each motion objective is related to the task and thus the synergy, i.e., $\psi_j = \psi_j(\boldsymbol{\theta})$, though an explicit model of this relationship is unavailable. Moreover, it is also assumed that the cost function is measurable at each iteration. It is assumed that the format of this cost function is iteration-invariant, or very slow changing over iteration domain.

Typical motion characteristics are target error (4.21) and hand jerk (4.22) [13]. Here, ψ_1 is the tracking error and ψ_2 is the jerk of hand movements.

$$\psi_1 = \|\mathbf{p}^i(T_f^i) - \mathbf{p}_f^*\|^2 \quad (4.21)$$

$$\psi_2 = \int_{T_o}^{T_f^i} \|\ddot{\mathbf{p}}^i(t)\|^2 dt, \quad (4.22)$$

T_o is the motion start time, which is iteration invariant, and $T_f^i > 0$ is the iteration varying motion end time satisfying $t_o \leq T_o \leq T_f^i \leq t_{f,max}$.

From equation (4.4) and the systems Σ_1 , Σ_2 , and Σ_3 , it is clear that hand trajectory $\mathbf{p}(t)$ is a function of the residual limb trajectory $\boldsymbol{\xi}_1(t)$ and synergy parameterisation $\boldsymbol{\theta}$. It has been shown that after learning, human motor behavior converges to a region around an optimal motion and motion completion time [100], such that given an optimal residual limb trajectory $\boldsymbol{\xi}_1^*(t)$ and end time T_f^* the following inequalities hold

$$\|\boldsymbol{\xi}_1^i(t) - \boldsymbol{\xi}_1^*(t)\| \leq v_q \quad (4.23)$$

$$\|T_f^i - T_f^*\| \leq v_t, \quad (4.24)$$

where $v_q, v_t > 0$. Then, a function composed of ψ_1 and ψ_2 has a unique extremum when $\boldsymbol{\xi}_1(t) = \boldsymbol{\xi}_1^*(t)$ and $\boldsymbol{\theta} = \boldsymbol{\theta}^*$.

Remark 4.1. The optimal motion $\boldsymbol{\xi}_1^*(t)$ and time T_f^* vary among individuals, and so do v_q and v_t . Particularly, v_q is a function of the joint torque variation $\Delta\boldsymbol{\tau}$ of each individual. $\circ$

4.2.2 Online Kinematic Synergy Identification

It is clear from the physical properties of systems Σ_1 , Σ_2 , and Σ_3 that the system is stable by ensuring $\boldsymbol{\theta}$ remains in the domain of interest with the projection method. By allowing the subjects sufficient training time to learn the task and its dynamics, equations (4.23) and (4.24) hold, and thus the cost function $J(\boldsymbol{\theta})$ has a unique extremum when $\boldsymbol{\theta} = \boldsymbol{\theta}^*$. Therefore, the system satisfies Assumptions 1-3 in [75].

Given the iterative nature of the problem, discrete-time ES [101] is suitable to the problem. Even though the task is iterative in task space, it is not necessarily finished within the same time interval in every iteration. However, in controlled environments,

e.g. training, a fixed completion time can be set to every iteration such that $T_f^i = t_{f,max}$. Thus the conditions for discrete-time ES in [101, 102] are satisfied.

An important aspect of the problem is the performance variation introduced by having a human-in-the-loop. This variation is reflected in the gradient of the cost function as a bounded non-vanishing perturbation. As has been discussed in [103], when this perturbation is sufficiently small (in this work v_q) stability and semi-global asymptotic convergence of the system is not affected. This can be satisfied by allowing sufficient training time for the human to learn the task and dynamics of the system.

Even though the task cost function is estimated by the selected cost function in (4.20), the explicit relationship between J and θ is unknown. Thus a discrete-time ES algorithm is used to estimate the gradient $\frac{\partial J}{\partial \theta}$ using only input-output measurements. By tuning parameters appropriately, the output of ES will converge to a small neighborhood of the optimal value. As the gradient method is used, local or regional convergence can be achieved. The diagram of the proposed online parameter estimation method is presented in Figure 4.3. Subscript $k = \{1, 2, \dots, S\}$ represents each parameter to be estimated, and thus one ES loop is used for each parameter.

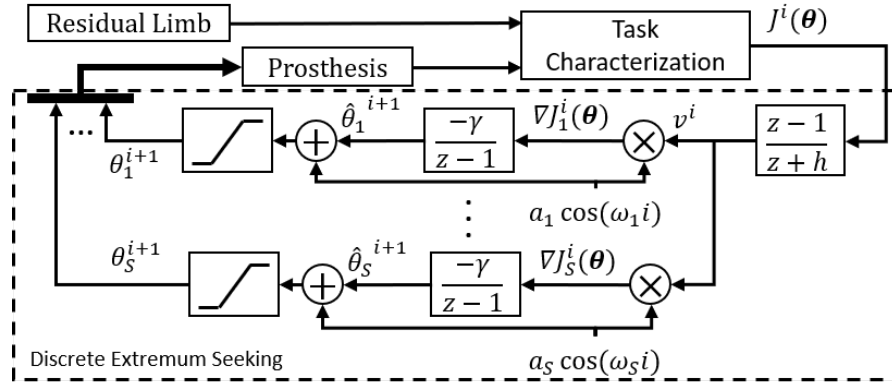


FIGURE 4.3: online synergy identification.

From this figure, the updating laws, for each ES loop k , can be presented as follows

$$v^i = -hv^{i-1} + J^i(\theta) - J^{i-1}(\theta) \quad (4.25)$$

$$\hat{\theta}_k^{i+1} = \hat{\theta}_k^i - \gamma a_k \cos(\omega_k i) v^i \quad (4.26)$$

$$\theta_k^{i+1} = \begin{cases} \theta_{\min}, & \hat{\theta}_k^{i+1} < \theta_{\min} \\ \theta_{\max}, & \hat{\theta}_k^{i+1} > \theta_{\max} \\ \hat{\theta}_k^{i+1} + a_k \cos(\omega_k i) & \text{else} \end{cases} \quad (4.27)$$

ω_k represents the dither frequency for each ES loop, satisfying the condition that they are not equal to each other, or their linear combinations [33]. $a_k \in \mathbb{R}$ is the dither amplitude. $0 < h < 1$ is the high pass filter cutoff frequency, which should be smaller than the smallest dither frequency ω_k . $\gamma > 0$ is a parameter related to the convergence speed of the algorithm. Equation (4.27) denotes the update law with projection on $\boldsymbol{\theta}$ to ensure the condition $\boldsymbol{\theta} \in \Theta$. The structure of ES in Figure 4.2 is similar to [101, 102], with the extra projection block added.

Remark 4.2. The dither frequencies ω_k are selected such that the following inequalities are satisfied

$$\omega_k \neq \omega_p, \quad p \neq k, \quad k, p = \{1, \dots, S\} \quad (4.28)$$

$$\omega_k \neq \omega_p + \omega_r, \quad \forall k, p, r = \{1, \dots, S\}, \quad (4.29)$$

in order to ensure sufficient persistency of excitation. ◦

4.3 Human-in-the-loop Feasibility Study

In order to evaluate the feasibility of the proposed framework, a human-in-the-loop experiment was performed. The experiment was designed to emulate a transhumeral amputee wearing an elbow prosthesis, as shown in Figure 4.4, by only considering motion of the upper arm of able-bodied subjects. The study was performed with two able-bodied subjects, one male (28) and one female (25). Measurements of the upper arm motion were obtained using Thalmic Labs' Myoband IMU [104], which provided shoulder joint position $\mathbf{q}_r$ and velocity $\dot{\mathbf{q}}_r$. The task consisted of a forward reaching task to be repeated 75 times.

A real-time human-in-the-loop simulation was done in MATLAB/Simulink 2017a on an Intel Core i7-6600 at 2.60GHz, 16.0GB of RAM. The simulation sample time was $dt = 0.02s$ with user interface (UI) refresh rate of 0.1s. The upper arm motion was measured at every sample. The UI showed a first person view of the target and arm, as shown in Figure 4.4, where the orange ball represents the starting point $\mathbf{p}_o^*$ and the blue ball the target $\mathbf{p}_f^*$.

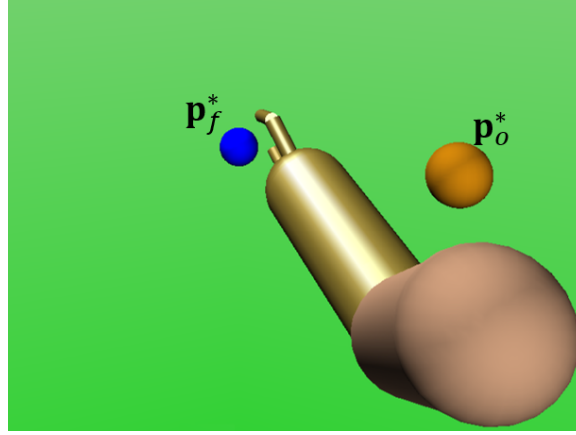


FIGURE 4.4: Experiment GUI.

Subjects were allowed training time with the task and environment in order to satisfy the conditions established in Section 4.2.2. The maximum time allowed for completion of motion was set to five seconds $t_{f,max} = 5$. A linear synergy parameterisation, as presented in equation (4.16), was chosen. Synergy parameters were initialised at zero $\theta^1 = 0$. The cost function consisted of tracking error ψ_1 and hand jerk ψ_2 , equations (4.21) and (4.22) respectively. The weights used in the cost function were $\alpha_1 = 1$, $\alpha_2 = 0.1$. The following tuning parameters for the ES algorithm were used $h = 0.001$, $\gamma = 30$, $w_1 = 0.8\pi$, $w_2 = \pi$, $w_3 = 0.6\pi$, $a_1 = a_2 = a_3 = 0.1$. θ limits were set to $\theta_{max} = 1$ and $\theta_{min} = -2$.

4.3.1 Experimental Results

Experimental results are presented in Figures 4.5, 4.6, 4.7, and 4.8, where results for Subject 1 are presented with solid lines and Subject 2 with dotted lines. Figure 4.5 shows an example of the shoulder trajectory followed in one iteration of the task, which is obviously bounded. The iteration chosen for comparison showed similar performance for both subjects. From this it is possible to observe the difference in human motor strategies followed by each subject. This is reflected in the elbow trajectory arising from the synergy, as shown in Figure 4.6.

Figure 4.7 shows the evolution of the synergy parameters throughout iterations while Figure 4.8 the value of the cost function. As expected, the difference in motion strategy followed by each subject is reflected in the optimal synergy parameters. This suggests that learning from individual data is thus needed to address variability coming from

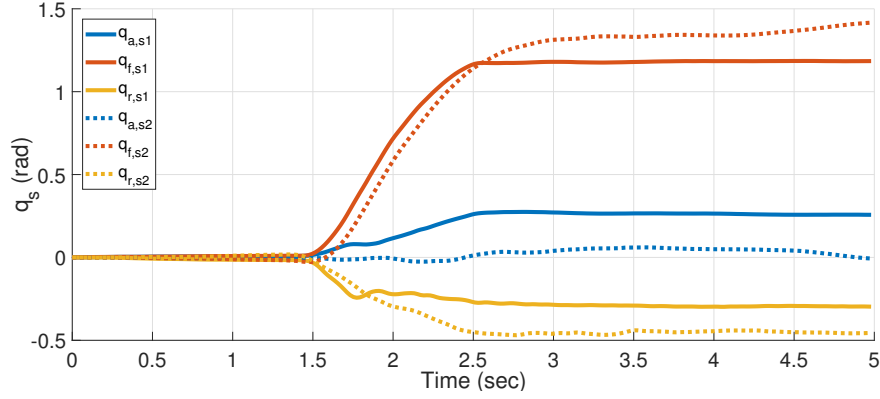


FIGURE 4.5: Sample shoulder trajectories for both subjects.

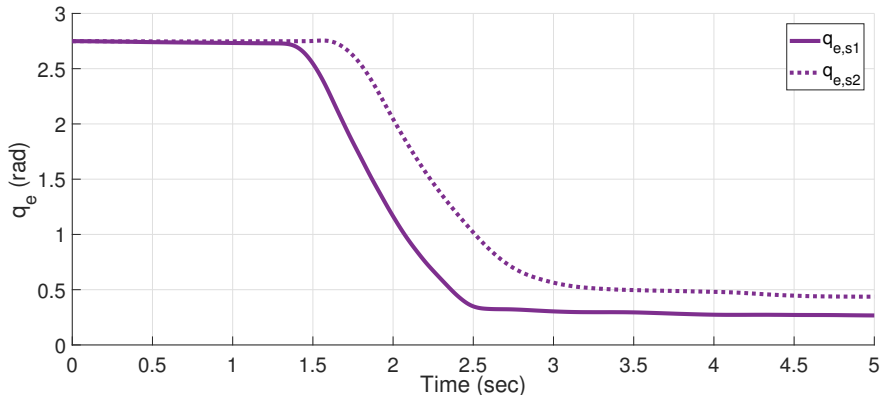


FIGURE 4.6: Sample elbow trajectories for both subjects.

human subjects. Any model from averaged behaviors will have problems. It is also noted that similarities can still be observed. An important observation arises in the results for Subject 2 in Figure 4.8 between iterations 20 and 40, where performance variation was significantly higher than in other iterations. This in turn can be observed in the convergence of the ES algorithm, as is shown in Figure 4.7 within the same iterations. This behavior is expected as human performance variation is reflected in the cost function as a bounded perturbation, and in turn affects the boundary of convergence of the ES algorithm.

Subjects were given sufficient training time to mitigate the transient behavior introduced by human motor learning and reduce performance variability. However, in a practical application, human learning will need to be considered if the system is to adapt to a range of individuals. Moreover, the framework relies on the assumption that there exists a local extremum in the input/output map of interest [105, Assumption 2]; which is a common requirement for gradient based online optimisation methods. It is established in the literature that human motor control strategy converges to a particular trajectory

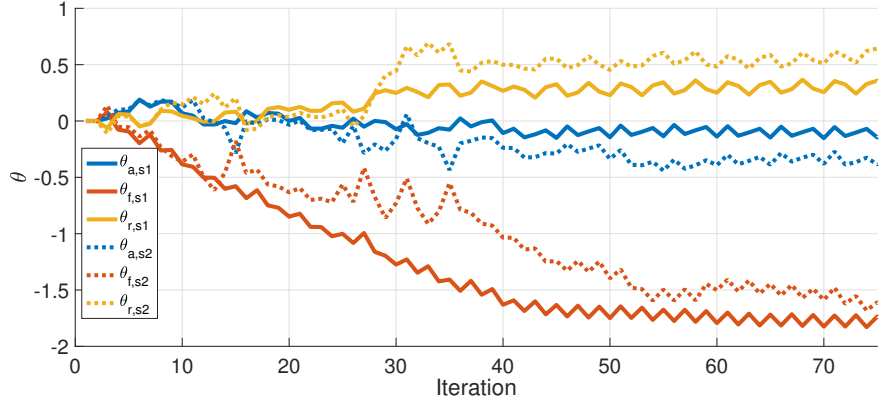


FIGURE 4.7: Synergy parameters identification results.

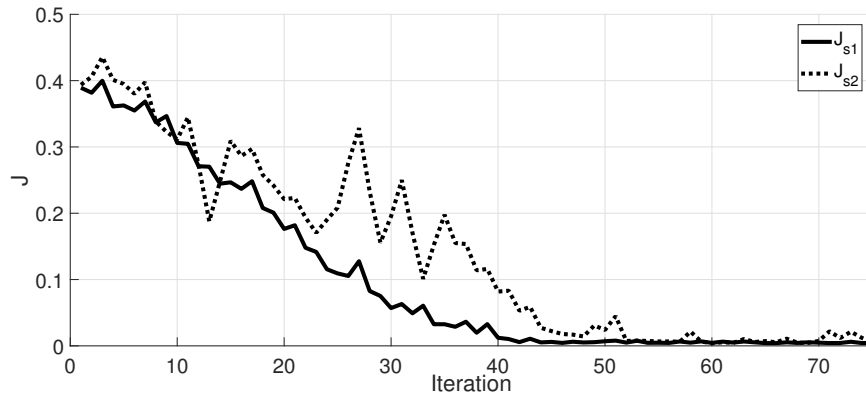


FIGURE 4.8: Cost function results.

of task execution when the task is learned (e.g. [98]). Nevertheless, it is yet to be experimentally established that given a range of possible kinematic synergies, when all the synergies are learned by the human (rather than focusing on a single synergy), there exists one where the performance of the task is better, by a specified measure, than with other synergies.

In the subsequent sections in this chapter, the relationship between the parameters of the synergy model (θ) and the measure of task performance (J) is established experimentally in order to test the applicability of online optimisation methods for the identification of synergies. For the experimental study, a cost function that captures the objective of the reaching task and a linear kinematic synergy model were chosen without loss of generalisation to other approaches that are linear in their parametrisation. The human experiment to determine the synergy-performance relationship for a set of synergies was performed in the VR platform presented in Chapter 3 on 10 able-bodied subjects.

4.4 Synergy-Performance Map Evaluation Methodology

4.4.1 Description of the Synergy and Measure of Performance

Given that the focus of this study is on finding the relationship between synergies and task performance rather than the choice of synergies, a scalar shoulder-elbow linear synergy model was chosen. This simplifies the presentation and analysis as the relationship between synergy and performance is presented as a map. Linear synergies have been observed to occur between the shoulder and elbow during reaching motion [60] and has been found to be able to represent the most significant relationship between shoulder and elbow motion for forward reaching tasks [28]. The elbow to shoulder flexion kinematic synergy is described by

$$\dot{q}_p = \theta \dot{q}_r, \quad (4.30)$$

where the subscripts r and p represent residual and prosthetic limb respectively. $\dot{q}_r$ is the individual's shoulder flexion angular velocity. $\dot{q}_p$ is the angular velocity of the prosthetic elbow. $\theta \in \Theta$ is the synergy parameter. Experimentally identifying the optimal parameters θ^* for a group of individuals and the relationship of θ to task performance is the main objective of the study herein.

Multiple cost-function-based motion characteristics have been proposed in the literature to represent reaching motion. Examples of these characteristics are tracking error, torque-change, and hand jerk [13]. Given the application and experimental hardware setting, tracking and hand jerk are more feasible for measurement than other methods. The cost function to measure performance according to hand tracking and jerk is given by equations (4.20), (4.21), and (4.22).

4.4.2 Experiment Description and Protocol

Subjects performed a center-out forward reaching task from a seated position while using a virtual synergistic prosthetic elbow. The start and end positions were constant throughout the experiment and were shown in the VR environment as presented in Figure 4.9.B. Ten different values of the scalar synergy parameter (θ) were explored.

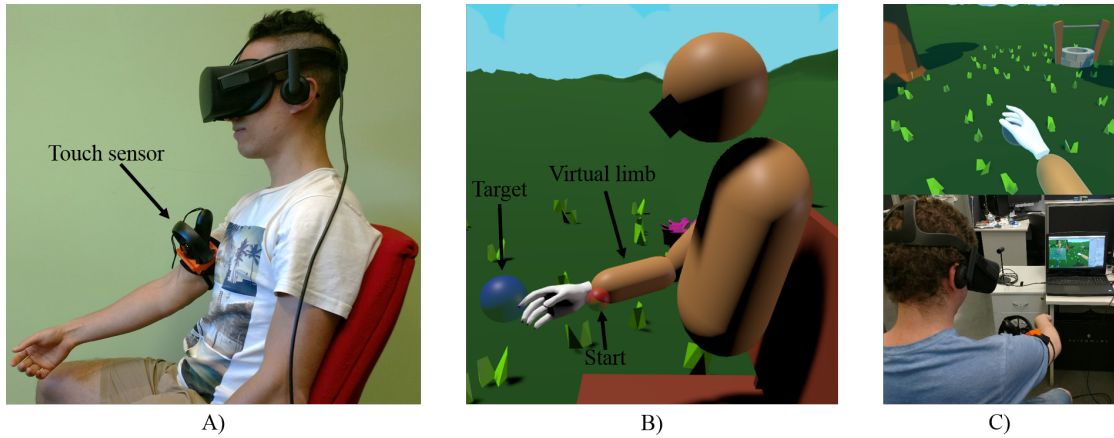


FIGURE 4.9: Experiment platform set-up: A) Subject position and sensor placing. B) Subject in virtual environment. C) Subject and VR views.

In order to be able to observe the mapping between Synergy and Performance, it was necessary to isolate the transient behavior due to task learning. Thus subjects repeated the reaching task for each value until it was deemed as learned.

Learning of the task was determined by the variability of the trajectory followed by the hand, with the successfully learned task condition being reaching a variability radius under $v_p = 2\text{cm}$. This condition was determined by following studies that demonstrated that as humans learn a hand reaching task, the variability of hand trajectories is reduced [106]. The $v_p = 2\text{cm}$ radius was chosen by testing the reaching capabilities of able-bodied people, hardware tracking precision, and additional tolerance to account for the virtual prosthesis.

Trajectory variability was determined by sampling hand trajectory and evaluating it at fixed time steps. Trajectory mean and standard deviation was calculated for a sliding window of 10 task repetitions at each sampling time step. This was used to generate a spheroid centered at the mean hand position with radius given by the standard deviation. The set of spheroids represents the mean trajectory and standard deviation [107]. The learning condition is achieved when the radius of all spheroids is smaller or equal to v_p .

The experiment was performed on 10 able-bodied subjects (A-J). The forward reaching task was repeated a minimum of 10 times and maximum of 50 times for each parameter to be analyzed, with successful learning triggering a parameter change. The parameter values for each subject were manually determined by the experimenter in order to explore the regions of the parameter space best suited to each subject, with the first three values

being predetermined to 1.5, 1.1, and 1.9, in the respective order. Subsequent values were chosen by alternating between the extremes of the identified search region in order to minimise skill transfer between synergy values. Cost functions (ψ_1, ψ_2) were normalised to be within the same range (0-1) and equal weights were given to them ($\alpha_1 = \alpha_2 = 1$). Each reaching motion had a time limit of 3 seconds. The hardware set-up was as described in Section 3.2, the experimental protocol as described in Section 3.3 and data gathering as described in Section 3.4.

4.5 Synergy-Performance Map Results and Discussion

Subjects were able to maintain a consistent level of trajectory variability across iterations, converging asymptotically to the desired threshold (v_p) as learning occurred, as has been observed with performance in other works [98]. Representative results of this are shown in Figure 4.10.A, where variability across iterations for subject E is presented. The sudden increases in variability are due to a change of θ value, which has been previously observed in humans when subjected to changing system dynamics [108]. In a few subjects where slower learning rate was observed, convergence to the desired level of trajectory variability v_p was not achieved within the allotted number of iterations in the experiment. In these cases, variability was observed to increase towards the last iterations as can be seen in Figure 4.10.B. This may be attributed to fatigue due to the larger number of repetitions performed during the experiment. These results suggests that the chosen learning condition should be able to accommodate for individual capabilities, learning rates and performance variation throughout the use of the device to properly isolate the transient behavior caused by human learning dynamics.

Figure 4.11 presents the relationship between the proposed cost function (J) in Equation (4.20) and the synergy parameter values (θ) for all able-bodied subjects (A-J), where the last 10 iterations per value (as per the learning condition presented in Section 4.4.2) were used to generate the box and whiskers plots. It was observed that the performance range (J) differs across individuals, and that the minimum cost (J^*) was observed at different synergy parameter values (θ^*) for different subjects. This highlights both individual variability in performance (J) and in synergies (θ). Furthermore, when the average best synergy across all subjects ($\theta_\mu^* = 1.7$) is considered and performance evaluated, it can be observed that for some subjects performance would be significantly impaired, e.g. by

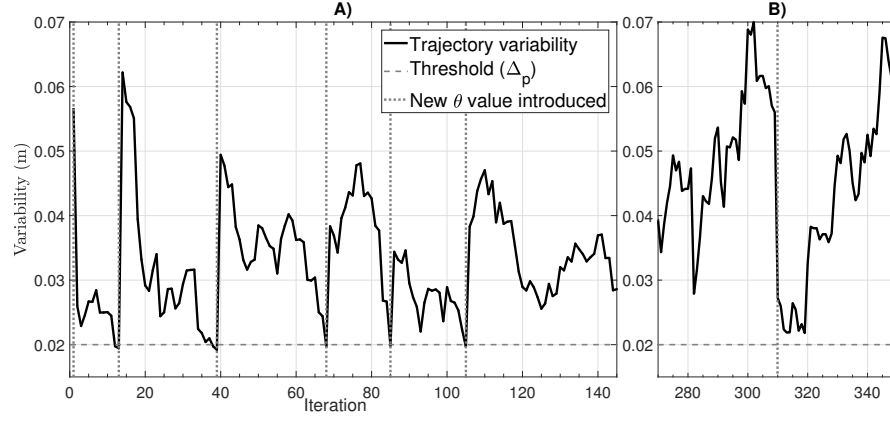


FIGURE 4.10: A) Subject E (whole experiment) and B) Subject F (last two θ values) trajectory variability across task iterations.

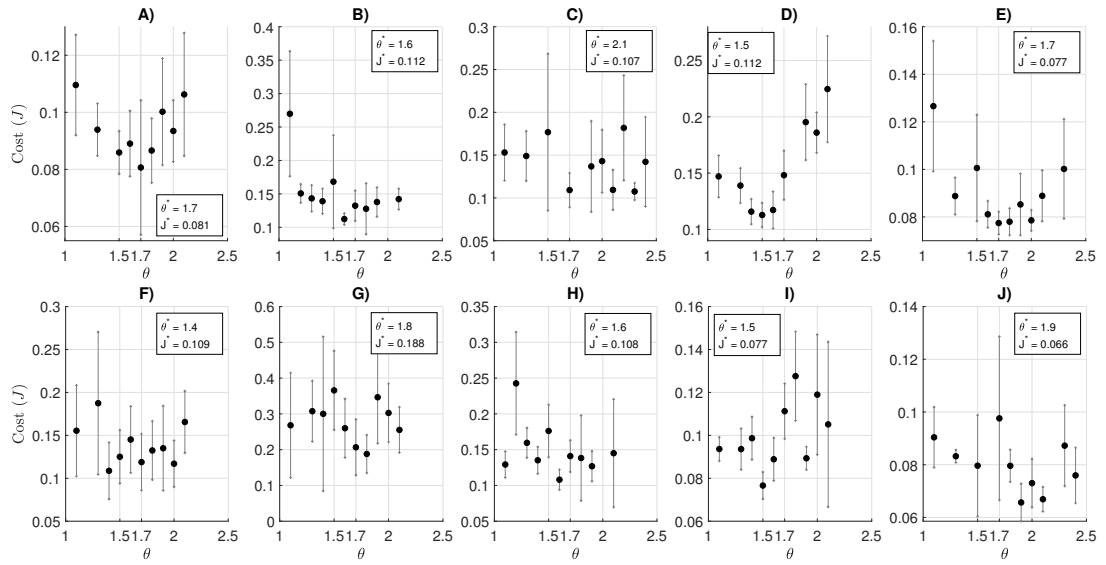


FIGURE 4.11: Performance vs Synergy ($J(\theta)$) relationship box and whisker plot results for all able-bodied subjects (A-J). The x -axis represents the synergy parameter values and the y -axis the cost. Circles represent the mean cost and lines the standard deviation.

32% for subject D and 66% for subject I. This highlights the significance of finding the best synergy parameter for each individual.

The purpose of this study was to observe a unique minimum in the synergy-performance $J(\theta)$ map for each person. Due to the relatively low number of subjects, a statistically significant quadratic map was not obtained. However, it can be observed in the subjects that achieved lower variability, see Figure 4.11.A-B and D-E, that there is a trend towards exhibiting a unique minimum as the task is learned; since lower variability can be attributed to the learning of a task [106]. This difference in learning of the task across subjects may be attributed to the different learning rates across individuals [98]. As such, the individuals that were able to learn the task within the allocated iterations

show a result more reflective of a quadratic map (e.g. A-B, D-E). This may suggest that when the task is yet to be “learned”, the $J(\theta)$ map is unreliable for the proposed purposes. On the other hand, as the task is learned and trajectories become more consistent, the map shows properties desirable for online optimisation algorithms, such as a local unique extremum.

4.6 Conclusion

The mathematical formulation of a human-prosthetic system was presented. A framework for online data driven optimisation was proposed to identify the optimal synergy for an individual performing a specific task during repeated use. An example of task characterisation and synergy parameterisation was demonstrated with a basic forward reaching task and linear shoulder-elbow synergy. Human-in-the-loop simulation results were presented, showing the feasibility of data driven optimisation for online synergy identification. However, the subjects required extensive training with the virtual prosthesis previous to the experiment to satisfy the conditions required by the framework.

An experiment to determine the relationship between the parameters of a linear synergy (θ) and a measure of motor control performance (J) that characterises a reaching task was presented. This experiment extended from typical experiments on human motor control by the exploration and learning of different motion settings, in the form of synergy parameters, rather than the learning of a single one. It was observed that values of the cost function differ across individuals, and that the minimum cost was observed for different synergy parameter values for different subjects. This highlights individual variability in performance, but also in synergies. While a statistically significant quadratic map was not obtained, it was observed that there is a trend towards exhibiting a unique minimum as the task is learned. This observation suggests that as the task is learned, the map obtained from the experiment shows properties desirable for online optimisation algorithms. This highlights the importance of developing a design framework that can determine successful learning of the task while accounting for individual capabilities, learning rate and filtering external disturbances.

The results in this Chapter demonstrated the applicability of the extremum seeking framework to the synergy identification problem in human-prosthetic interfaces. However, these studies required subjects to undergo significant training before with the virtual prosthetic device in order to minimise the effects of motor learning on the results. This training can take a long time, and having to do the training for each synergy parameter value that is explored may be undesirable in practice. The next Chapter addresses this issue by taking advantage of the structure of human motor learning to inform the design of an algorithm that does not require the user to undergo previous training with the prosthesis.

Chapter 5

Personalized Online Adaptation of Kinematic Synergies for Human-Prosthesis Interfaces

This chapter presents a grey-box online personalisation algorithm that takes advantage of known characteristics of human motor behaviour in its formulation. This knowledge of human motor behaviour informs the design of the algorithm without requiring specific individual data, and allows the personalisation process to occur concurrently to human motor learning. In contrast to the algorithm presented in the previous chapter, the algorithm presented herein does not require individual tuning and reduces the time required for the personalisation process as it neither requires the human to reach motor learning steady-state before proceeding to the next synergy parameter nor extensive previous training with the prosthetic device. This is achieved by first characterising human motor behaviour into a grey-box model with two components, motor preference and motor adaptation. The characteristics obtained from this model are used to inform the design of the personalisation algorithm which is based on a Fast Extremum Seeking (FES) algorithm [35, 36]. The algorithm is then demonstrated through human experiments in a virtual reality environment.¹

¹The content presented in this chapter has been published in [78].

5.1 Introduction

Two major challenges hinder the efforts of realizing personalised HPIs. The first challenge is related to the process of human motor adaptation. An individual needs to learn how to use the prosthesis for each given synergy setting. The best possible performance of the individual for a given setting is not known until the motor adaptation process has reached its steady-state, which may take many iterations of the task [77]. Therefore, a significant amount of time will be required to evaluate all possible settings in an exhaustive process, which renders it impractical. The second challenge is related to the motor learning dynamics of individuals, which differ from person to person. Each individual learns at a different rate, which is initially unknown. Determining that an individual has indeed reached the steady-state in motor learning, thus capturing the best performance for a given synergy setting, is challenging. For example, it is insufficient to generalise that steady-state in motor learning is reached after a set number of iterations for every individual [77].

This chapter seeks to address the two challenges presented above to allow the systematic personalisation of synergistic HPIs. A model-guided data-driven optimisation approach is proposed, providing a systematic method to explore and continuously adjust the synergy setting towards a personal optimum, avoiding the need for exhaustive testing or calibration. The suggested method enables the identification of the best synergy setting to take place while the prosthetic device is being used to perform a task, a process referred to as “online personalisation” herein. In the previous chapter, the online personalisation of synergistic HPIs was performed through a data-driven optimisation procedure where the individual’s performance is given by a pre-defined objective function that is evaluated from sensor measurements in the prosthetic device. However, that method suffers from the previously discussed challenges as it requires the user to undergo significant previous training with the synergistic prosthesis in order to treat the personalisation of synergistic HPIs as a static optimisation problem, i.e. the algorithm did not account for the transient dynamics of human motor learning and the algorithm learning rate had to be manually adjusted for each individual. Similar attempts have been performed in lower limb prostheses [109].

The method proposed in this chapter enables the online personalisation of synergistic HPIs to operate concurrently to the individual learning to use the prosthetic device. This

bypasses the need for the algorithm to wait for human motor learning to reach steady-state at each synergy setting before evaluating the performance in a new setting. This also avoids the need for the algorithm to be tuned for each individual. This is achieved by realizing that the human motor behavior involved can be captured in a model composed of a non-linear mapping between individual performance and the given synergy setting, and a linear time invariant system that describes the transient dynamics of human motor learning. This model then informs the design of a class of online optimisation algorithm that takes advantage of the structure contained in the model independently of its parameters.

The chapter is presented as follows. First, a grey-box model is proposed that captures the observed common human motor behavior in its structure and individual variation in its parameters. Then, an online optimisation approach to the personalisation of HPIs, realised through an extremum seeking-based algorithm [35, 36], is presented; which takes advantage of the knowledge of human motor behavior that is captured by the grey-box model. Lastly, the experimental methodology and results for an experiment performed in virtual reality with able-bodied subjects are presented. The experiment demonstrates the proposed method can consistently adjust the prosthetic synergy setting to allow individuals to achieve their highest performance score as the prosthesis is continuously used. The proposed strategy is shown to be effective in personalizing a synergistic HPI to individuals learning to use the prosthetic device.

5.2 Preliminaries

The following notation is used throughout the chapter. The set of real numbers is denoted as $\mathbb{R}$, the set of positive real numbers is denoted as $\mathbb{R}_+$. The term “synergy” is used to describe the parametrisation of the human-prosthesis interface. For a given static mapping $y_x = h(x) : \mathbb{R} \rightarrow \mathbb{R}$, its gradient is expressed as $y'_x = \partial h(x)/\partial x$, and curvature (Hessian) as $y''_x = \partial^2 h(x)/\partial x^2$. The subscript x_i is used to indicate the iteration domain, such that x_i indicates the i th iteration of x , where an iteration represents a repetition of the task. The “bar” notation on a variable, e.g. $\bar{\lambda}$, indicates that the variable is individual dependent. The measured performance of a given task is characterised by the performance $\hat{J}_i \in \mathbb{R}_+$. The synergy parameters are given by $\theta_i \in \Theta$, where Θ is a compact set in $\mathbb{R}$ representing the parameter set of interest.

A scalar linear relationship between the velocity of the shoulder and elbow flexion for the task of reaching forward is selected in this work as the specific example of kinematic synergy to exemplify the application of the method presented herein. However, the proposed method is generalisable to other parametrisations of synergies of higher complexity and dimensionality. This scalar synergy, even though it is simple, has been found to be able to represent the most significant relationship between shoulder and elbow motion for forward reaching tasks [28], and has been successfully applied to prosthetic elbow studies [58]. In this chapter, the elbow to shoulder flexion kinematic synergy is described by

$$\dot{q}_p = \theta \dot{q}_r, \quad (5.1)$$

where the subscripts r and p represent residual and prosthetic limb respectively. $\dot{q}_r$ is the individual's shoulder flexion angular velocity. $\dot{q}_p$ is the angular velocity of the prosthetic elbow.

Furthermore, the measured performance for a given reaching task in this chapter is defined by the following objective function:

$$\hat{J}_i(\theta) = \frac{0.25 \|\tilde{\mathbf{p}}_{fmax}\|^2}{\max(0.25, \|\tilde{\mathbf{p}}_{f,i}\|^2)} + \frac{16.67 t_{fmax}}{\max(0.5, t_{f,i})}. \quad (5.2)$$

Here, $\tilde{\mathbf{p}}_{f,i}$ is the hand end position error from target, and $\tilde{\mathbf{p}}_{fmax} = 10\text{cm}$; $t_{f,i}$ is the reach time; and $t_{fmax} = 3\text{s}$. Note that both $\tilde{\mathbf{p}}_{f,i}$ and $t_{f,i}$ are influenced by θ and $\dot{\mathbf{q}}_r$, where $\dot{\mathbf{q}}_r$ is the angular velocity of the residual limb. The values used in the objective function normalise its components to be in a $[0 - 100]$ range.

5.3 Human Motor Preference and Adaptation Model

In this section, the common features observed in motor behavior for individuals using a HPI based on kinematic synergies are discussed and their formalisation within a grey-box model is proposed. Knowledge of the structure of human motor behavior captured by the grey-box model informs the design of the proposed personalisation algorithm in Section 5.4, as well as its applicability to HPIs. Previously obtained experimental results

showing these features [77] are presented first, followed by the grey-box model proposed to characterise them. Lastly the experimental validation of the model is performed.

5.3.1 Common Features in Human Motor Behavior

It has been demonstrated that by characterizing an upper-limb reaching task, while using a synergistic prosthesis, by an objective function, equation (5.2), and by parameterizing the HPI, equation (5.1), two common motor features arise [77]. The first feature will be referred to as “motor preference”, which relates to the observed preference in synergy value that leads to the best performance of the task for a given individual. The second feature will be referred to as “motor adaptation” which represents an individual’s improvement in performance over iterations of the task that eventually reaches a steady-state.

5.3.1.1 Motor Preference

There exists a non-linear steady-state input-output relationship between synergies and a characterisation of the task as an objective function (performance). This means that for a given individual and each synergy value, there will be specific steady-state performance (after learning) that the individual can achieve. This relationship is dependent on the formulation of the objective function, which can be designed such that the resultant synergy-performance map has an extremum [77].

An example of the relationship between the synergy (θ) and performance ($\hat{J}$) is shown in Figure 5.1. An individual’s average performance over multiple iterations of the task for a range of synergy values conforms to an Input-to-Steady-State-Output (I-SSO) map whose extremum and shape differ across individuals. This individual variation in the best performing parameter suggests the existence of preference in the configuration of the prosthetic interface. The shape of this average map for individuals has been identified as the common feature while the parameters that define the map and its extremum as individual variations. In this work, the average synergy-performance map feature will be referred to as “motor preference”, which represents an individual’s preference in synergy parameter that leads to the best performance of the task. This implies that through the

personalisation of the synergy it is possible to improve the performance the prosthesis user can achieve when compared to the use of the population average synergy value.

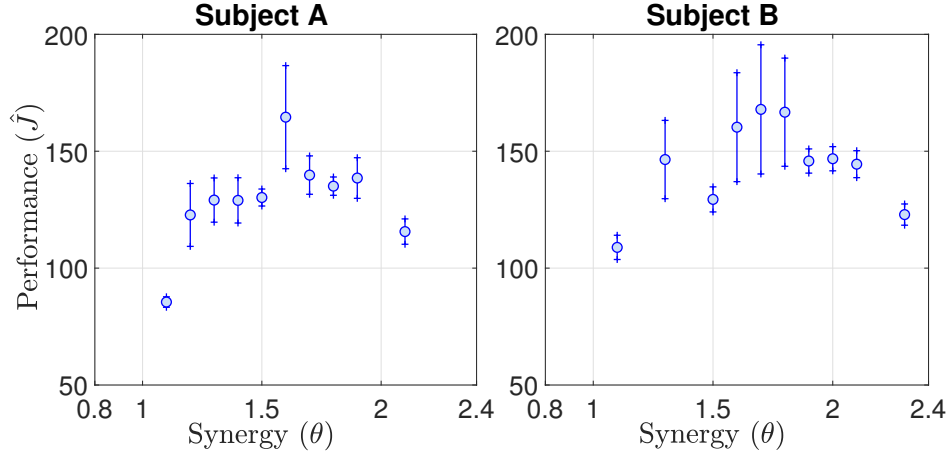


FIGURE 5.1: Experimentally obtained synergy-performance map for two representative subjects. The blue circles represent mean performance while the whiskers the standard deviation. Task performance was characterised by a quadratic-like objective function, while synergy represents a kinematic-synergy parametrisation of the human-prosthesis interface.

5.3.1.2 Motor Adaptation

A transient behavior was observed in performance as the synergy setting was changed from one value to the next, where the dynamics are individual dependent. As expected from human behavior, the performance across iterations of the task is affected by the variability inherent in human motor control [110]. An example of this transient behavior is presented in Figure 5.2, where the transient behavior can be seen before the 60th iteration of each synergy value, and a steady-state otherwise. In this work, this transient dynamics feature will be referred to as “motor adaptation”, which represents an individual’s improvement in performance over iterations of the task that eventually reaches a steady-state. As previously discussed, this is the behavior that introduces a challenge to the personalisation of synergies due to the time (the number of iterations of the task execution) required to obtain the best performance that an individual can achieve using a given synergy setting.

This type of transient learning behavior has been extensively modeled for able-bodied individuals in the literature, with state-space models, exponentially decaying responses, and Linear Time Invariant (LTI) with output additive Gaussian white noise being widely accepted, e.g. [98, 111–113]. Although many models have been developed to characterise

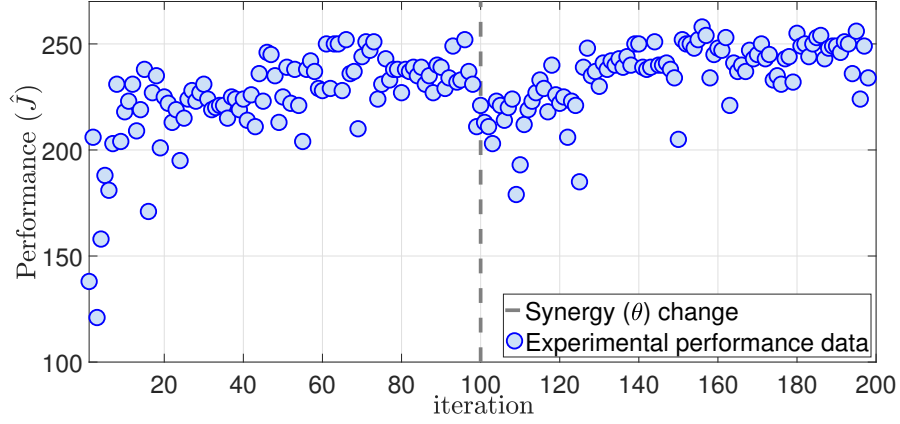


FIGURE 5.2: Experimentally obtained performance across iterations data for two synergy values for a representative subject. The dashed line represents the change in the value of the kinematic-synergy parametrisation (synergy) of the human-prosthesis interface. Performance was characterised by a quadratic-like objective function.

the dynamics of motor adaptation in able-bodied individuals and there is a growing body of work investigating the effects of prosthetic interfaces on motor adaptation [114, 115], a direct link between the dynamic models of able-bodied motor adaptation and the prosthetic case is yet to be established. It is worthwhile to highlight that the motor adaptation observed in Figure 5.2 is captured by the increase in performance, as described by a given objective function, for a task by repetition, i.e. iteratively. The observed behavior suggests that a transient response in the iteration domain has a common structure and individual dependent parameters.

5.3.2 Grey-box Model for Motor Preference and Adaptation

The proposed model for an individual's performance as a function of the synergy is constructed by the serial combination these two features: the average non-linear convex map (motor preference) and a perturbed LTI system in the iteration domain (motor adaptation). Figure 5.3.(A) shows the diagram of the proposed model. Figure 5.3.(B) shows the combined human-prosthesis system whose performance as a function of the synergy is being captured by the model. Although there exist models that incorporate transient motor learning behavior in the iteration domain [98], to the best of the authors' knowledge, a model that incorporates both preferences in motor behavior and individual transient learning behavior is novel in the literature.

The steady-state relationship between synergy and performance in the model represents the measured synergy-performance I-SSO map obtained experimentally as presented in

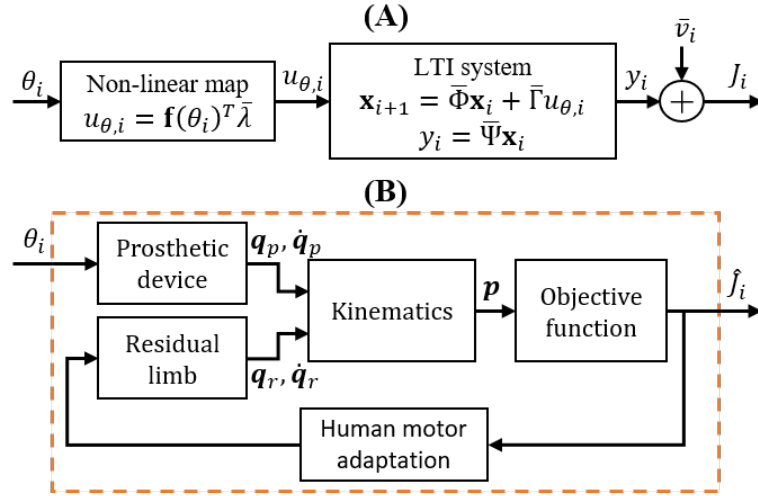


FIGURE 5.3: Overview of proposed human motor preference and adaptation model. (A) The grey-box model composed of a non-linear map and a LTI system in the iteration domain. (B) The block diagram of the human-prosthesis system represented by the model, as per the characterisation of the task through an objective function ($\hat{J}_i$) and a parametrisation of the prosthetic interface (θ_i).

Figure 5.1. The scalar v_i characterises human motor performance variation. $u_{\theta,i} \in \mathbb{R}$ is the output of the average static map representing motor preference. One can think of $u_{\theta,i}$ as the best performance an individual can achieve for the specific synergy setting θ_i , which occurs at the steady-state of motor learning. $y_i \in \mathbb{R}$ is the output of the LTI system representing motor adaptation, which introduces transient dynamics to the average static map. This represents the internal cost, which is subsequently approximated using $\hat{J}_i$ from (5.2).

5.3.2.1 Motor Preference

Given the average I-SSO relationship observed experimentally [77], motor preference is then modeled as a non-linear static input-output map. This map can be represented in general by a linearly-parameterised non-linear function

$$u_{\theta,i} = \mathbf{f}(\theta_i)^T \bar{\lambda}, \quad (5.3)$$

where $\mathbf{f}(\cdot) : \Theta \rightarrow \mathbb{R}^{n_\lambda}$ is the vector of continuously differentiable characterizing functions, which is common across a population, and $\bar{\lambda} \in \mathbb{R}^{n_\lambda}$ is a constant vector of parameters, which is individual dependent and represents motor preference. In this case $u_{\theta,i}$ represents the average steady-state performance for a given θ_i . The synergy θ_i is the current

setting of the parameterisation of the HPI and is considered as an input to the non-linear mapping.

The following assumption is made regarding the characterisation of motor preference.

Assumption 5.1. *There exists a unique maximum $\theta^* \in \Theta$ such that for any given $\bar{\lambda} \in \mathbb{R}^{n_\lambda}$, there is $u_\theta^* = \mathbf{f}(\theta^*)^T \bar{\lambda}$, $\theta^* \in \Theta$, and*

$$u'_\theta(\theta) = 0, \quad \text{iff } \theta = \theta^*, \quad (5.4a)$$

$$u''_\theta(\theta) < 0, \quad \forall \theta \in \Theta. \quad (5.4b)$$

Remark 5.2. Assumption 5.1 can be satisfied by carefully formulating the interface parametrisation and measure of task performance, as previously presented in [77]. Although u_θ^* depends on the parameter $\bar{\lambda}$, the optimal parameter θ^* is independent of the parameter $\bar{\lambda}$. From experimental results [77], it was observed that individuals who reached steady-state task performance with a virtual synergistic prosthetic device satisfy this assumption locally, as seen in Figure 5.1. $\circ$

5.3.2.2 Motor Adaptation

A model to characterise the transient behavior observed in performance (J) as the synergy setting (θ) changed from one value to the next, which can be attributed to motor adaptation, is presented next. In this work, due to repetitive nature of the tasks being considered, a Linear Time-Invariant (LTI) state-space model in the iteration domain is utilised to represent human learning behavior. Human motor variation is represented as additive noise with respect to the given performance. Such representation is natural to represent the experimental and application setting as performance over one iteration of the task is used as an output. At the i^{th} iteration, the proposed model takes the following form:

$$\mathbf{x}_{i+1} = \bar{\Phi} \mathbf{x}_i + \bar{\Gamma} u_{\theta,i} \quad (5.5a)$$

$$J_i = \bar{\Psi} \mathbf{x}_i + \bar{v}_i, \quad (5.5b)$$

where $\mathbf{x} \in \mathbb{R}^{n_h}$ represents the internal states of human motor adaptation and $n_h > 0$ is the order of the model. The matrices $\bar{\Phi}$, $\bar{\Gamma}$, and $\bar{\Psi}$ have the appropriate dimensions and

are individual dependent. Performance is perturbed by human motor variation, which is represented by the output additive noise $\bar{v}$ [111]. An example of the observed motor adaptation behavior is presented in Figure 5.2. The following assumption is utilised:

Assumption 5.3. *System (5.5) has unity steady-state gain. ($G_{ss} := \bar{\Psi}(I_n - \bar{\Phi})^{-1}\bar{\Gamma} = 1$).*
 ◦

Remark 5.4. Assumption 5.3 allows the map $u_{\theta,i}$ (5.3) to represent an individual's average static relationship between synergy (θ) and performance (J). Furthermore, at steady-state y_{ss} approaches $u_{\theta,ss}$. This can be readily satisfied through the selection of $\bar{\lambda}$.
 ◦

This concludes the proposed model structure to represent human motor preference and adaptation. It is important to highlight that the parameters of this model are individual dependent. Next, the identification of the parameters for two individuals, used for validation, is presented.

5.3.3 Model Parameter Identification

In order to validate the proposed model structure, system identification was performed on synergy-performance data for two representative able-bodied subjects. Transhumeral amputation and prosthesis use was emulated through a Virtual Reality Environment (details in Section 5.5). The simulation of the identified systems was compared to a different synergy-performance data-set from these individuals. The identification procedure is as follows: first, the data collected is used to identify the parameters of the non-linear I-SSO map (motor preference), followed by the identification of the normalised LTI system (motor adaptation). Finally, the characteristics of motor performance variation ($\bar{v}_i$) are obtained from the analysis of residuals between the validation data and the identified underlying model.

The dataset for the two individuals used for system identification was taken from the authors' previous work in [77] and a new dataset from the same individuals was generated for comparison with the identified model and validation. The original dataset was generated by holding a synergy constant over multiple iterations of a forward reaching task with a synergistic prosthetic elbow. This procedure was followed in order to capture both the transient and steady-state behavior for each synergy. This was repeated for

multiple synergies to obtain the non-linear map. The validation dataset was generated with the same task and subjects; however, the synergy was changed linearly in every task iteration instead; capturing both features in the response.

5.3.3.1 Motor Preference

In order to identify the average I-SSO map representing motor preference, the structure of $\mathbf{f}(\theta)$ is needed. As in [77], the nonlinear mapping was approximated as a quadratic polynomial. The linearly parameterised non-linear function representing motor preference is given by

$$J(\theta) = u_{\theta,ss}(\theta) = \mathbf{f}(\theta)^T \bar{\boldsymbol{\lambda}} = \begin{bmatrix} \theta^2 & \theta & 1 \end{bmatrix} \bar{\boldsymbol{\lambda}}, \quad (5.6)$$

with $\bar{\boldsymbol{\lambda}} \in \mathbb{R}^3$ being the parameters identified for each individual. The map was identified from experimental data using a least squares method. Figure 5.4 shows the identified $J(\theta)$ map for two subjects using a quadratic polynomial along with the experimental data used for identification. The identified map parameters $\bar{\boldsymbol{\lambda}}$ for both subjects are the following.

$$\bar{\boldsymbol{\lambda}}_A = \begin{bmatrix} -158.15 & 529.18 & -293.34 \end{bmatrix}^T, \quad (5.7a)$$

$$\bar{\boldsymbol{\lambda}}_B = \begin{bmatrix} -96.18 & 342.13 & -147.86 \end{bmatrix}^T. \quad (5.7b)$$

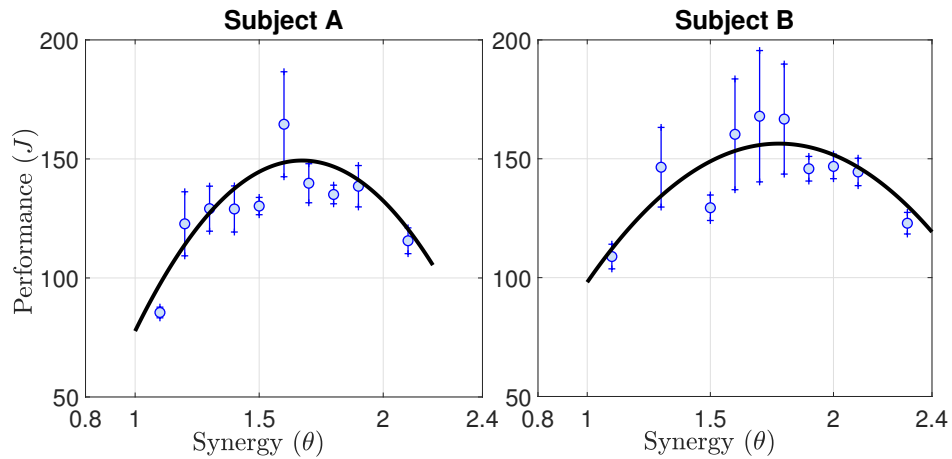


FIGURE 5.4: Non-linear map observed experimentally with quadratic fit for two representative subjects. The blue circles represent mean performance, the whiskers the standard deviation, and the black line the quadratic polynomial representing the identified map.

5.3.3.2 Motor Adaptation

There are two components in (5.5) that need to be identified in order to characterise an individual's learning dynamics: the underlying LTI model and the associated noise ($\bar{v}$). Undershoot in performance has been observed to occur following step synergy changes, as illustrated in Figure 5.2. This can be attributed to the individual's reduced performance due to the sudden change in the synergy setting applied and the gradual re-adaptation to the dynamics of the new synergy setting. Thus, systems of order greater than one are considered for identification, as these are the minimum required to capture undershoot. Furthermore, as overshoot is non-physical in the timescales considered, constrained least squares was used for identification in order to limit the identified systems to be overdamped. The identified non-linear I-SSO map from the previous section was used as the input u_θ to the LTI subsystem.

The experimental data for the transient response corresponding to a single synergy value was used for validation of the identified LTI system. Validation was performed through the comparison of the Mean Square Error (MSE) between the response of the identified underlying model and the validation data-set for different system orders [116]. Table 5.1 contains the resultant MSE for the second and third order cases for both subjects.

TABLE 5.1: Mean Square Error (MSE) for the second and third order LTI system models.

Subject	2nd order MSE	3rd Order MSE
A	277.76	274.36
B	489.93	467.37

As seen in the validation results presented in Table 5.1, both the second and third order models achieve similar MSE. Since it is desirable to use the lowest complexity model, and the second order model captures the key transient behavior, the second order model is selected. The identified normalised LTI system matrices representing the underlying individual transient behavior for subjects A and B are listed below.

$$\bar{\Phi}_A = \begin{bmatrix} 0 & 1 \\ 0.068 & 0.35 \end{bmatrix}, \quad (5.8a)$$

$$\bar{\Gamma}_A = \begin{bmatrix} 0.839 & 0.037 \end{bmatrix}^T, \bar{\Psi}_A = \begin{bmatrix} 1 & 0 \end{bmatrix}, \quad (5.8b)$$

$$\bar{\Phi}_B = \begin{bmatrix} 0 & 1 \\ -0.017 & 0.25 \end{bmatrix}, \quad (5.9a)$$

$$\bar{\Gamma}_B = \begin{bmatrix} -0.091 & 0.834 \end{bmatrix}^T, \bar{\Psi}_B = \begin{bmatrix} 1 & 0 \end{bmatrix}. \quad (5.9b)$$

Finally, an analysis of the residuals between the validation data and the identified LTI system was performed in order to obtain the characteristics of motor performance variation ($\bar{v}_i$). This was done by performing a whiteness (independence) test of the residuals in order to establish whether $\bar{v}_i$ can be characterised by Gaussian white noise, and the mean and variance characteristics for each subject [116]. The whiteness test was performed with a 95% confidence interval and the validation data-set for each subject contained 50 samples, such that the validation criterion was 0.277. This criterion represents the maximum auto-correlation permitted between the residuals in order to accept the hypothesis that the residuals have a Gaussian distribution. The resultant normalised auto-correlations from the analysis of residuals were 0.1495 and 0.227 for subject A and B respectively, both smaller than the validation criterion. Therefore, it is concluded with 95% confidence that $\bar{v}_i$ has a Gaussian distribution. The individual $\bar{v}_i$ characteristics for each subject are presented in Table 5.2.

TABLE 5.2: Mean and standard deviation of residuals obtained from whiteness test.

Subject	Mean (μ)	Standard deviation (σ)
A	0	16.81
B	0	22.36

5.3.4 Model Validation

The identified model of the individual subject behavior (subject A and subject B above) is numerically simulated and the output was compared to an independently obtained validation data-set for the respective subjects. The experimental data-set for validation was generated for the same forward reaching task as the identification data-set. However, in this case the synergy was changed at each iteration according to:

$$\theta_i = 0.8 + \frac{i}{125}, \quad (5.10)$$

where i represents the i th iteration of the task. The synergy range studied, $\theta_{min} = 0.8$ and $\theta_{max} = 2.4$, was informed by preliminary results in [77]. Performance of the task for a given iteration was measured by the objective function (5.2). Figures 5.5 and 5.6 present the experimental data and simulation results for subjects A and B respectively.

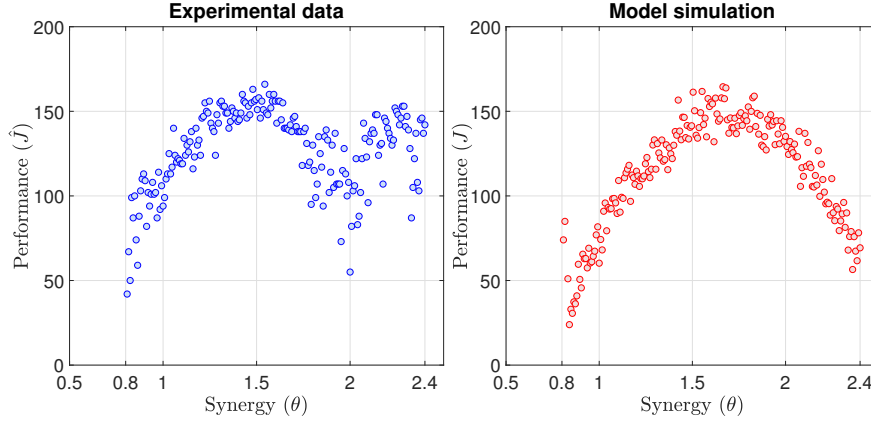


FIGURE 5.5: Subject A experimental and model simulation synergy sweep performance response.

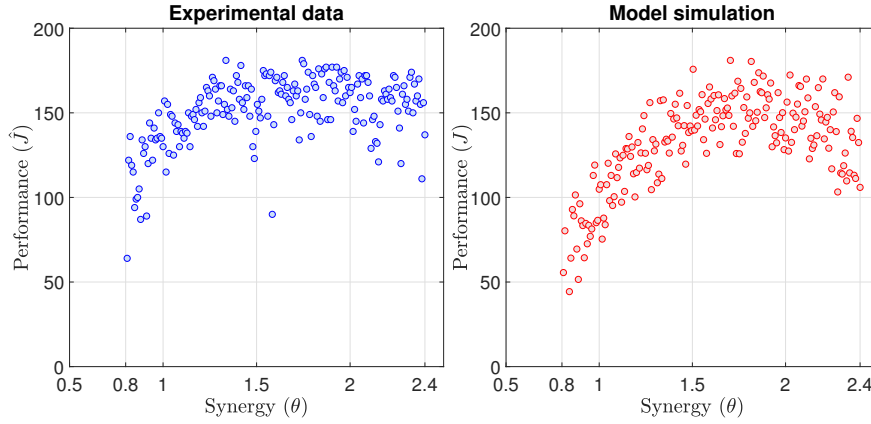


FIGURE 5.6: Subject B experimental and model simulation synergy sweep performance response.

It can be seen from Figures 5.5 and 5.6 that the structure of the model is able to qualitatively capture the common features of motor preference (the shape of the non-linear I-SSO map) and adaption (the transient behavior) across the population, as well as human variation given the identified parameters $\bar{\lambda}, \bar{\Phi}, \bar{\Gamma}, \bar{\Psi}, \bar{v}$ depend on individuals. In the validation data for subject A, presented in Figure 5.5, an increase in performance can be observed for $\theta > 2$. This behavior may be attributed to the subject changing their motor strategy in order to improve their performance for that synergy range. It was anecdotally observed, however, that this change in strategy relied on upper body and shoulder compensation motion. This highlights a limitation of the chosen measure

of performance (5.2), as it does not capture compensation motion or metabolic effort. Nonetheless, even with such diverse human variation, both individually and across the population, the model adequately captures both the underlying common behavior of a population and individual behavior.

With the existence of a personalised interface parameter optimal value and the common model structure identified from experimental results, a grey-box based online optimisation technique [35, 36] can be naturally linked to the kinematic synergies personalisation problem in HPIs. This technique is able to find the optimal personalised solution to the interface parameter to performance problem in the presence of human variation. Differing from black-box online optimisation techniques with personalised tuning of parameters and personalised convergence performance, the grey-box online optimisation technique utilises the common model structure to obtain a uniformly convergent performance among the population with tuning parameters that are less sensitive to human variation.

5.4 Human-Prosthesis Interface Personalisation Algorithm

The online personalisation algorithm is presented in detail in this section, followed by simulation results using the proposed grey-box model. Simulations were done to tune the algorithm, test its behavior, and observe its performance. The algorithm takes advantage of the previously modeled structure of human motor preference and learning by allowing it to estimate the steady-state performance from online measurements for the given synergy value regardless of the stage of learning (transient behavior). Furthermore, it is able to extract additional information from the estimates of the non-linear map to adjust its update rate to accommodate individual motor behavior characteristics. The algorithm is adapted from [35] and [36] for the HPI application. The major change is that the current setting is in the iteration domain due to the event-driven iterative nature of the problem.

Figure 5.7 presents the diagram of the proposed framework for personalisation of human-prosthesis interfaces. The framework is composed of four different components: a filter, a gradient and curvature observer, an optimiser, and a dither generator; which will be

detailed next. This particular structure is designed to operate under the conditions satisfied by the model of human motor preference and adaptation.

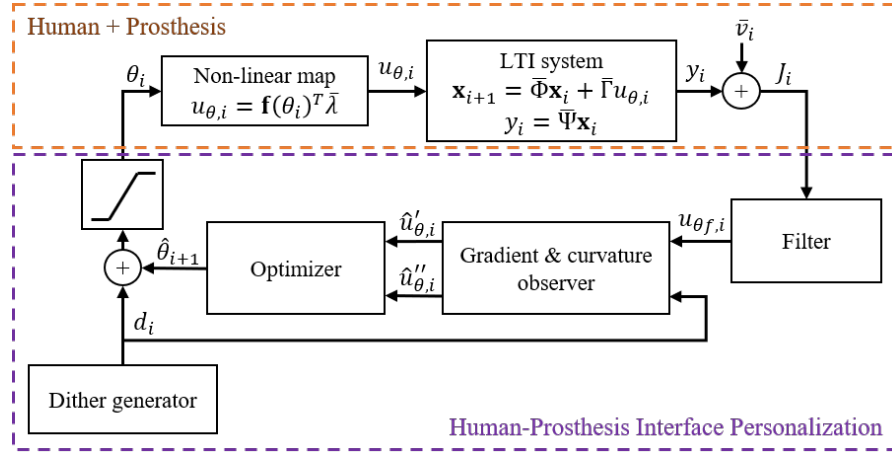


FIGURE 5.7: General overview of the proposed framework for personalisation of human-prosthesis interfaces.

The algorithms in [35] and [36] require that certain conditions are satisfied to ensure that the parameter θ will converge close to the optimal θ^* . A summary of these conditions is presented herein.

Condition 5.5. *There exists an extremum θ^* in the non-linear steady-state map $J(\theta)$ and the map is twice continuously differentiable [35, Assumption 2].*

Condition 5.6. *The relative degree of the LTI dynamic system is known [35, Condition 6].*

Condition 5.7. *The serial combination of the LTI System and the Filter (Figure 5.7) is minimum phase [35, Condition 6].*

Condition 5.8. *Persistency of excitation (PE) is satisfied for parameter estimation.*

Assumption 5.1 ensures that Condition 5.5 is satisfied. Section 5.3 identified that the normalised LTI system has a relative degree one, thus Condition 5.6 is satisfied. Given that the system (5.5) represents human motor adaptation behavior, it indicates that the matrix Φ is stable, thus satisfying Condition 5.7. Persistency of excitation is a common condition required in adaptive systems. Condition 5.8 can be satisfied by introducing a known dither (perturbation) signal that excites the parameters (synergy setting) that need to be identified.

5.4.1 Filter

The role of the filter is to extract the information of the motor performance non-linear map u_θ from the measured task performance J , which is subject to learning dynamics and contains performance variability and measurement noise. It is the component that ensures that the tuning parameters are independent of individual motor adaptation dynamics.

Conditions 5.6 and 5.7 are needed for filter design since the objective of the filter is to invert the dynamics of the LTI system. Ideally, this allows the estimation of the non-linear map to be insensitive to the individual's learning behavior. With these conditions satisfied, then the stability of the closed loop can be ensured and an appropriate filter for the LTI system can be designed. In this work, a band-pass filter is used in order to maintain causality. Let the dither signal frequency range be $[\omega_o \quad n\omega_o]$, then the band-pass filter can be represented in state-space as follows.

$$\mathbf{w}_{i+1} = \Phi_f(\omega_o, n\omega_o)\mathbf{w}_i + \Gamma_f J_i, \quad (5.11a)$$

$$u_{\theta f,i} = \Psi_f(\omega_o, n\omega_o)\mathbf{w}_i, \quad (5.11b)$$

where $\mathbf{w} \in \mathbb{R}^{n_f}$ is the state of the filter. The order of the filter $n_f > 0$ is dependent on the LTI system. As the LTI system identified from the experiments has relative degree one, a second order filter is used with $n_f = 2$. Hence, the matrix $\Phi_f(\omega_o, n\omega_o)$ is in $\mathbb{R}^{2 \times 2}$, the matrix Γ_f in $\mathbb{R}^2$, and the matrix $\Psi_f(\omega_o, n\omega_o)$ in $\mathbb{R}^{1 \times 2}$.

5.4.2 Gradient and Curvature Observer

This component estimates the gradient and curvature information from the motor performance non-linear map u_θ that is used in the optimiser to find the optimal individual synergy θ^* , provided that Condition 5.8 is satisfied. There are multiple methods for performing these estimates, such as demodulation [76] and observer based [35].

In this work, a discrete version of the Luenberger observer method presented in [36] is used. The observer takes the following form

$$\hat{u}_{\theta f,i} = \Psi_o \hat{\mathbf{z}}_i \quad (5.12a)$$

$$\hat{\mathbf{z}}_{i+1} = \omega_o \Phi_o \hat{\mathbf{z}}_i + \omega_o \mathbf{L}(u_{\theta f,i} - \hat{u}_{\theta f,i}) \quad (5.12b)$$

where $\mathbf{L} \in \mathbb{R}^5$ is the observer gain which is designed such that $\Phi_o - \mathbf{L}\Psi_o$ is stable, so that the estimated gradient and curvature will converge to the true values. The matrices of the observer take the following form as in [36]:

$$\Phi_o = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & -2 & 0 \end{bmatrix}, \Psi_o = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \\ -0.25 \end{bmatrix}^T. \quad (5.13)$$

Then u'_{θ} and u''_{θ} can be estimated by demodulating the states $\hat{\mathbf{z}}$, such that

$$\hat{u}'_{\theta,i} = \frac{1}{a} \Psi' \hat{\mathbf{z}}_i, \quad \Psi' = \begin{bmatrix} 0 & \mathcal{S}_1 & \mathcal{C}_1 & 0 & 0 \end{bmatrix}, \quad (5.14a)$$

$$\hat{u}''_{\theta,i} = \frac{1}{a^2} \Psi'' \hat{\mathbf{z}}_i, \quad \Psi'' = \begin{bmatrix} 0 & 0 & 0 & \mathcal{S}_2 & \mathcal{C}_2 \end{bmatrix}, \quad (5.14b)$$

where $\mathcal{S}_n = \sin(n\omega_o i)$ and $\mathcal{C}_n = \cos(n\omega_o i)$, $n = 1, 2$ are the dithers needed for estimation, and $i > 0$ is the iteration index. By using $\mathcal{S}_n$, $\mathcal{C}_n$, and standard averaging techniques [117, Chapter 10], the output of the observer will converge close to the gradient and curvature of the non-linear map.

Remark 5.9. Curvature estimation is on a faster time-scale than that of gradient estimation due to Condition 5.8. Hence the demodulation dither signals $\mathcal{S}_2$ and $\mathcal{C}_2$ operate on a $2\omega_o$ frequency. Given the iterative nature of the system, care must be taken when selecting ω_o to avoid issues such as aliasing. $\circ$

5.4.3 Optimiser

Once the gradient and curvature of the non-linear map are estimated, they can be used in an optimiser to find the optimal θ^* . With consideration of human variations, the

optimiser is designed such that it can achieve uniform convergence performance, which is independent to the shape of the non-linear map $u_\theta(\cdot)$, i.e. operates similarly on individuals with different motor behavior characteristics.

A widely used optimiser is gradient-ascent, see for example [33, 93] and references therein. The gradient-ascent method with a fixed step size is simple to implement, but the convergence speed is determined by the shape of the non-linear map (given by $\bar{\lambda}$ in this work). In order to achieve uniform convergence speed across individuals, the derivative based optimiser employed in this algorithm switches between a gradient-ascent and a Newton-like approach. The reason to add the Newton-like approach is two-fold. First, the faster convergence speed. Second, its performance being less sensitive to the shape of the non-linear map. Although, the shape of the non-linear map varies over the population, convergence speed of the proposed HPI personalisation algorithm is insensitive to this variation.

Assumption 5.1, particularly equation (5.4b), is needed to ensure that the Newton-like optimiser is applicable. However, this can only be satisfied locally as shown from experimental results in [77]. This local region is usually smaller than the region where gradient-descent can converge. Thus the Newton-like optimiser must operate within the region in which equation 5.4b is satisfied. The gradient-descent optimiser operates outside that region. As such, the following switching mechanism is used.

$$\hat{\theta}_{i+1} = \hat{\theta}_i + k\omega_o\Delta_i \quad (5.15a)$$

$$\Delta_i = \begin{cases} -\frac{\hat{u}'_{\theta,i}}{\hat{u}''_{\theta,i}} & \|\hat{u}'_{\theta,i}\| < -\varepsilon\hat{u}''_{\theta,i}, \\ \hat{u}'_{\theta,i} & \text{otherwise,} \end{cases} \quad (5.15b)$$

where $\varepsilon > 0$ determines the size of the region where a Newton step is employed, and $k > 0$ is the optimiser gain. The condition $\|\hat{u}'_{\theta,i}\| < -\varepsilon\hat{u}''_{\theta,i}$ serves two purposes. First, to ensure that when the Newton-like optimiser is used, equation 5.4b of Assumption 5.1 is satisfied. Second, to avoid numerical issues arising when $\hat{u}''_{\theta,i}$ is close to zero.

Remark 5.10. An important consideration with the tuning of this algorithm is the time-scale separation between the observer and the synergy (θ) rate of change. The change in θ needs to be sufficiently slow to ensure that the observer provides relatively accurate estimation of the gradient and curvature. By carefully tuning the optimiser gain (k), such time-scale separation can be achieved. The tuning guideline can be found in [36].◦

5.4.4 Dither Generator

In order to be able to estimate the gradient and curvature of the non-linear map $u_\theta(\cdot)$, as a standard requirement in parameter identification, Condition 5.8 is needed. This is done by perturbing the system with a known dither vector [36]. Since gradient and curvature need to be estimated, two different dither signals are required.

Let the estimation frequency to be used for gradient be ω_o . In this work, a sinusoidal dither generator is used, leading to the following dither vector:

$$\mathbf{d} = \begin{bmatrix} a\mathcal{S}_1 & a\mathcal{S}_2 \end{bmatrix}^T \quad (5.16)$$

where $a > 0$ is the dither amplitude.

Remark 5.11. It has been found that high variability can impair human motor learning [118], so care must be taken to ensure the dither amplitude is not too large. $\circ$

5.4.5 Personalisation Algorithm Implementation with Simulated Humans

With the multiple conditions that need to be satisfied for the application and tuning of the algorithm, it is desirable to test it on simulated humans before it is applied to human-in-the-loop applications. This simulation can be performed using the proposed model and identified parameters presented in the previous section. Here the kinematic synergies personalisation simulation results for the two subjects previously modeled are presented.

Tuning of the algorithm was performed by first selecting the dither frequency ω_o and amplitude a as they play an important role to ensure convergence. Considering the application, it is desirable to achieve convergence of algorithm within the time for a prosthesis fitting and training session. From previous experiments with reaching tasks, it was found that 100 to 200 iterations are acceptable for a training session as this number of iterations take 30 to 60 minutes to perform. In the sequel, the dither frequency needed is selected as $\omega_o = \pi/4$. Given that the system is of relative degree one, a second order band-pass Q-filter was chosen. The following parameters were used for its design: $H = 0.5$ and $Q = 5.0$.

The choice of a presents one of the first challenges for a human-in-the-loop system (see Remark 5.11). From the point of view of the human, it would be difficult to learn to use a device that is constantly and unpredictably changing its behavior. Furthermore, the choice of a will affect the estimator. From previous experiments, it was found that $a \leq 0.05$ is well received by subjects, thus a dither amplitude of $a = 0.02$ was chosen. Finally, the optimiser parameters were chosen by evaluating the system response with a range of optimiser gain k values. Final algorithm parameters were: observer gain $\mathbf{L} = \begin{bmatrix} 1.5 & 0.25 & 0.25 & 2.0 & -2.0 \end{bmatrix}$, $\varepsilon = 0.1$, and $k = 0.05$.

The algorithm the authors previously presented in [93] was also implemented. Such algorithm uses a “black-box” online optimisation technique without exploring the transient behavior of human learning. Hence it suffers the disadvantage that the tuning parameters are sensitive to person-to-person variation. In order to demonstrate such sensitivity, the same tuning parameters are used for both individuals. Algorithm parameters a and w were equivalent to those used for the proposed algorithm, while k was modified to $k = 0.005$ as required by the different optimiser. Simulation results for the algorithm in [93] are presented in Figure 5.8, where performance and synergy for the two subjects is shown.

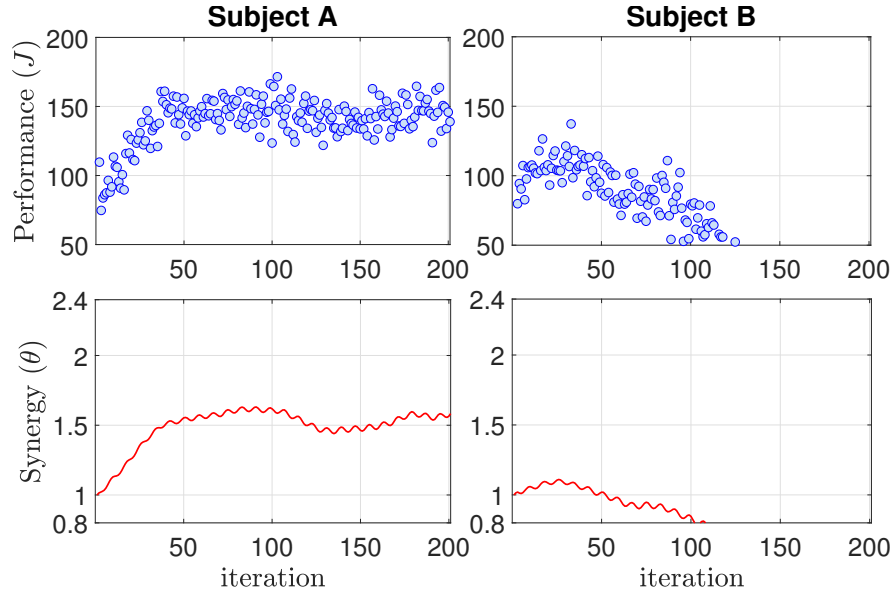


FIGURE 5.8: Simulation results for the previous algorithm for the two modelled subjects. Top plots show performance across iterations while bottom plots show synergy across iterations. The algorithm fails to identify the optimal synergy for subject B which leads to the subject not being able to achieve the task accurately and thus diminishing performance.

It is clear in Figure 5.8 from the decreasing performance of subject B that the previous algorithm [93] failed to identify the synergy for this subject when the same algorithm parameter tuning was used for both subjects. The decrease in performance implies that the subject was not able to perform the task fast and accurately with the given synergy values, as defined by the objective function. Practically, this means that the elbow does not extend sufficiently for the given shoulder flexion and thus the subject cannot reach adequately. The failure to identify the optimal synergy is due to the tuning parameters of this algorithm being dependent on each individual.

Simulation results for the algorithm proposed herein are presented in Figure 5.9, where performance (J) and synergy (θ) of the two modeled subjects is shown. As can be observed in Fig. 5.9, the proposed algorithm updates the synergy over iterations of the task until the maximum performance (as defined by the identified map used for simulation) is reached. Thus, the proposed algorithm was able to successfully identify the synergy for the two modeled subjects with different motor behavior characteristics while using the same tuning parameters. This demonstrates the capability of the proposed algorithm to handle individual motor preference and adaptation dynamics without the need for individual tuning.

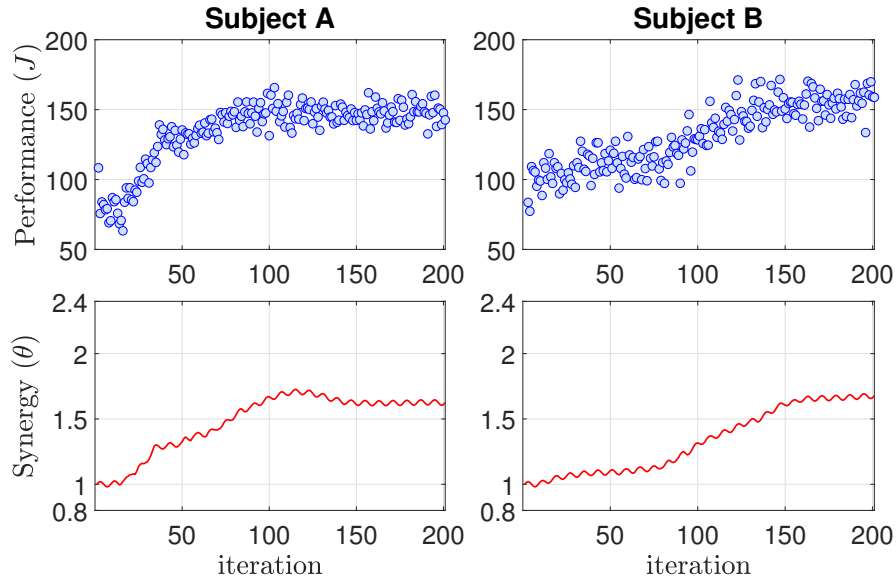


FIGURE 5.9: Proposed algorithm simulation results for performance and synergy for the two modelled subjects. The top plots show performance across iterations while the bottom plots show synergy across iterations. The algorithm successfully identifies the optimal synergy for both subjects.

5.5 Synergistic Prosthesis Online Personalisation Experiment

A human-in-the-loop experiment in a Virtual Reality Environment (VRE) was designed to emulate upper limb loss and prosthesis use in able-bodied subjects. The objective of the experiment was to experimentally evaluate the effectiveness of the proposed algorithm to realise online personalisation for a forward reaching task. Furthermore, to demonstrate that the proposed algorithm does not require the individual tuning for a population of subjects with different motor behavior and learning characteristics.

For ease of presentation, a simple point-to-point forward reaching task and scalar linear synergy between shoulder and elbow flexion/extension were chosen, where shoulder flexion translated to elbow extension. This scalar synergy, however, has been found to be able to represent the most significant relationship between shoulder and elbow for forward reaching tasks [28]; and has been successfully applied to synergistic prosthetic elbow studies [58]. It should be noted that the general case method proposed herein is designed to accommodate a wide variety of tasks through the choice of objective function, and more complex synergy parametrisations and structures due to its black box approach to parameter identification.

5.5.1 Experiment Description

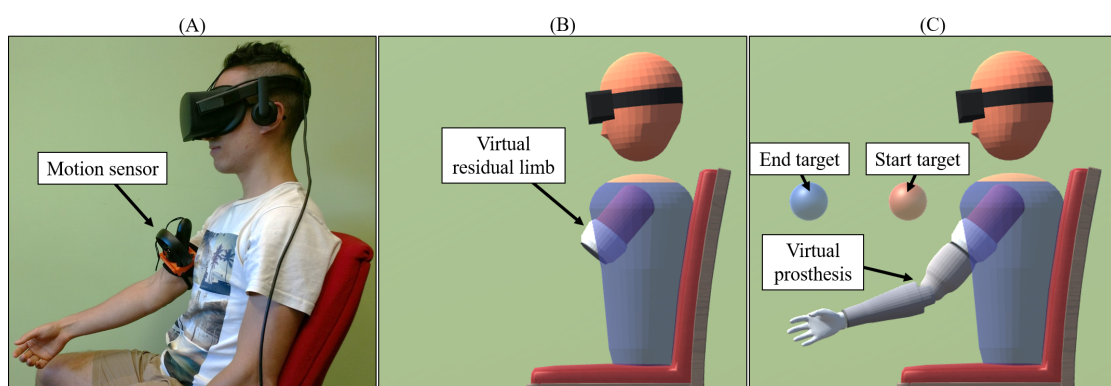


FIGURE 5.10: Virtual Reality (VR) experimental platform set-up. (A) Subject position and motor sensor placing. The motion sensor is placed on the subjects upper-arm to emulate transhumeral amputation. (B) Virtually amputated subject in VR environment. The virtual residual limb tracks the subject's upper-arm as per the motion sensor. (C) Subject's avatar with virtual prosthesis. The lower-arm is replaced by a prosthetic device. The task requires subjects to reach between the start (red) and end (blue) targets.

The experiment required subjects to perform a center-out forward reaching task between two static targets in a VR environment while using a virtual synergistic prosthetic elbow. The virtual targets were 23 cm apart and were placed at the subject's chest level with the start target being placed 20 cm from the target's chest. The position of the targets is shown in Figure 5.10.(C). One reach motion between the two targets was considered as an iteration of the task. Each reaching motion had to be completed within 3 seconds. Reaching attempts that were not completed within this time were discarded and had to be repeated. The task was deemed as completed if the virtual prosthetic hand stopped within 5cm of the target. The task was performed from a seating position with trunk motion restricted, which was ensured through a "seat belt"; shoulder and upper arm motion was unrestricted. Transhumeral amputation was simulated by tracking only the absolute motion of the subject's dominant upper arm, coupled to the trunk and shoulder motion, which determined the motion of the virtual residual limb. Motion tracking sensor placement is shown in Figure 5.10.(A) while the subject's virtual avatar with residual limb is shown in Figure 5.10.(B).

The scalar linear kinematic synergy related to shoulder flexion/extension chosen for the HPI parameterisation was given by equation (5.1), with θ being the parameter to be identified. The synergy range was set as $\theta \in [0.8, 2.4]$. These limits were chosen to constrain the adaptation algorithm in case of undesirable behavior. The lower limit allowed for sufficient elbow extension for the subjects to be able to perform the task while the upper limit ensured a "safe" speed. An initial synergy $\theta_o = 1.0$ was chosen for the task.

Performance of the task for a given iteration was determined by the objective function presented in equation (5.2), which is related to reaching accuracy and the time to complete the reaching motion. This measure of performance was presented to the subject as a "score" at the end of each iteration of the task. This was done in order to control the variable that relates to the difference between an individual's internal measure of performance and the designed function. The first period of the dither, equivalent to 8 iterations of the task, was used to initialise the different filters and components of the algorithm; therefore, no synergy update was performed during this period. The same algorithm tuning as in the simulation implementation was used.

5.5.2 Experimental Protocol

The experiment was performed on 12 able-bodied subjects, 7 female and 5 male. The mean age and range were 30 and 19-68 respectively. Subjects received instructions on how to perform the task and performed the motion with their dominant arm before going into VR. First, the position of the sensor was calibrated, and the virtual arm was fitted to resemble their actual limb in size as close as possible as with fitting of a prosthetic device. Subjects received instructions about the task and scoring system in VR and were allowed 5 practice iterations with no time limit. Subjects had to perform the task for 150 iterations, receiving 1 minute rest every 25 iterations to minimise upper arm fatigue, and received 5 minutes rest outside VR after the 75th iteration in order to reduce VR induced fatigue. Subjects' experience with VR environments ranged from no previous experience to casual users for gaming. No noticeable difference in performance of the task was seen among subjects with different exposure to VR. The hardware set-up was as described in Section 3.2 and data gathering as described in Section 3.4. A video explanation of the experimental set-up can be found in <https://youtu.be/Thtjyw9IUVo>.

5.5.3 Experimental Results

Figure 5.11 shows a representative subject's hand path on the sagittal plane for the first and last 10 iterations of the forward reaching task. In the first 10 iterations of the task the synergy remained constant in order to initialise the filter, and gradient and curvature observer in the algorithm. As such, Fig. 5.11.(A) shows the hand path for the case when the synergy is set at the initial value of $\theta_o = 1$. Fig. 5.11.(B) shows the hand path of the subject when steady-state was already reached at a personalised synergy value of $\theta_{ss} = 1.5$.

There are two main differences that can be observed in Figure 5.11: the accuracy at the end point and the variance of the hand path. Given that end-point accuracy was used as part of the measure of performance (5.2), it is important to highlight how the synergy can affect end-point accuracy and how it led to the observed difference. Intuitively, a value of $\theta < 1$ means the elbow extends less than the shoulder and vice versa. A larger θ also means a larger change in elbow extension for a change in the shoulder flexion, which makes it easier to reach further (thus to reach the target) but at the same time

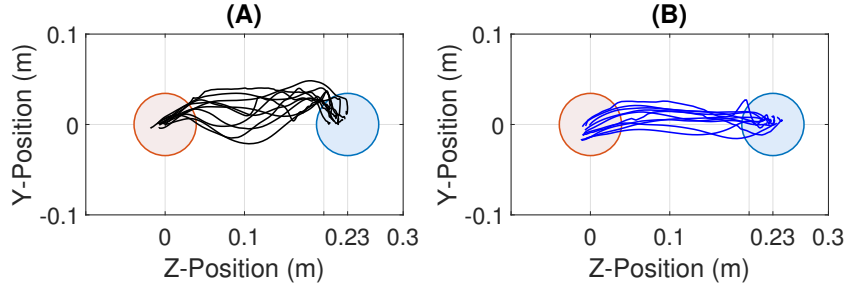


FIGURE 5.11: Representative subject's hand path in the sagittal plane. Start and end targets shown in red and blue respectively. The x-axis represents the forward direction while the y-axis the elevation. (A) The hand path for the first 10 iterations of the task. (B) The hand path for the last 10 iterations of the task.

increases the difficulty to control the position of the hand. Therefore, as θ increases, the overall performance increases until the subjects are able to achieve their best accuracy, which will be limited by their individual motor behavior. The difference between Fig. 5.11.(A) and (B) with respect to the variability of the hand path may be attributed to human motor learning [106].

Figure 5.12 shows a representative subject's hand forward displacement over time for the first and last 10 iterations of the forward reaching task. Similarly to Fig. 5.11, Fig. 5.12 shows how the synergy affects one of the components of the measure of performance (5.2), namely the task completion time. Again, Fig. 5.12.(A) shows the case of the initial synergy $\theta_o = 1$, and Fig. 5.12.(B) the case of the personalised synergy $\theta_{ss} = 1.5$. It is important to highlight in this figure that the rise time and task completion time are both reduced after the synergy reaches steady-state ($\theta \rightarrow \theta_{ss}$).

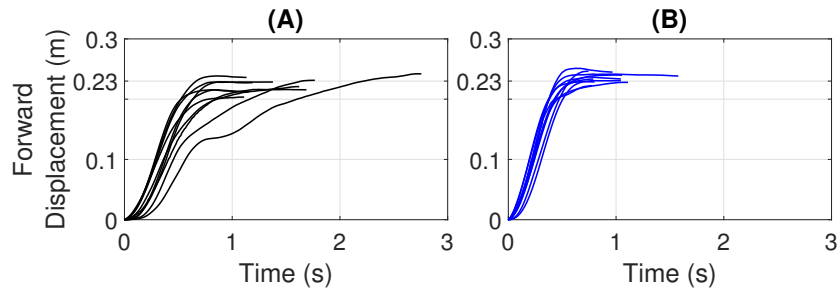


FIGURE 5.12: Representative subject's hand forward displacement across time. (A) The hand forward displacement for the first 10 iterations of the task. (B) The hand forward displacement for the last 10 iterations of the task.

Intuitively, a larger synergy value allows the elbow to travel faster, and thus the hand, for a given shoulder flexion, in turn reducing the task time. However, given that the synergy also affects hand displacement, a value that is too large will lead to over-extension and

a decay in accuracy. Thus, there is a trade-off between speed and accuracy, which is determined by the objective function (equation (5.2)), and determines the optimal personalised synergy. Given that different people have different motor behavior and capabilities, the best synergy value will differ across individuals.

The change in synergy across the 150 iterations of the task are presented in Figure 5.13. This shows how the personalisation algorithm adapted the synergy for each individual until reaching a steady-state, which is considered as the personalised synergy. Each subject's performance across the 150 iterations of the task is presented in Figure 5.14. Each data point in Fig. 5.14 represents the subject's performance as defined in equation (5.2) for a given reaching attempt. Together with Fig. 5.13, Fig. 5.14 shows how the change in synergy led to a change in performance. In general, it can be observed that an increase in the synergy value led to an increase in performance. As previously discussed in Figs. 5.11 and 5.12, this is expected as a larger synergy value means that further elbow extension will be performed w.r.t. shoulder extension, allowing the hand to travel further and thus closer to the target; and to travel faster, thus reducing the task time.

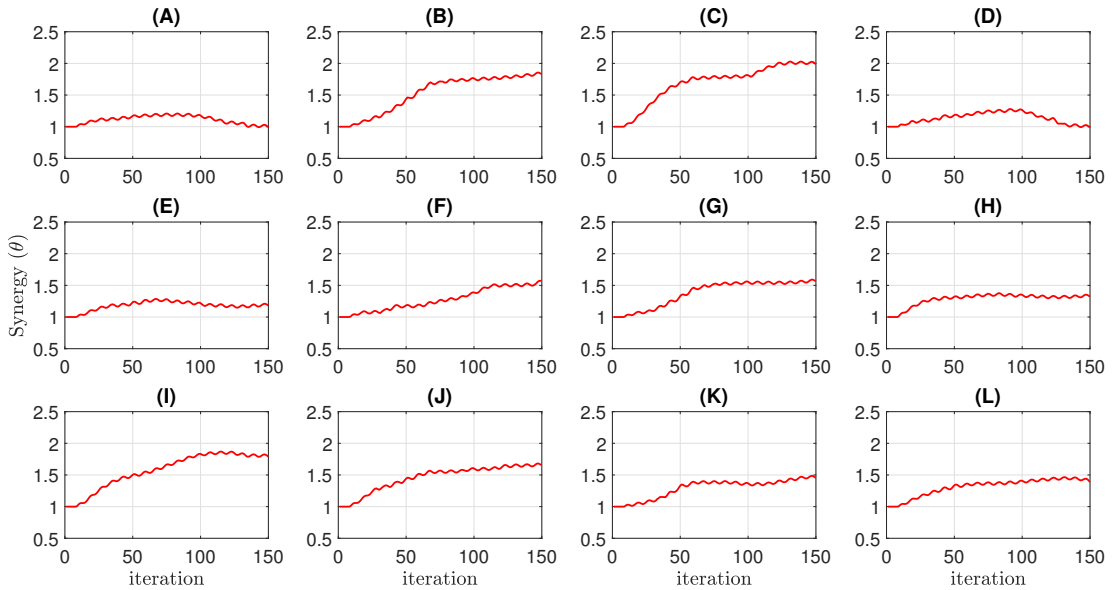


FIGURE 5.13: Synergy value across iterations of the task for all subjects in the experiment. The personalisation algorithm was capable of uniformly adapting and identifying the synergy to allow all subjects to improve and reach a steady-state performance within the 150 iterations regardless of their particular motor preference and adaptation characteristics.

Regarding the performance of the proposed personalisation algorithm itself, it can be observed in Fig. 5.14 that performance steady-state was reached under 50 iterations on average, which was achieved uniformly across most subjects. In other approaches, such

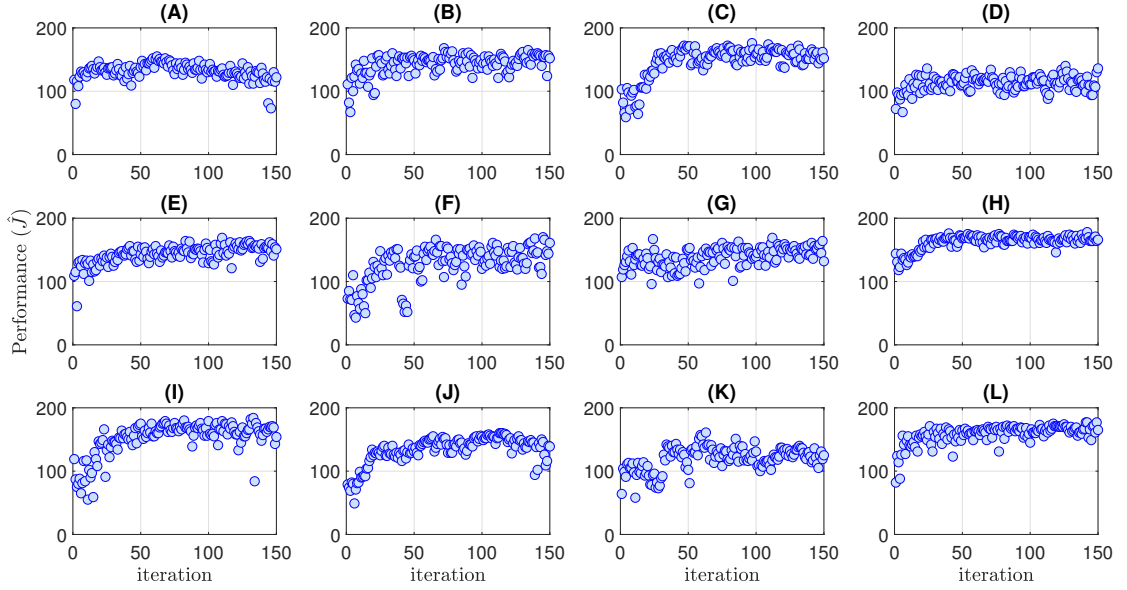


FIGURE 5.14: Performance across iterations for all subjects in the experiment, where one reach motion between the two targets was considered as an iteration of the task. A wide variety of capabilities can be observed among the different subjects, such as multiple different performance steady-states and levels of performance variability.

as [93], the performance of the algorithm depends on the motor performance map and the tuning of the algorithm to accommodate individual motor learning characteristics. However, the personalisation algorithm proposed herein achieved this uniform performance regardless of the individuals' motor behavior and learning characteristics without the need to re-tune. While motor learning characteristics are difficult to discern from Fig. 5.14, individual differences motor behavior can be seen in the initial and steady-state (best) performance, as well as in the relationship between the synergy Fig. 5.13 and performance Fig. 5.14. The shape of the relationship between synergy and performance differs across individuals. For instance, this synergy-performance relationship can be quite flat which can cause gradient-based optimisation algorithms, as in [93], to respond slowly. A case of such relationship can be seen in Figures 5.13 and 5.14 in subject (G), where a large change in synergy lead to a small change in performance. However, the proposed personalisation algorithm was able to adapt its update rate, through the proposed optimiser, to accommodate for this synergy-performance relationship as can be seen by the number of iterations needed to reach convergence.

A wide variety of capabilities are observed among the different subjects which is expected of human behavior. Multiple different performance steady-states with different identified best synergies can be seen across subjects. This further highlights the person to

person variations, and the importance and need of personalisation in human-prosthesis interfaces. Motor performance variation ($\bar{v}$) is another clear indicator of individuality, with different people having different levels of variability. In subjects with small identified $\bar{v}$, very clear performance steady-state and convergence of synergy are observed, such as subjects (H) and (L). On the other hand, in subjects with higher $\bar{v}$, the performance steady-state is not as clear and a wider drift in synergy is observed, such as with subjects (F) and (K). This shows how human motor behavior variability can affect the performance of the algorithm and motivates further improvements to algorithm to address this aspect of human behavior.

In light of the observed diversity in behavior, the personalisation algorithm was capable of adapting the synergy regardless of individual motor learning characteristics to allow all subjects to improve their performance while using the same algorithm tuning across all subjects. This demonstrates the advantages of the proposed algorithm for online personalisation of synergistic HPIs.

5.6 Discussion

This section discusses the applicability of the proposed personalisation algorithm to other tasks and prosthetic interfaces. This algorithm is based on a general framework that can be used in a wide variety of applications through the choice of the objective function and system parametrisation, which define the task and the parameters to be identified respectively. As such, these components will play an important role in the applicability of the personalisation algorithm to practical scenarios, each presenting its own challenges. In the case of the objective function, the challenge is the formulation of a significant and practical measure of performance; in the case of the parametrisation, it is in the synergy's dependency to the task. These two challenges are discussed next.

Even though accuracy and completion time are common measures of upper limb motion performance, they rely on knowledge of the reaching task, such as object location, which would be difficult to measure. Formulation of an objective function to evaluate performance in a practical application is paramount to the success of the proposed personalisation method. Given that obtaining the desired target object information from the prosthesis user can be difficult, it may be possible to use measurements of the user's

upper body motion to determine the performance of the prosthesis as an assistive device instead. Thus, changing the focus of the objective function, and thus the measure of performance, to be human-behavior centered, rather than task-space centered. For instance, upper-body motion can be used to determine the compensation motion an amputee needs in order to achieve a task with a prosthetic device [69]. Moreover, it has been observed that synergistic HPIs can reduce compensatory motion [11]. In the study presented in this chapter, a change in the upper-body motion of the subjects due to the personalised synergy was anecdotally observed. An example of this behavior is presented in Figure 5.15, where the subject's arm position at the end of the reaching task is shown for a representative reach of the first and last 10 iterations. The figure shows a difference in shoulder protraction between non-personalised and personalised synergy. As such, it is the authors' opinion that compensation motion may be a good candidate to evaluate performance of the prosthetic device and could be used to formulate an objective function for the personalisation algorithm. This will be quantitatively studied in future work.



FIGURE 5.15: Subject's difference in arm position at the end of reach for a representative iteration of the first and last 10 iterations of the task. A difference in shoulder protraction can be observed. (A) Arm end position for a representative iteration within the first 10 iterations of the experiment. (B) Arm end position for a representative iteration within the last 10 iterations of the experiment.

In the case of the parametrisation of the HPI, a significant challenge with the use of synergies is their evident dependence on the given task. Hence the difficulty in generalizing the personalised synergy from a particular point-to-point task to multiple directions, or more complex tasks. A possibility to address this problem is to consider higher-dimensional synergies or more complex synergy parametrisations in order to take advantage of the redundancies in the human arm to determine the intended direction of motion. Furthermore, other HPI modalities could be included in the parametrisation

in order to compliment the information obtained from the synergy with explicit user intention, such as how synergies and sEMG were combined in [58].

5.7 Conclusion

In this chapter, an algorithm for online personalisation of kinematic synergies for Human-Prosthesis Interfaces whose tuning is independent of individual motor behavior and learning was proposed. The algorithm is able to achieve uniform convergence performance across the population. In order to achieve this, the algorithm takes advantage of common motor preference and adaptation behavior observed experimentally in a group of individuals using a synergistic upper limb prosthetic device in a virtual reality environment. This motor behavior was formally characterised with a model structure which captures the common behavior across a population.

The application of the proposed personalisation algorithm was undertaken in a virtual reality environment with able-bodied subjects by emulating amputation and prosthesis use. The algorithm was capable of adapting the synergy while subjects used the prosthetic device in a forward reaching task, allowing all subjects to improve their performance despite the demonstrated person-to-person variations. Convergence performance of the algorithm was uniform across subjects using the same parameter tuning, avoiding the need for manual tuning for each individual.

The personalisation algorithm requires both the human and prosthesis to share the same objective function. Here, this was ensured by presenting a score to the subjects which was indicative of the prosthesis objective function. However, this may not be practical in practice as task information may not be known or it may not be possible to continuously display task performance information to prosthesis users. The next chapter addresses this challenge through the use of a prosthetic objective function which is based on implicit human motor behaviour.

Chapter 6

The Use of Implicit Human Motor Behaviour in the Online Personalisation of Prosthetic Interfaces

The personalisation algorithm presented in the previous chapter requires that the human and the prosthesis personalisation algorithm have same pre-defined objective function. This was ensured by providing explicit objective function feedback to the human. However, constantly displaying this information to the prosthesis user is impractical. Moreover, the method utilised task information in the objective function which may not be available from the wearable sensors typically available in prosthetic applications. In this chapter, the approach is extended to use a prosthesis objective function based on implicit human motor behaviour, which represents able-bodied human motor control and is measureable using wearable sensors. The approach is tested in a hardware implementation of the personalisation algorithm on a prosthetic elbow, where the prosthetic objective function is a function of upper-body compensation, and is measured using wearable IMUs. Experimental results on able-bodied subjects using a supernumerary prosthetic elbow mounted on an elbow orthosis suggest that it is possible to use a prosthesis objective function which is implicit in human behaviour to achieve collaboration without providing explicit feedback to the human.¹

¹The content presented in this chapter has been submitted for publication in [119].

6.1 Introduction

The measure of performance used for the personalisation of a human-prosthetic interface defines the prosthetic's objective, while the human has its own internal measure of performance and thus objective. In collaborative human-robot applications, such as motion-based synergistic prosthesis [31, 58, 62], it is required that these objectives align, i.e. that both the human and the robot have the same objective functions [78, 120]. In the previous chapter, this was ensured by using explicit task feedback (reach accuracy and time) which was used by the personalisation algorithm and presented to the user. However, in practice this may not be possible as the data obtained by the prosthesis is given by wearable sensors, and thus explicit task information may not be available. Moreover, it may not be possible and desirable to constantly display performance information to the user.

A possibility to address the need of having the same measure of performance between the user and prosthesis is to use knowledge of the implicit motor behaviour of humans. Implicit motor behaviour refers to the processes that occur subconsciously in humans when performing physical tasks. Here, it is hypothesised that by utilising a measure of performance that is theorised to be implicit in human motor behaviour, no explicit performance feedback will need to be provided to the prosthesis user to achieve human-prosthesis collaboration.

A block diagram of the human-prosthesis system and the personalisation algorithm is shown in Figure 6.1. The human (residual) limb and prosthetic device interact to achieve a resultant hand motion, where the motion of the prosthetic device is a function of the synergy value and the human limb motion. As a result of human motor learning, humans change their motor behaviour over repeated use of the prosthetic device in order to use the device effectively according to an internal objective function (J_h). There are currently multiple propositions for the internal composition of internal optimisation metrics used to generate optimal motor behaviour [13, 121, 122]. This human-internal objective function is referred to as the “implicit” objective function henceforth.

On the other hand, the prosthesis objective function (J_p) used in the synergy personalisation algorithm is explicitly defined and chosen to achieve an objective with the prosthesis. Due to the recent development of such adaptive system in [78], the effects of

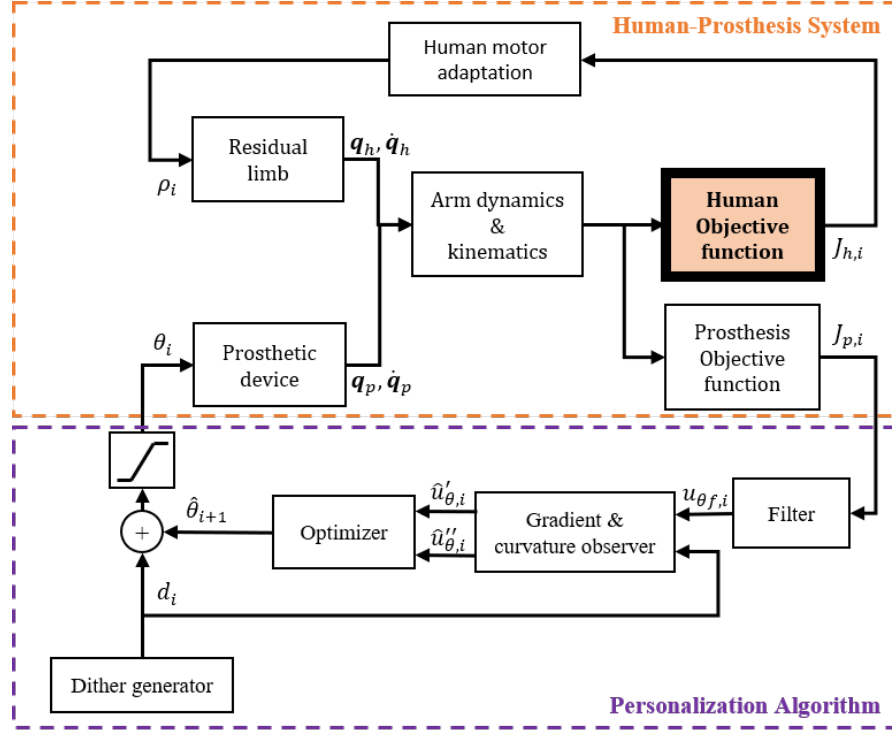


FIGURE 6.1: Human-prosthesis system with adaptive synergies. This work focuses on J_h .

the choice and design of the objective function on the resultant human motor behaviour are unknown. However, in order to design such objective functions, a set of conditions must be met. This is described in a model of the resultant synergy-to-performance behaviour inherent in the human-prosthesis system [78]. In summary, the objective function must be designed such that there exists a synergy (θ^*) that achieves the best performance (J_p^*), and human motor learning must be reflected in the performance (J_p) as monotonically increasing until reaching a steady-state.

To achieve collaboration, and thus convergence of the personalisation algorithm, the human and prosthetic objective functions must be as close as possible ($J_p \rightarrow J_h$) [78, 120]. Here, the use of a measure of implicit human motor behaviour in the prosthesis objective function is proposed. The hypothesis is that the use of a prosthesis objective function that acts as a surrogate for the internal human objective function will allow the personalisation process to take place without the need to provide explicit feedback to the human. The hypothesis is tested by using upper-body compensation motion as a surrogate for human effort while performing a reaching task, which is determined by data gathered from two wearable IMUs.

6.2 Upper-body Compensation as a Measure of Performance for Prosthesis Personalisation

This section presents the methodology followed to determine an IMU-based measure of performance for prosthetic reaching. The choice of using compensation motion is based on its use as a clinical measure of prosthetic performance [5, 69]. Compensation motion can be measured with body-mounted IMU sensors [11], making it a good candidate for a wearable sensor-based measure of performance in prosthetics. Moreover, upper-body compensation motion is used by prosthesis users to overcome the limitations of their prosthetic devices, is observed in a wide range of ADLs, and trunk and shoulder motion are the natural range extenders of reach in able-bodied motion [5, 69].

The following steps were followed to develop the objective function: 1) the relationship between the prosthesis synergy and upper-body motion was experimentally evaluated to determine the relevant components to be used in the design of the objective function (Section 6.2.1). 2) An objective function was designed such that the necessary conditions for its use in the personalisation algorithm are satisfied (Section 6.2.2).

6.2.1 Evaluating the Relationship Between Synergy and Upper-body Motion

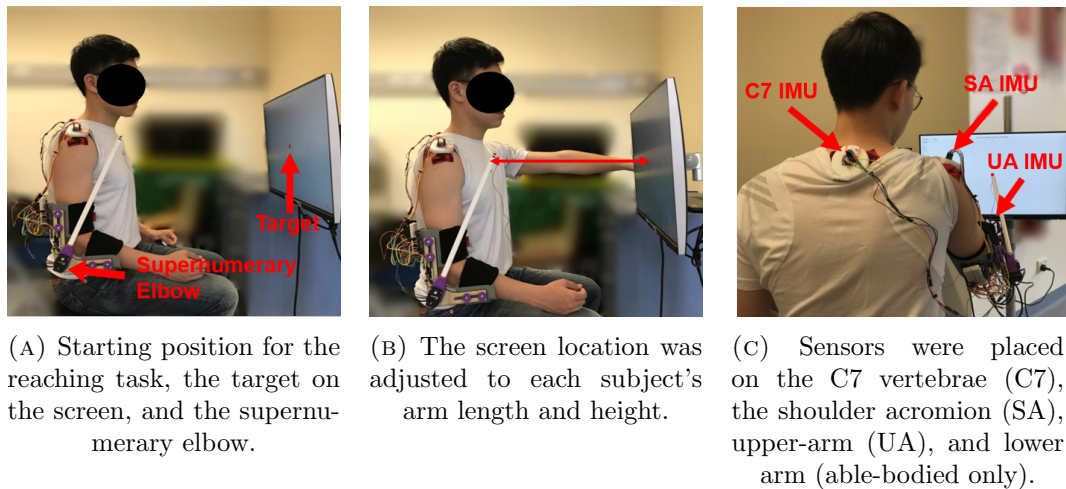


FIGURE 6.2: Experimental set-up used for determining the relationship between synergy and upper-body motion, and to demonstrate the proposed measure of performance.

To determine the relationship between the synergy and upper-body compensation motion an experiment with three able-bodied subjects wearing a supernumerary prosthetic elbow mounted on an elbow orthosis (Figure 6.2a) was performed.

6.2.1.1 Hardware Set-up

Bosch BNO055 IMUs were mounted on the subject's C7 vertebrae to measure trunk motion (C7), on the shoulder acromion (SA) to measure shoulder displacement, on the upper-arm (UA) to be used for the synergy, and on the lower-arm (LA) to get able-bodied elbow motion data. Sensor placement is shown in Figure 6.2c. The C7 and SA sensors were used to determine the trunk and shoulder forward displacement respectively. This was calculated using the subject's body measurements, trunk length and C7 to shoulder acromion distance, and the estimated joint angle from the IMUs. The upper-body was considered to be a set of rigid links. Data gathering was done using an Arduino M0 Zero and an application developed in Visual Studio/C#.

6.2.1.2 Task Description

The task required subjects to reach forward from a neutral seating position and touch a target on a screen. The starting position and target are shown in Figure 6.2a. The screen location was adjusted for each subject to be within their able-bodied reaching distance. The screen position was set with the subject's arm as a reference while the arm was held straight forward as shown in Figure 6.2b. The forward distance and height of the screen were set at the subject's wrist joint, while the lateral position was such that the centre of the screen was aligned with the centre of the subject's chest. This screen position ensured that the task was within the able-bodied workspace of the subject's upper-limb. It is important to note that in this case tasks outside of the able-bodied workspace are not considered as these may require motion where trunk recruitment is necessary. Such cases would require further considerations in the synergy design as the trunk effectively becomes an additional DOF for the synergy.

6.2.1.3 Protocol Description

Subjects were first asked to perform the task with their arm (able-bodied) for 30 iterations to obtain their able-bodied motor behaviour as benchmark. This is referred to as the able-bodied case henceforth. Then the supernumerary synergistic prosthetic elbow was mounted on their arm using an elbow orthosis and were provided with sufficient training with the device in order to minimise the effects of motor learning on the synergy-motion results. This is referred to as the prosthetic case henceforth. Subjects repeated the reaching task for 200 iterations, with the synergy value changing every 5 iterations ($\Delta\theta = 0.05$). the synergy used was $\dot{q}_e = \theta\dot{q}_s$, where $\dot{q}_e$ is the prosthetic elbow extension, $\dot{q}_s$ the shoulder extension, and $\theta \in [0.8, 2.7]$ the synergy parameter. A scalar linear relationship between the velocity of the shoulder and elbow flexion for the task of reaching forward is selected in this work as the specific example of kinematic synergy to exemplify the application of the method presented herein. However, the proposed method is generalisable to other parametrisations of synergies of higher complexity and dimensionality.

The procedure was approved by the University of Melbourne Human Research Ethics Committee, project number 1750711.2. Informed consent was received from all subjects in the study. Results from the experiments in this Chapter can be found in <https://git.io/JvRZs>.

6.2.1.4 Synergy vs. Trunk Compensation

Experimental results for trunk forward compensation for the three subjects are presented in Figure 6.3. The blue line represents average trunk displacement for the able-bodied case while the blue circles for the prosthetics case. It can be observed that trunk displacement for the able-bodied case is close to zero for the given reaching task. In the prosthetics case, trunk displacement has a near linear relationship with the synergy. Moreover, it can be seen that the prosthetic case data intersects the subject's able-bodied displacement line. This intersection represents the subject's optimal synergy value which achieves able-bodied-like trunk displacement. Intuitively, this means that as the synergy value moves away from the optimal, the individual will recruit trunk motion to compensate for the elbow not extending enough, or over-extending. This

behaviour is highly desirable for personalisation purposes as it suggests that there is a unique synergy that minimises trunk displacement. Moreover, the able-bodied line intersection is at a different synergy value across subjects and the slope of the synergy-displacement map differs across subjects, highlighting individuality in motor behaviour.

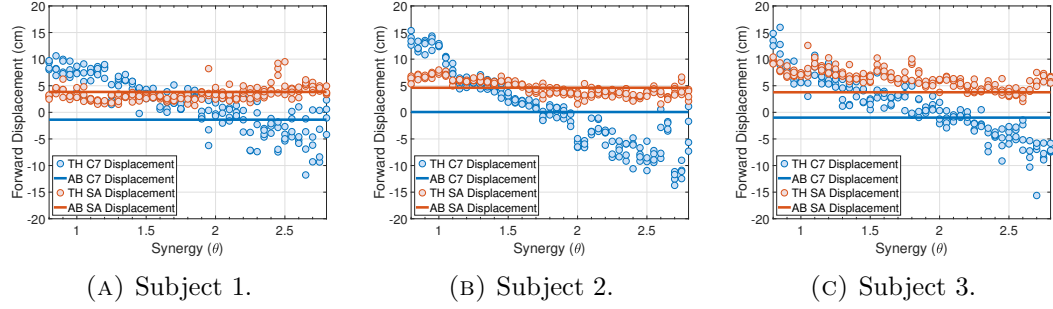


FIGURE 6.3: Relationship between trunk (C7) and shoulder (SA) forward displacement, and synergy (θ) for three subjects. The x-axis presents the synergy value while the y-axis the trunk and shoulder forward displacement. Blue and red circles represent C7 and SA displacements for the prosthetic case, respectively. Blue and red lines represent mean able-bodied C7 and SA displacements, respectively.

6.2.1.5 Synergy vs. Shoulder Compensation

Experimental results for shoulder forward compensation for the three subjects are presented in Figure 6.3. The red line represents average able-bodied shoulder displacement while the red circles the prosthetics case. From these results, it can be seen that shoulder forward displacement is always present in the reaching motion, with able-bodied displacement of about four centimetres for the given task. In the prosthetics case, different compensation strategies can be observed across subjects in the shape of the synergy-displacement map. This highlights individuality and preference in motor behaviour. Similarly to trunk compensation, a crossing of the synergy-displacement map with the able-bodied average displacement is present, which in this case is at 4cm.

6.2.2 A Compensation Motion-based Objective Function for Prostheses Personalisation

The purpose of the design of the objective function is to drive the behaviour of the personalisation algorithm. In this work, this means minimising compensation motion.

Therefore, the resultant synergy-compensation map needs to satisfy the convexity assumption in [78, Assumption 1]. Given that the synergy-displacement relationship observed in Figure 6.3 is nearly linear, a candidate objective function that satisfies this assumption is the convex combination of quadratic terms. For compensation motion, this is given by:

$$J_p = \alpha(\bar{x}_t - x_t)^2 + (1 - \alpha)(\bar{x}_s - x_s)^2, \quad (6.1)$$

where $0 < \alpha < 1$ is the weight to be determined, x_t the trunk forward displacement, $\bar{x}_t$ the desired trunk forward displacement (able-body-like), x_s the shoulder forward displacement, and $\bar{x}_s$ the desired shoulder forward displacement (able-body-like). Due to the minimisation objective, J_p will be referred as cost henceforth.

A rigorous choice of the weight α would require determining the involvement of each joint in the reaching motion, and thus an analysis of human motor behaviour and the theorised internal optimisation mechanisms for human motion planning [13, 123]. This is out of the scope of this paper and will be investigated in future work. Therefore, it was chosen to equally minimise both trunk and shoulder displacement by setting $\alpha = 0.5$, and focus on determining the viability of the proposed method from a practical perspective.

The obtained synergy-cost maps ($J_p(\theta)$) for the three subjects are presented in Figure 6.4. The experimental data is represented by the blue circles, while the quadratic polynomial fit to this data is shown by the black lines. The estimated optimal synergies (θ^*), given by the polynomial, are 1.99, 1.90, and 1.92, for each respective subject. However, it is important to note from the experimental data that the minimum cost is observed for a range of synergy values. As expected the synergy-cost maps ($J_p(\theta)$) show desirable features for online personalisation. These results shows that the proposed compensation motion-based objective function satisfies the condition for the implementation of the algorithm presented in [78].

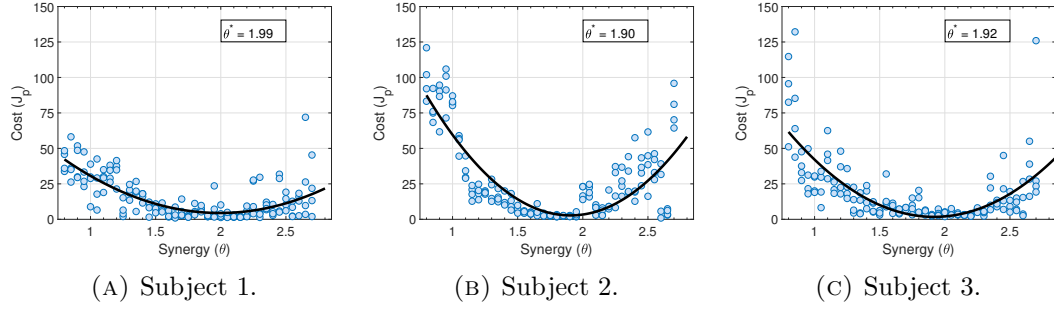


FIGURE 6.4: Synergy-Performance map ($J_p(\theta)$) for three subjects. The x-axis presents the synergy value while the y-axis the performance as given by eqn. 6.1. The experimental results are shown in blue while the fitted quadratic map is shown in black. The optimal synergy (θ^*) for each subject, as given by the fitted quadratic map, is shown in each plot.

6.3 Compensation Motion-based Prosthesis Personalisation Experiments

An experiment using the same set-up presented in Section 6.2.1 was performed to evaluate the behaviour of the personalisation algorithm with the proposed measure of performance. The experiment involved nine able-bodied subject, the same three subjects in Section 6.2.1 and six additional subjects that were completely new to the set-up and task. These experiments were performed three months after the original sweep experiments to minimise the bias introduced by motor learning on the results of the first three subjects. The same task as in 6.2.1 was performed by the subjects; however, in this case, the personalisation algorithm was used to iteratively adjust the synergy parameter (θ) instead of performing a synergy value sweep. The following algorithm tuning parameters were used: $\omega_o = \pi/4$, $a = 0.06$, $k = 0.0008$, $\varepsilon = 0.1$, and $L = [0.3840 \quad 0.6067 \quad -0.2273 \quad -0.8977 \quad -1.0302]^T$.

Subjects were not informed to what was being evaluated by the prosthesis and were only indicated to perform the reaching task with the supernumerary prosthetic elbow. Subjects performed the task for 80 iterations, with a one minute rest after 40 iterations. The target displacements trunk and shoulder displacements, $\bar{x}_t$ and $\bar{x}_s$, were set to zero. The choice of zero trunk displacement is based on able-bodied trunk displacement. The choice of zero shoulder displacement was to determine whether the implicit prosthetic objective function could influence “natural” human motion.

Figure 6.5 presents algorithm performance results. These results show the synergy value and cost, as defined in equation (6.1), over the 80 iterations of the task. On average, the algorithm reached steady-state within 30 iterations of the task. With this given synergy steady-state (θ_{ss}), subjects significantly minimised the cost (J_p), driving it close to zero, meaning that compensation motion was close to zero. This personalisation algorithm behaviour is comparable to the results presented in [78]. However, it is important to highlight that these two approaches may not converge to the same optimal synergy. This is due to the different objective functions in use. There are two other significant observations. First, for subjects 1-3, the steady-state synergy converged to a synergy within the range that minimises the cost identified in the synergy-cost map in Figure 6.4. Second, the motor behaviour of subjects 1 and 9 is irregular and is reflected in the performance of the algorithm. These will be discussed in the next section

Figure 6.6 presents trunk (C7) and shoulder (SA) displacement over the 80 iterations of the task. From this it can be observed that all subjects reduced their trunk motion and achieved under 5cm trunk displacement at the steady-state, except for subject 4 which did not reach steady-state. This steady-state trunk behaviour is comparable to the able-bodied behaviour presented in Figure 6.3 On the other hand, subjects maintained their “natural” shoulder displacement regardless of the objective function using a desired zero shoulder displacement. This can be seen by the constant shoulder displacement throughout the experiment. Only in the results for subject 9, Figure 6.6i, can a change in shoulder strategy can be observed. Nevertheless, these results demonstrate that the personalisation algorithm successfully achieved its objective of minimising compensation motion without providing explicit feedback to its user, for a variety of individuals with different motor strategies. This supports the hypothesis that a surrogate of implicit human motor behaviour can be used as the objective function to drive prosthesis personalisation without the need to provide the prosthesis user with explicit performance feedback. The next section presents a discussion of the important observations arising from these results.

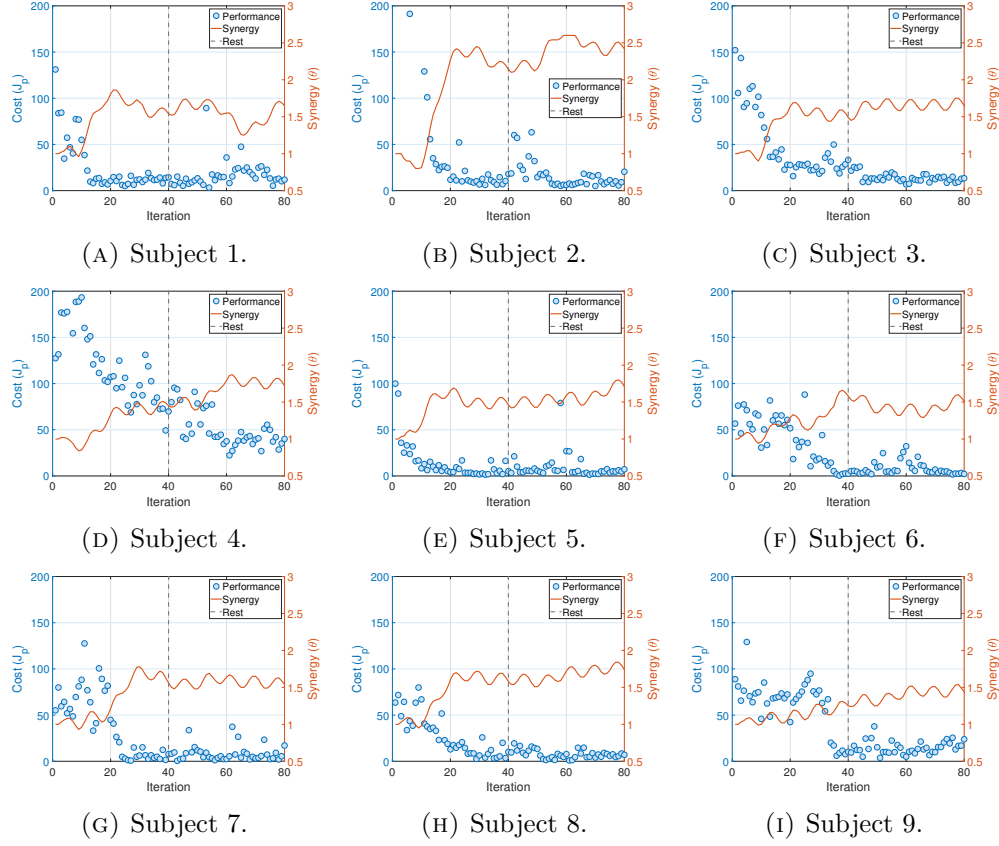


FIGURE 6.5: Synergy value (θ) and cost (J_p) over iterations results for nine able-bodied subjects. The red line represents the synergy value (θ) while the blue dots the cost (J) as defined by eqn. (6.1). The grey dotted line represents when the subjects were given rest time.

6.4 Discussion

6.4.1 Non-linearities in Human Motor Learning

The results from subjects 2 and 9, Figures 6.5b, 6.5i, 6.6b, and 6.6i, highlight some of the non-linear phenomena present in human motor learning which directly affect the performance of the personalisation algorithm. In the case of subject 2, one of such non-linear phenomena can be observed in a transient change in performance after the rest time. This transient change can be considered as a “warm-up decrement”, which is commonly observed at the beginning of experiment sessions that are performed days apart [124, 125]. This phenomenon is characterised by a decrease in performance between sessions, followed by a systematic increase in performance which satisfies the monotonic increase to a steady-state condition required by the algorithm. However, in the case of subject 2, it is present within a session as rest time was provided halfway through

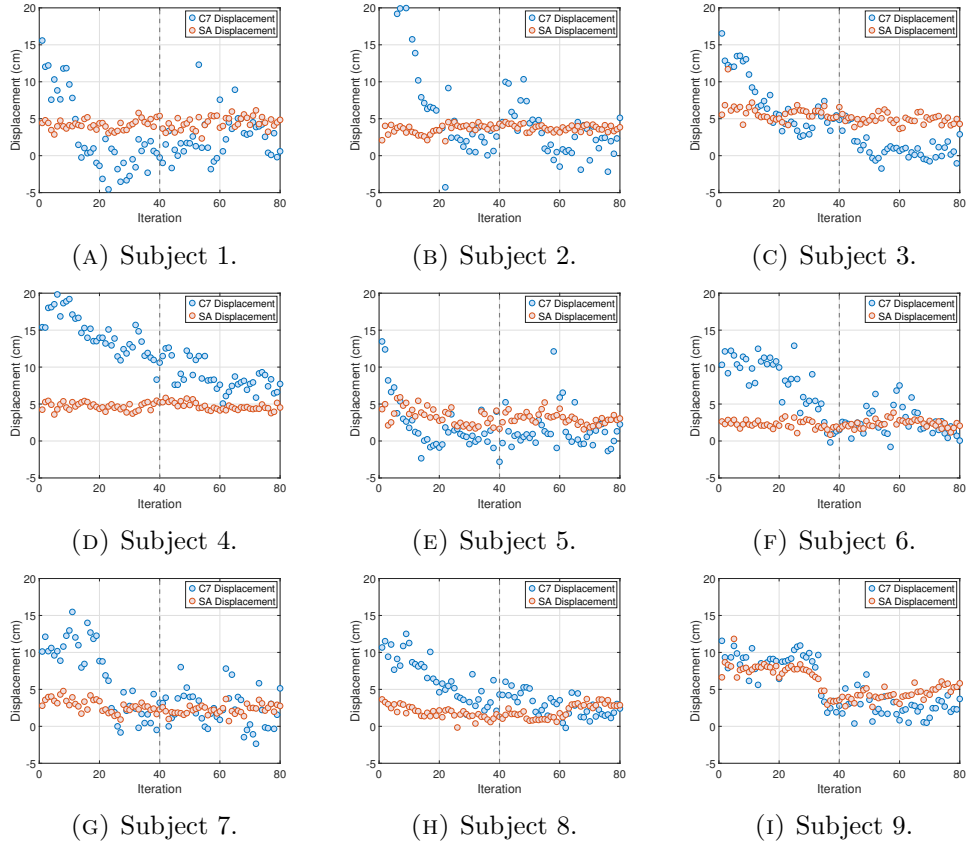


FIGURE 6.6: Trunk (C7) and shoulder (SA) displacement over iterations results for nine able-bodied subjects. The blue circles show trunk displacement while the red circles show shoulder displacement. The grey dotted line represents when the subjects were given rest time.

the experiment. This highlights individual variation in motor learning, which in the case of subject 2 this particular aspect was more prevalent. As can be seen in Figure 6.6b, these results suggests that within the rest time the subject “forgot” the steady-state upper-body and arm motion, and had to re-learn it. This phenomenon could be prevalent in day-to-day prosthesis use and thus is relevant for the further development and subsequent deployment of adaptive systems in human applications.

In the case of subject 9, Figures 6.5i and 6.6i, there is a sudden change in performance around iteration 35, where the cost (J_p) was significantly reduced from one iteration to another. This corresponds to a change in strategy that led to a reduction in trunk displacement, as seen in Figure 6.6i. The change of strategy can be attributed to natural motor variability and exploration, which can lead to the discovery of new strategies that result in improved performance [124, 126]. This highlights a challenge of using a surrogate of implicit human behaviour as the measure of performance for the personalisation algorithm. The use of incomplete information on the human internal objective

function, which relies on certain assumptions, does not fully capture the whole human motor and learning behaviour. This can lead to undesirable phenomena in the measure of performance as observed. In this instance, the discovery of the new strategy led the subject to a new motion steady-state with reduced upper-body compensation, which did not affect the performance of the personalisation algorithm. However, the effects of reduced information on the measure of performance, and motor strategy changes, ought to be thoroughly investigated as these will naturally occur in daily prosthesis use.

6.4.2 Effects of the Implicit Objective Function on Human Motor Behaviour and Prosthesis Personalisation

There are two observations on the influence of the proposed objective function on motor behaviour that warrant discussion. The first observation is related to compensation (cost) minimisation being achieved for a range of synergy values. As shown in the identified synergy-cost maps in Figure 6.4, minimum cost is observed in a range of synergy values. Results in Figure 6.5 for subjects 1-3, show how the algorithm converges to a value within this range (for subject 2, iterations 40-50 as per the previous discussion). This is as expected as the algorithm's objective is cost minimisation. However, the possible reasons behind why the map has such flat regions instead of a more convex shape as observed in [78] warrants discussion. Two possible causes for such behaviour were identified. 1) There may be a synergy range where the resultant compensation motion is within the subject's natural variation, and thus any synergy on that range may be suitable for the subject. 2) The flat region could be a result of a loss of information due to the use of only trunk and shoulder displacement, and wearable sensors. However, given the results obtained for this study, it is not possible to conclude which was the cause. This will be considered in future work as testing these possibilities may require longitudinal studies that include the change of the synergy-performance map over multiple sessions and time. This includes determining the effects of long-term motor learning on the synergy-performance map and the effects of information uncertainty and loss on the personalisation procedure.

The second observation is related to the influence of the prosthesis objective function on natural human motor behaviour. The use of a non-natural desired shoulder motion ($\bar{x}_s = 0$) in the cost function did not influence the resultant human motor behaviour.

This can be seen in Figure 6.6, where most subjects maintained their natural shoulder motion (SA displacement of 5cm) throughout the experiment regardless of the synergy value. A possible explanation for this is that the human internal objective function penalises shoulder more heavily than trunk for this type of motion, thus most subjects prefer to recruit their trunk to compensate for the inaccurate synergy. In subjects 8 and 9 (Figures 6.6h and 6.6i) a clear change of shoulder displacement was observed. Subject 8 gradually reduced shoulder displacement to close to zero displacement until iteration 60, where a gradual increase started that eventually converged to about 4cm, close to the population average natural shoulder displacement (5cm). This happened around the same iteration that the subject's trunk displacement reached the vicinity of natural trunk motion. On the other hand, subject 9 had a change of strategy around iteration 35, where both trunk and shoulder displacements changed from compensatory-like to near natural. These results suggest that regardless of the implicit cost function used in the prosthesis, individuals will converge to their natural motor behaviour when the synergy is within the range that allows for it. Similar results have been observed in rehabilitation applications [127]. This agrees with the previous discussion point, suggesting that there is a range of synergy values that achieve minimum compensation. This may be advantageous from a practical implementation perspective as it may be possible to simplify the personalisation procedure and sensor requirements.

While there are important observations that arise from the results in the study presented herein, the successful implementation of the prosthesis personalisation algorithm under practical constraints using a prosthesis objective function unknown to the human proves the hypothesis considered in this work. These results motivate further studies to better understand the interaction between the human and the adaptive prosthesis.

6.5 Conclusion

This chapter presented a method that uses implicit human motor behaviour as the basis for the personalisation of human-prosthetic interfaces. The method allows the personalisation algorithm proposed in the previous chapter to operate without the need to provide explicit performance feedback to the human and using only wearable sensors. A measure of performance that acts as a surrogate for internal human measures of motor performance was used, ensuring that both the human and prosthesis have the same

objective. A hardware implementation was performed where the prosthesis measure of performance was based on compensation motion gathered from wearable IMUs. These initial results are promising and indicate using this surrogate approach can lead to successful interface personalisation with reduced compensatory motion in individuals.

While the methods presented so far in this thesis address the issue of personalisation in synergistic HPIs, these remain dependent on the task they were trained on. This task dependency is a major limitation to the deployment of synergistic HPIs. The next chapter proposes a model-based method which uses explicit task information in its formulation, unlike other synergy formulations in HPIs to date where task information is encoded in their parameters.

Chapter 7

Task-space Synergies for Reaching using Upper-limb Prostheses

The previous chapters demonstrated that developing human-prosthetic synergies in joint-space must consider individual motor behaviour and the intended task to be performed, requiring personalisation and task calibration. In this chapter, an alternative synergy-based strategy, utilising a synergistic relationship expressed in task-space, is proposed. This task-space synergy has the potential to replace the need for personalisation and task calibration with a model-based approach requiring knowledge of the individual users arm kinematics, the anticipated hand motion during the task and voluntary information from the prosthetic user. The proposed method is compared with surface electromyography-based and joint-space synergy-based prosthetic interfaces in a study of motor behaviour and task performance on able-bodied subjects using a VR-based transhumeral prosthesis. Experimental results showed that for a set of forward reaching tasks the proposed task-space synergy achieves comparable performance to joint-space synergies without the need to rely on time-consuming calibration processes or human motor learning. Case study results with an amputee subject motivate the further development of the proposed task-space synergy method.¹

7.1 Introduction

The previous chapters have demonstrated that differential kinematic synergies can be personalised to their user during task execution; however, a library of task-specific and

¹The content presented in this chapter has been published in [79].

individually personalised synergies would be needed to provide the large range of movements required by ADLs [1]. The dependency of synergies on human individuality and the task performed is an unavoidable challenge to their application in fields such as prosthetics. Current methods do not utilise task information, such as the location of the target, as it is challenging to obtain it in a prosthetic setting. However, using this information may be beneficial in improving the robustness and performance of synergistic interfaces, and avert the need of generating a library of task specific synergies. While obtaining this information may be a challenge with current methods, this may be overcome with future technologies or interface modalities that assist with determining reaching intention and direction [72].

It is therefore necessary to develop and evaluate alternative strategies capable of explicitly using task information in the design of synergistic prosthetic interfaces. This serves to overcome task dependency and human motor behaviour variations while maintaining voluntary user control and involvement. In this chapter, an alternative synergy-based strategy, utilising a synergistic relationship expressed in task-space, is proposed. The synergy generated by this method couples the residual limb and prosthesis motion to achieve a task-space constraint. This could be seen as coupling the residual limb motion to a task-space motion, hence the method will be referred to as task-space synergy henceforth. The method is referred to as synergy because of its use in the context of coordinating multiple DOF in the human-prosthesis arm, which is similar to joint-space methods [27, 55, 128].

The task-space synergy method has the potential to replace the need for personalisation and task calibration with a model-based approach requiring knowledge of the individual users arm kinematics, the anticipated hand motion during the task and voluntary information from the prosthetic user. Using classic robotics tools, the proposed task-space synergy can be generated using the manipulator's Jacobian [129, 130], under the assumption that knowledge of the initial conditions and the desired end-effector (hand) motion is available. Here, a simplified case of such formulation under constrained motion is proposed. Location of the target is explicitly specified by the human user prior to the reaching motion, thus overcoming the assumption of the knowledge of the target location.

7.2 A Task-space Kinematic Synergy

The objective of a task-space kinematic synergy is to determine the motion of the prosthesis given the motion of the residual limb and the desired hand path. However, knowing the exact desired hand path before execution of the task is a challenge as information on the desired target is only known to the prosthesis user. While there exist methods to obtain this information through other interfaces (e.g. gaze-tracking [72]); here, a path-constraint approach is taken to allow the prosthetic user to convey the information of the target prior to commencing the reaching motion. This is done by the user aligning an imaginary straight line between the shoulder point, the target, and end effector (Figure 7.1a) prior to a forward reaching motion. This determines the path of the hand reaching motion, described by the vector r_{SH} (Figure 7.1b). The path r_{SH} can be thought of as the radial direction of a spherical coordinate centered at the shoulder point S. Once determined, the reaching motion, which is now constrained to move only along r_{SH} , can be produced through coupling the elbow prosthesis flexion-extension to the user's shoulder flexion-extension. This stage of the user aligning the hand along the target and the shoulder in a straight line will be referred to in this chapter as the “aiming” stage, used to provide the information of the target in the proposed Task Space synergy approach. The aiming stage is performed by the user when the elbow is locked in a fixed position and adjusts the residual-limb pose to align the prosthetic hand in the direction of the desired target. When the aiming stage is completed, the user can signal the prosthesis, through a separate HPI, to calculate the constraint and start coordinating the residual-limb and the prosthesis.

The protocol for the user to determine the constrained path r_{SH} is presented as follows. Let $\mathbf{v} \in \mathbb{R}^3$ be the hand velocity in task-space. $\mathbf{q}_s$ and $\dot{\mathbf{q}}_s$ are the residual limb joint angular displacement and velocity respectively (Figure 7.1c). In the transhumeral amputation case under consideration, $\mathbf{q}_s \in \mathbb{R}^3$ and $\dot{\mathbf{q}}_s \in \mathbb{R}^3$. $\mathbf{q}_e$ and $\dot{\mathbf{q}}_e$ represent prosthesis joint angular displacement and velocity respectively (Figure 7.1c), for the elbow prosthesis case $\mathbf{q}_e \in \mathbb{R}$ and $\dot{\mathbf{q}}_e \in \mathbb{R}$.

The reference frame $\{R\}$ has its origin at the center of the shoulder joint and is attached to the shoulder with its x -axis pointing forward and the y -axis upwards w.r.t. the upper body. There are two reasons for the choice of the location of $\{R\}$. First, in practice, measurement of limb motion are obtained from IMUs and require a reference IMU to

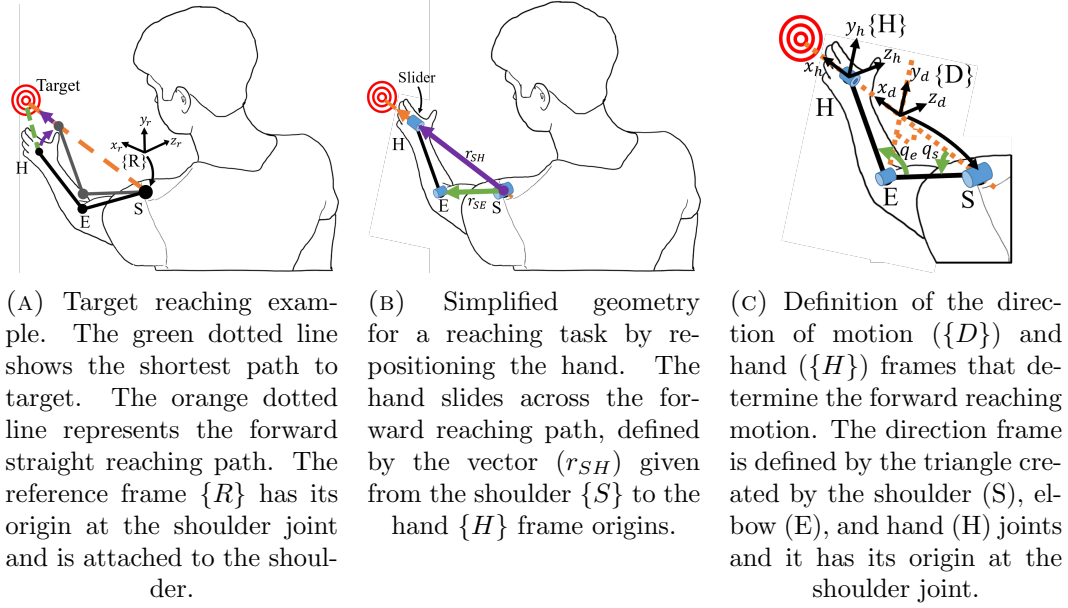


FIGURE 7.1: Formulation of the forward reaching task and reference motion for the task-space synergy.

determine the limb's relative motion to the body. This IMU is typically placed on the upper-body. Second, to allow changes in the direction of motion with respect to the world coordinates. Since the motion of the arm is defined with respect to the trunk, any motion of the trunk (or rest of the body) allows the user to correct for initial errors in the direction of motion.

The coordinate frame $\{D\}$ has its origin at the shoulder joint and is attached to the direction of reach. The shoulder angle $\mathbf{q}_s$ is given by the angle between the upper-arm (SE) and the direction of reach (SH). The frame $\{H\}$ has its origin at the centre of the hand (end-effector) with x_h aligned to x_d .

Initially, the length of the upper arm (d_{SE}) and lower arm (d_{EH}) are measured and determined. Once the aiming process is completed, the following is carried out:

- A. A coordinate frame $\{D\}$ is defined with its x -axis (x_d) aligned with the direction of reaching r_{SH} and on the plane formed by the shoulder (S), elbow (E), and hand (H) joints.
- B. The frame transformation $({}^D_R\mathbf{R})$ is determined in order to express shoulder and elbow joint angular displacements with reference to frame $\{D\}$.
- C. The Jacobian matrix $\mathcal{J}(\mathbf{q}_s, \mathbf{q}_e)$ is obtained to relate the incremental movement of the hand (end-effector) to the incremental joint displacement of the shoulder and

elbow, taking into account the reaching path the hand motion is constrained to $({}^D\dot{x}_h)$.

- D. $\dot{\mathbf{q}}_e$ is solved as a function of $\mathbf{q}_s$, $\mathbf{q}_e$, and $\dot{\mathbf{q}}_s$ to determine the elbow motion reference that satisfies the desired hand path.

These four steps are elaborated in the subsections below. The following assumption is used:

Assumption 7.1. *The angular position and velocities of the residual limb are measurable.*

Remark 7.2. Inertial Measurement Unit (IMU)-based measurements of residual limb motion have been demonstrated for synergistic elbow prostheses in [57, 58].

7.2.1 Direction of Motion Reference Frame

The direction of motion frame $\{D\}$ determines the direction of the forward reaching task as exemplified in Figure 7.1, and is defined w.r.t. the reference frame as follows:

- x_d -axis: The unit vector given in the direction from the shoulder joint center to the initial hand position ${}^R\mathbf{p}$.

$${}^R\mathbf{x}_d = \frac{{}^R\mathbf{p}}{\|{}^R\mathbf{p}\|_2} \quad (7.1)$$

- z_d -axis: The unit vector perpendicular to the plane given by the S-E-H triangle, in the direction of z_r . This can be defined by

$${}^R\mathbf{z}_d = \frac{{}^R\mathbf{r}_{SE} \times {}^R\mathbf{x}_d}{\|{}^R\mathbf{r}_{SE} \times {}^R\mathbf{x}_d\|_2} \quad (7.2)$$

where ${}^R\mathbf{r}_{SE}$ is the vector from the origin of the shoulder frame $\{S\}$ to the origin of the elbow frame $\{E\}$.

- y_d -axis: Follows the right hand rule.

With this the direction of motion reference frame $\{D\}$ is defined and motion of the arm and hand can be expressed with it as reference. This concludes step A.

7.2.2 Frame Transformation

Assuming that measured data is obtained in frame $\{R\}$ then it is necessary to transform these angles to the task frame $\{D\}$. This assumption arises from the common use of relative measurements from two IMUs to produce residual limb pose measurements [57, 58]. This transformation can be performed through the Euler angles (α, β, γ) in a Y-X-Z sequence. The transformation angles can be obtained as follows:

- α : The first rotation is along the y_r -axis. α can be obtained from ${}^R\mathbf{x}_d$, as given by:

$$\alpha = \tan^{-1} \left(\frac{{}^R\mathbf{x}_{d,x}}{{}^R\mathbf{x}_{d,z}} \right), \quad (7.3)$$

where ${}^R\mathbf{x}_{d,x}$ and ${}^R\mathbf{x}_{d,z}$ are the x and z components of ${}^R\mathbf{x}_d$.

- β : The second rotation is along the x_r -axis. β can be obtained from ${}^R\mathbf{z}_d$, as given by:

$$\beta = \tan^{-1} \left(\frac{{}^R\mathbf{z}_{d,y}}{{}^R\mathbf{z}_{d,z}} \right). \quad (7.4)$$

- γ : The last rotation is along the z_r -axis. γ can be obtained from ${}^R\mathbf{x}_d$, as given by:

$$\gamma = \tan^{-1} \left(\frac{{}^R\mathbf{x}_{d,y}}{{}^R\mathbf{x}_{d,x}} \right). \quad (7.5)$$

The transformation is therefore given by:

$${}^D_R\mathbf{R} = \mathbf{R}_y(\alpha)\mathbf{R}_x(\beta)\mathbf{R}_z(\gamma), \quad (7.6)$$

where $\mathbf{R}_x(\alpha)$ is an x -axis standard rotation of the given angle α . Thus it is possible to transform arm motion data from the reference frame $\{R\}$ to the task frame $\{D\}$. This concludes step B.

7.2.3 Arm Jacobian

By performing the adequate transformations, as previously presented, the forward reaching task can be simplified to a 2D task on the $x-y$ plane of the $\{D\}$ frame. This simplifies the kinematics required for the synergy to those of a 2-DOF planar arm. The differential

kinematics of the simplified arm are well known and given by [130]:

$$\bar{\mathbf{v}} = \begin{bmatrix} {}^D\dot{x}_h \\ {}^D\dot{y}_h \end{bmatrix} = \begin{bmatrix} -\ell_u S_s - \ell_l S_{se} & -\ell_l S_{se} \\ \ell_u C_s + \ell_l C_{se} & \ell_l C_{se} \end{bmatrix} \begin{bmatrix} \dot{q}_s \\ \dot{q}_e \end{bmatrix}. \quad (7.7)$$

where $C_s = \cos(\bar{q}_s)$, $S_s = \sin(\bar{q}_s)$, $C_{se} = \cos(\bar{q}_s + \bar{q}_e)$, $S_{se} = \sin(\bar{q}_s + \bar{q}_e)$, $\bar{q}_s = {}^Dq_s$, and $\bar{q}_e = {}^Dq_e$. ℓ_u and ℓ_l are the lengths of the upper and lower arm respectively. This concludes step C.

7.2.4 Elbow Motion Reference

As previously discussed, through the simplification of the task only forward reaching motion is required along the direction of motion plane, i.e. only motion along the x_d -axis. This means that it is desired to satisfy the constraint ${}^D\dot{y}_h = 0$. With this constraint in consideration, it is possible to solve for the desired elbow velocity $\dot{q}_e$ from (7.7), such that

$$\dot{q}_e = -\frac{\ell_u C_s + \ell_l C_{se}}{\ell_l C_{se}} \dot{q}_s. \quad (7.8)$$

It is important to note that an elbow singularity occurs when $\bar{q}_s + \bar{q}_e = n\pi$, $n = 0, 2, 4, \dots$ [131]. This happens when the arm is at full extension or folded back into itself. The first configuration can be avoided by limiting the range of motion of the elbow such that $\|q_e\| > \epsilon_q$, where ϵ_q is a positive non-zero constant. The second configuration is not physically possible. This concludes step D.

7.3 Experimental Methodology

An experiment was designed to analyse the performance of the proposed task-space synergy method when used in a basic prosthetic elbow. The resultant behaviour with the proposed task-space synergy-based prosthetic interface was compared with able-bodied behaviour, a traditional sEMG-based prosthetic interface, and a basic joint-space synergy-based prosthetic interface. The experiment was performed in a Head Mounted Display-based (HMD) Virtual Reality Environment (VRE) on able-bodied subjects (Figure 7.2d). The use of a VRE allowed the gathering of data from able-bodied subjects for both able-bodied and prosthetic cases by virtually removing their

lower arm and fitting them with a virtual prosthesis. The case study with an amputee subject used the same VRE-based methodology. A video description of the VR platform used for the experiment can be accessed from <https://youtu.be/vvq4tjShdB4>.

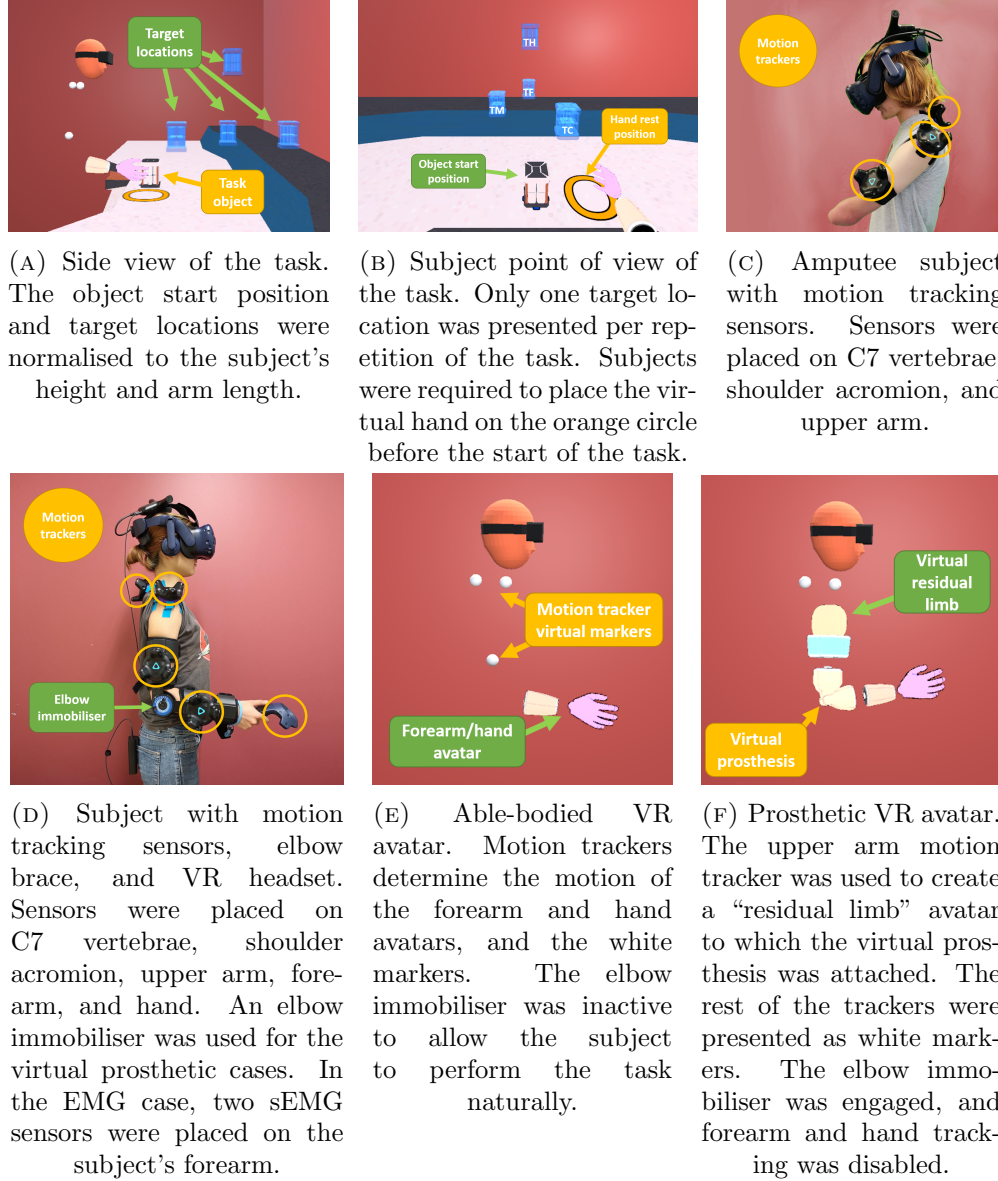


FIGURE 7.2: Experimental platform and task set-up. (a) presents the side view of the task and (b) the subject point of view in VR. (c) and (d) show the motion tracking sensor placement, and (e) and (f) the VR avatars for the able-bodied and prosthetic cases, respectively.

7.3.1 Experiment Task and Set-up

The task required subjects to pick and place an object in 3D space in the forward direction from a standing position without stepping. The execution of the task is considered

as one iteration from the moment the object was grasped until the object was placed. To ensure repeatability of the task, canonical examples containing fixed start and target position were posed. The choice of start (elbow at 90°) and target positions (four different targets) was done to focus the experiment on the reaching phase of motion, which is critical in the use of above-elbow prostheses. One object start position and four target positions were used and were placed at a location relative to each subject's height (h) and arm length (ℓ). The target location details are presented in Table 7.1, these locations are relative to the subject's initial standing position. Figure 7.2a shows the start and target locations in the VRE from a side view, while Figure 7.2b shows them from a subject point of view.

TABLE 7.1: Object start and target positions.

Target	$x(m)$	$y(m)$	$z(m)$	Comment
Start	0.5ℓ	$0.5h$	0	Reachable from a neutral, relaxed position with the upper-arm down and elbow bent 90° .
Close	0.75ℓ	$0.65h$	0.12	Reachable with upper-body motion only.
Mid	1.0ℓ	$0.65h$	-0.12	Reachable with either upper-body motion or arm extension only.
Far	1.5ℓ	$0.65h$	0	Reachable with both upper-body motion and arm extension only.
High	1.0ℓ	$0.9h$	0	Reachable with both upper-body motion and arm extension only.

Four different experiment cases were used, one able-bodied and three transhumeral prosthetic.

- A. **AB** (Able-bodied): This case was used to determine the benchmark motor behaviour and task performance for each subject.
- B. **EP** (sEMG Proportional): A standard dual-site differential surface EMG proportional prosthetic interface was used to command the prosthetic elbow's joint velocity [8]. The rectified and thresholded sEMG signals from two antagonistic

muscles were used to determine the direction and angular velocity of the prosthetic elbow joint. This case was used as the traditional prosthetic interface for comparison.

- C. **TS** (Task-space Synergy): The proposed task-space synergy method as described in equation (7.8).
- D. **JS** (Joint-space Synergy): A Joint-space synergy method (JS) given by a shoulder-elbow flexion synergy was used as the synergistic prosthetic interface case for comparison.

The range of motion of the elbow was limited to $5^\circ \leq q_e \leq 140^\circ$ to avoid singularities. The JS was given by $\dot{q}_e = \theta \dot{q}_s$; where $\dot{q}_e$ is the prosthetic elbow velocity, $\dot{q}_s$ the shoulder extension velocity, and $\theta = 1$ the synergy parameter. This joint-space synergy, based on [58], was chosen because it is the closest to the proposed task-space synergy as it does not require training or calibration to determine the best synergy for the given task and initial arm pose. Instead, the prosthesis user can enable/disable the synergistic operation through the use of a separate HPI, which allows the user to compensate for the inaccuracies in the synergy by choosing when in the reach to enable the synergistic operation.

Subjects were fitted with an elbow orthosis with two motion tracking sensors attached to it, one for the lower-arm and one for the upper-arm. Two additional motion tracking sensors were placed on the C7 vertebrae (trunk motion), the shoulder acromion (shoulder motion), and the hand (see Figure 7.2d). The elbow orthosis allowed to immobilise the subject's elbow in the prosthetic cases to better represent muscle conditions in amputees, as done in [58]. The amputee subject was fitted as able-bodied on his right arm for the AB case, while for the prosthetic cases he had the upper-arm sensor strapped to his left upper arm (see Figure 7.2c).

In the AB case, motion of the upper-body, the whole arm and hand was directly mapped to the VRE through a virtual avatar as shown in Figure 7.2e. For the case study with the subject with limb difference, his able-bodied (right) arm was used for the AB case. In the prosthetic cases, transhumeral amputation was emulated in able-bodied subjects in the VRE by using the data from the upper-arm motion tracker to determine the motion of the virtual residual limb. A virtual prosthetic elbow, forearm, and hand were

attached to the virtual residual limb as seen in Figure 7.2f. For the case study with the subject with limb difference, his arm with limb difference (left) was used for the prosthetic cases. Only the virtual prosthetic elbow was actuated, while the forearm and hand were fixed.

Muscle activation was gathered using sEMG electrodes placed on the forearm as the elbow orthosis interfered with the biceps/triceps electrode placement typically used in transhumeral amputees. While the forearm electrode position does not reflect the physiological placement of sEMG sensors for transhumeral prostheses, it can provide comparable functional capabilities in able-bodied subjects as observed in [58].

The following prosthetic interface simplifications were done to reduce the cognitive load on the subjects and to focus the experiment on the motor behaviour aspect of prosthesis use. Firstly, the functionality of the prosthetic elbow was enabled in a toggle fashion by a press of the centre button (thumb) of the Vive controller (Figure 7.2d), which was held in the able-bodied hand of the amputee subject. This was done to avoid relying on complex sEMG commands, such as co-contractions, which are a major issue with active prostheses to date [6]. For the task-space synergy, this allowed subjects to lock the elbow in position so they could point the hand in the desired direction of motion (targeting phase), and then enable the elbow for the reaching phase of the movement. The wrist joint was not actuated. Secondly, grasping and releasing of the object were done automatically when the hand stopped moving and was touching the object (grasp) or within the target area (release), avoiding the need to use complex sEMG commands to switch between elbow and hand control.

7.3.2 Experimental Protocol

The experiment was performed on 15 able-bodied subjects, six female and nine male. The age range was [22, 34] and the median age 28. The amputee case study was performed on a single male subject aged 23. The subject has a congenital limb difference in his left forearm as seen in Figure 7.2c. He is not a prosthesis user and does not use his left arm in daily tasks relevant to the task tested in this experiment. The experiment was performed in two sessions lasting two hours each, on two different days not more than a week apart. Each session tested two cases. The first case tested for all subjects was AB which was used as the benchmark for individual motor behaviour. The order of

the following cases was randomly selected from the three cases representing prosthetic-use (EP, TS or JS) to minimise the bias introduced by the effects of learning on the data gathered. The session procedure is presented in Table 7.2.

TABLE 7.2: Experiment session protocol.

Step	Time (minutes)	VR/No-VR
Introduction	5	No-VR
Sensor placement	15	No-VR
Case 1	50	VR
Break	5	No-VR
Case 2	50	VR

Each block of case testing consisted of 120 iterations of the task separated into three sets of 40 iterations, the procedure is presented in Table 7.3. During the Training block of the experiment, subjects were instructed outside the VRE on how to use the prosthetic interface and were allowed to familiarise themselves with it. This was done by presenting a third person view of the virtual residual limb and prosthetic device on a screen. The procedure was approved by the University of Melbourne Human Research Ethics Committee, project number 1750711.2. Informed consent was received from all subjects in the study.

TABLE 7.3: Case testing block protocol.

Step	Task iterations per target	Time (minutes)	VR/No-VR
Training	-	5	No-VR
Practice	5	-	VR
Set 1	10	-	VR
Break	-	1	VR
Set 2	10	-	VR
Break	-	1	VR
Set 3	10	-	VR

7.3.3 Data Gathering and Analysis

The data gathered from motion tracking sensors and the VRE was used to analyse the performance of subjects in terms of the task, quality of motion, and the resulting motor behaviour. Given that target locations were personalised to each subject, hand trajectories were normalised to the subject's arm length for all cases and targets. This was done by applying a spatial normalisation to all the trajectories. The resulting normalised

reaching paths had starting position coordinates $(0, 0)$, target position coordinates $(1, 0)$, and the trajectories occurred on a plane. To allow comparisons between trajectories that are temporally different for a given target and modality, trajectories were padded in the time domain with their respective end coordinate to match the temporal length of the trajectory with the longest time duration, i.e., as if subjects held the hand constant in the terminal position. The normalisation procedure follows the methods described in [64]. The metrics used for data analysis are presented next.

Two metrics of task performance were used: completion time and reach terminal error. The median task completion time (t_f^μ) over iterations of the task is used to determine the effects of prosthetic interfaces on the time required to complete the task. As this metric is commonly used in the literature, it is used to compare the performance of the synergistic interfaces in this chapter to other studies in the literature. The mean of the reach terminal error (δ^μ) over iterations of the task is used to verify that the task is being performed adequately. Reach terminal error is calculated as $\delta^\mu = \|\mathbf{p}^i(t_f) - \mathbf{p}_d^i\|_2$, where $\mathbf{p}^i(t_f)$ is the hand position at the end of the reach and $\mathbf{p}_d^i$ is the desired hand position for the given target.

Two metrics of quality of motion were used: path smoothness and variability. Continuous, well coordinated movements are characteristic of trained and healthy motor behaviour. Hand and joint path smoothness are well documented and accepted measures of the quality of upper-limb motion [13, 132, 133]. Here Spectral Arc Length (SAL), represented by (η) , is used as the metric for smoothness [134] due to its characteristics which include sensitivity to changes in motor characteristics, robustness to measurement noise, and dimensionless monotonic response. SAL measures the arc length of the curve generated by the Fourier magnitude spectrum of the velocity trajectory to quantify movement smoothness [134]. Low path variability, both of the hand and joints, is characteristic of trained and healthy motor behaviour [106, 132]. Here the mean standard deviation of the hand and joint paths across the time domain (σ_μ), is used as the metric for path variability. The standard deviation of the paths for each subject, modality and target is calculated at sample across the time domain using the normalised paths, and the mean over time of the standard deviation is used as the metric σ_μ .

Two metrics of motor behaviour were used: hand/joint path difference and upper-body displacement. The first metric of motor behaviour is path difference (Δ_μ). This metric

evaluates the difference between the mean able-bodied hand/joint path and the mean prosthetic hand/joint path. It is used to determine the closeness of the resultant prosthetic motor behaviour to the individual's natural able-bodied motor behaviour. Let the mean hand/joint path for the able-bodied case (AB) be given by $\mathbf{x}_{AB}^\mu(nt_s)$ and the mean path for the prosthetic case (PC) given by $\mathbf{x}_{PC}^\mu(nt_s)$, where t_s is the sampling time and $n \in \mathbb{N}$. The normalised paths are used to calculate the at sample mean paths $\mathbf{x}_{AB}$ and $\mathbf{x}_{PC}$, such that both AB and PC cases have the same normalised start and end positions, and time length. The path difference (Δ_μ) is defined as the sum of the Euclidean distances between the mean paths across the time domain as follows:

$$\Delta_\mu = \sum_{n=0}^N \|\mathbf{x}_{AB}^\mu(nt_s) - \mathbf{x}_{PC}^\mu(nt_s)\|_2. \quad (7.9)$$

The second metric of motor behaviour is upper-body displacement (ϕ^μ). Upper-body displacement is calculated as the Euclidean distance between in initial and final positions of the C7 and shoulder sensors. This metric evaluates the amount of upper-body motion used for the task. When a prosthetic device is not used effectively or is not adequate for the task this metric represents compensation motion. Some level of upper-body motion is also part of natural able-bodied motion during reaching tasks.

Statistical analyses of the of these metrics were performed in Minitab 19. The data for all metrics except smoothness and shoulder displacement was transformed to a logarithmic scale to satisfy the assumptions of the general linear model, in particular, the constant variance for the random error. The data was fitted to a general linear model using both the subjects and modalities as model factors. The general linear model was used to perform two-way analyses of variance and comparison tests between the modalities with a confidence level of 95% ($p < 0.05$) after adjustment for multiple comparisons using Tukey's method. The analyses were used to determine whether statistical significant superiority, inferiority, or non-inferiority of the TS method against EP and JS in terms of the evaluation metrics exists. Statistical analyses were performed in consultation of the University of Melbourne Statistical Consulting Platform.

7.4 Results & Discussion

Results for the experiment with able-bodied subjects and the case study with an amputee subject are presented next. The data-set of the results (raw and processed) can be downloaded from <https://github.com/Rigaro/TaskSpaceSynergyData2020>.

7.4.1 Experiment with Able-bodied Subjects

Regression was performed on the hand path difference (Δ_μ) and completion time (t_f^μ) data for each modality and target to determine their change throughout the experiment. A quadratic polynomial was fitted to the data and the gradients of the fitted polynomial were calculated for the first and last iterations. These gradients were used to infer conclusions on the learning progress of the subjects.

The results for the hand path difference over iterations of the task are presented in Figure 7.3, where the population median of the hand path difference for each iteration of the task is presented for each target. The gradients obtained from the regression analysis for each modality and target are presented in Table 7.4.

TABLE 7.4: Hand path difference (Δ_μ) regression gradients.

		Gradients		
Target	Iteration	EP	TS	JS
Close	1	-1.3492	-1.8790	-0.9932
	30	1.4882	1.3201	0.4334
Mid	1	-0.3061	-0.4777	-1.5685
	30	0.1650	-0.6993	0.8759
Far	1	-0.1152	-2.1066	-0.6782
	30	-0.5669	0.1083	-0.4350
High	1	-0.0686	-1.3322	-2.9105
	30	-0.7398	-0.2177	1.5518

From these results, it can be seen how subjects, over iterations, try to reproduce their able-bodied hand path with the prosthesis. In general, it can be observed that there was a gradual reduction of the difference over the first 10 iterations after which the progress slowed down.

The gradients obtained suggest that there was a negative trend to the hand path difference across modalities and targets at the start of the experiment, which was largely reduced by the end of the experiment. This was particularly evident for the TS and

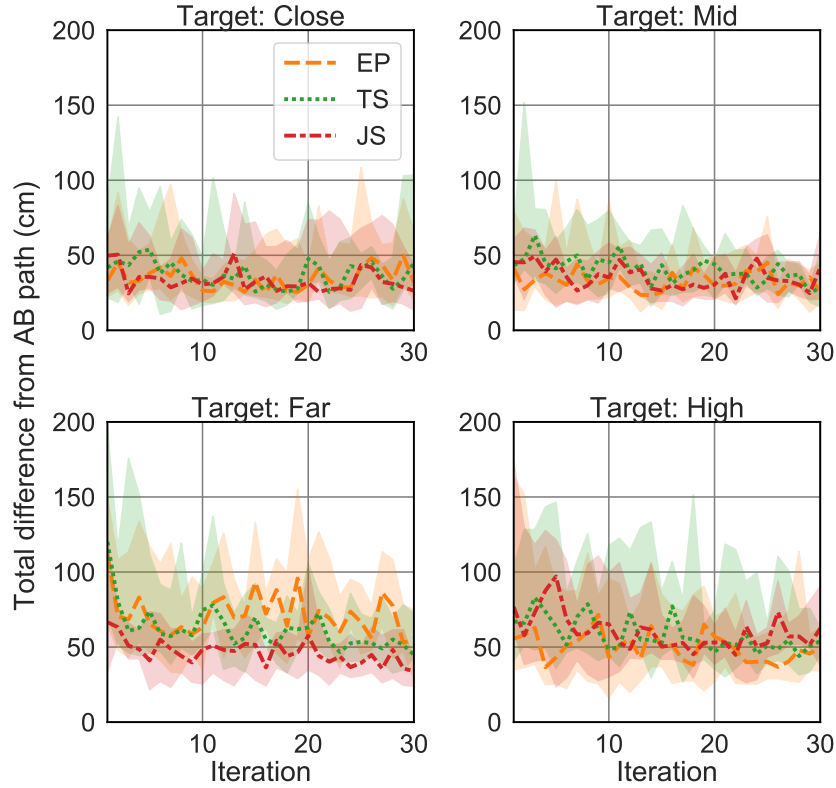


FIGURE 7.3: Population median experimental results for hand path difference from AB (Δ_μ) over iterations of the task for each target.

JS modalities in the Far and High targets. However, the gradients obtained for the EP modality suggest that there was no significant change for this modality throughout the experiment. The reduction in the path difference over iterations suggests that individuals try to reproduce able-bodied motion with the synergistic modalities. Thus, leading to an improvement on their performance. The clear difference from the AB path shows that despite their best effort, the introduction of limb loss and the artificial limb inherently changes the dynamics of reaching. This means that the natural/dynamically optimal motion when using a prosthesis is different from one's AB motion.

Statistically significant superiority of JS over EP was found for the Far target, which requires more joints to be coordinated to be reached (trunk, shoulder and arm), performing 25% better on average. However, the rest of the comparisons showed equivalent performance across the three modalities. These results highlight the advantage of kinematic synergies over traditional sEMG, which only allows for joint-by-joint control of the prosthesis as opposed to coordinated motion.

The improvement in task performance can be observed in the task completion time,

shown in Figure 7.4, which is reduced over iterations of the task. The gradients obtained from the regression analysis for each modality and target are presented in Table 7.5.

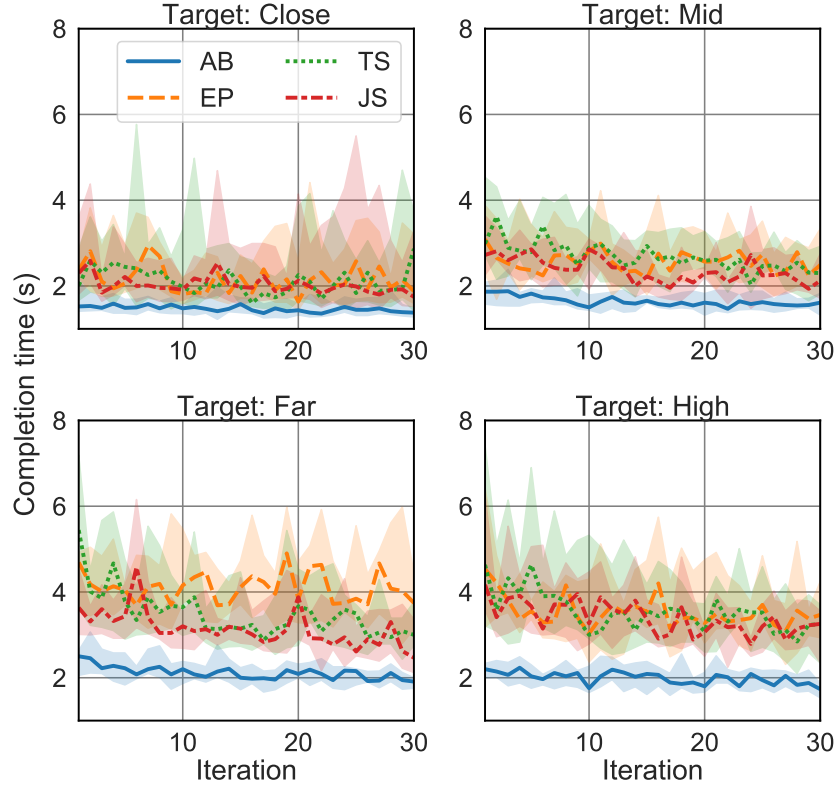


FIGURE 7.4: Population median experimental results for task completion time (t_f^μ) over iterations of the task for each target.

TABLE 7.5: Task completion time (t_f^μ) regression gradients.

		Gradients			
Target	Iteration	AB	EP	TS	JS
Close	1	-0.0071	-0.0419	-0.0699	-0.0073
	30	-0.0025	0.0244	0.0518	-0.0145
Mid	1	-0.0298	-0.0053	-0.0414	-0.0491
	30	0.0117	-0.0039	-0.0145	0.0066
Far	1	-0.0283	0.0023	-0.1265	-0.0377
	30	0.0052	-0.0097	0.0426	-0.0213
High	1	-0.0101	-0.0575	-0.0816	-0.0511
	30	-0.0093	0.0235	0.0157	-0.0038

The gradients obtained show a negative trend across all modalities and targets at the start of the experiment which is reduced by the end. Similarly to Δ_μ , the major differences in gradient at the start and end of the experiment are observed for the Far and High targets and the AB, TS, and JS modalities. The statistical analysis showed that there were significant differences between the synergistic interfaces (TS and JS) and EP. Synergistic interfaces had on average a 20% shorter task completion time than sEMG

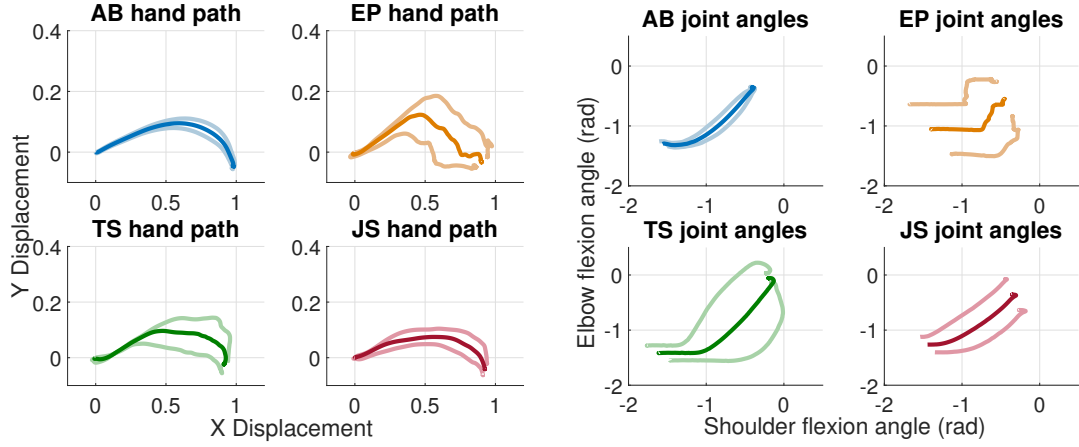
for the Far target, which requires more joints to be coordinated (upper-body and upper-arm). Moreover, no significant advantage between TS and JS was found. This suggests that TS is as effective as JS in reducing the time required to perform reaching tasks. While in [58] it was reported that JS had a significant advantage over EP in terms of completion time, from the results there it was not possible to conclude whether it was because of the motion-based prosthetic joint-switching mechanism proposed therein or the synergy (JS) itself. The results presented herein suggest that the significant difference between EP and JS reported in [58] may be due to the switching mechanism, as a major difference is only observed for the reaching task that requires more joints to be coordinated.

There was no statistical significant difference between the results for the reach terminal error metric (δ^μ) across all targets and modalities, with the subject's hand end position being within 4cm of the desired target position. This verifies that subjects were capable of performing the task adequately and with similar final position error through the experiment.

The results from the regression analyses validate that the effects of human motor learning on the results are less evident during the last set of task iterations. Thus, the rest of the analyses are done on the last 10 iterations of the experiment for each modality and target. Given that the results for the Far target show the most significant difference between modalities, the hand and joint path analysis will focus on that target. The mean and standard deviation hand paths and joint angles of the last 10 iterations (steady-state) of the Far target for a representative subject are presented in Figure 7.5. Figure 7.6 presents the population mean hand path and joint path variation, hand path and joint-space smoothness, and trunk and shoulder displacement results.

7.4.1.1 Reaching Motion Variability and Smoothness

The hand path in Figure 7.5a was normalised between zero and one, representing the start of the movement and the target location, respectively. From the TS results, the initial aiming movement can be identified from the low variability part of the reach, as this is only performed with the residual limb (shoulder) and thus is less variable. This is followed by the straight hand forward movement generated by the synergy, which has higher variability. The aiming phase can also be seen in the joint movement, as shown



(A) Mean and standard deviation hand paths. (B) Mean and standard deviation joint paths.

FIGURE 7.5: Mean and standard deviation hand paths and joint angles of the last 10 iterations (steady-state) of the Far target for a representative subject

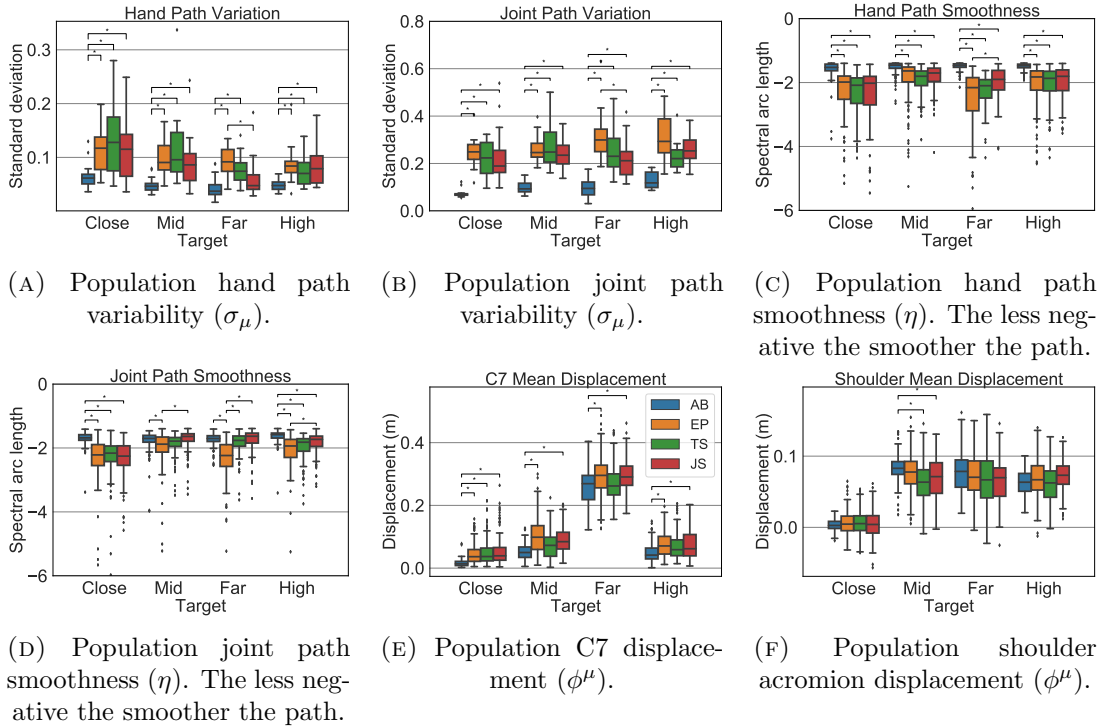


FIGURE 7.6: Population experimental results for the Quality of Motion and Motor Behaviour metrics for the last 10 iterations per target. Statistically significant differences between modalities ($p < 0.05$) are shown by asterisks (*).

in Figure 7.5b, where the mean and standard deviation of shoulder and elbow angles are presented. The TS movement starts with a shoulder-only aiming motion, followed by a smooth curve. This is further corroborated by the variability and smoothness results, presented in Figure 7.6.

JS showed statistically significant lower hand path variability over EP for the Far target

(31%) while being non-inferior to AB. While TS showed a 16% reduction in variability over EP, it was not statistically superior to EP nor inferior to JS. Similarly, JS showed a statistically significant reduction of 31% in joint path variability over EP for the Far target. TS saw an average reduction of 20% over EP, though it was not statistically significant. However, TS was found non-inferior to TS. All other targets showed no statistical difference between the prosthetic modalities for both variability metrics.

In terms of hand path smoothness the JS interface shows a statistically significant improvement of 10% for the Far target with respect to EP. While TS showed no improvement, it was also found non-inferior to JS. This may be attributed to the need with TS to pre-position the hand before executing the movement, which affects the resultant smoothness metric. On the other hand, joint motion for the JS case was found statistically superior than EP by 18%, 24%, and 15% for the Mid, Far, and High targets, respectively; while being non-inferior to AB. On the other hand, the TS case only shows a statistically significant improvement in joint smoothness of 17% for the Far target with respect to EP. However, it was found to be non-inferior to JS for the Mid, Far, and High targets.

The joint path of subjects with the EP interface, in Figure 7.5b, shows a mostly horizontal line representing the initial shoulder only movement, followed by a combined elbow and shoulder movement where subjects use EMG to extend the elbow while using the shoulder to do the fine adjustments of hand position. Lastly, JS shows a mostly smooth curve as it was identified that subjects learned the timing to activate the synergistic movement to minimise the error at the end of the motion. Interestingly, this resulted in more natural and joint paths, further demonstrating the capabilities of human motor learning and adaptation. Overall, it appears that regardless of the type of synergy humans will adapt to the best of their capabilities to use the synergy effectively.

7.4.1.2 Joint Range and Trunk Movement

Another important feature that arises from Figure 7.5b is the range of joint angles used. It can be observed that out of all cases, TS utilises a wider range of arm joint angles suggesting more arm utilisation, inclusive of the aiming phase. This is corroborated with the trunk and shoulder displacement metrics, shown in Figures 7.6e and 7.6f, which show that TS has the lowest trunk and shoulder forward displacements. While neither TS nor

JS were found to be statistically superior to EP in terms of compensation motion, TS was found to be non-inferior to AB for the Mid, Far, and High targets. Nevertheless, trunk displacement for the TS case shows a 60% and 45% reduction over EP and JS, respectively, for the Mid target; while a 60% reduction over EP and JS for the Far target. These results agree with those reported in [11], which present a fully calibrated synergy, where a reduction in trunk compensation motion was reported with a JS method over EP, suggesting that TS may further reduce compensatory movement at the expense of a less natural movement (point and reach). However, this is due to the constraint imposed on the reaching path. If the location of the reaching target is known in the formulation of the task-space synergy, then it may be possible to generate a human-prosthesis motion that closely resembles able-bodied behaviour, while retaining the user's control over the movement. Moreover, as the task-space synergy is based on the arm kinematics, no individual synergy training or personalisation may be required, and could be generalised to any point-to-point reaching task. Therefore, this scenario will be explored in future studies.

7.4.2 Case Study with Amputee Subject

Results for the case study are presented in Figures 7.7, 7.8, 7.9, and 7.10. Given the limited dataset for the case study, statistical significance cannot be obtained for the results. The results for the subject's hand path difference over iterations of the task are presented in Figure 7.7. Linear regression for this subject showed no particular trend in the data for the first and last 10 iterations. Moreover, the subject did not show a significant change in reaching strategy over iterations of the task, regardless of the interface modality. This may be due to reaching motion being new to the subject as he had never done this type of coordinated motion with his left arm.

The results for task completion time over iterations of the task are presented in Figure 7.8. Similarly to hand path difference, there is no apparent improvement in time over iterations of the task. Linear regression analysis of the completion time results for each task block did not reveal any significant trends. This may be a result of the short time allowed for the experiment and the novelty of the experience for the subject. As he had never used a prosthetic device nor performed the type of tasks in the experiment

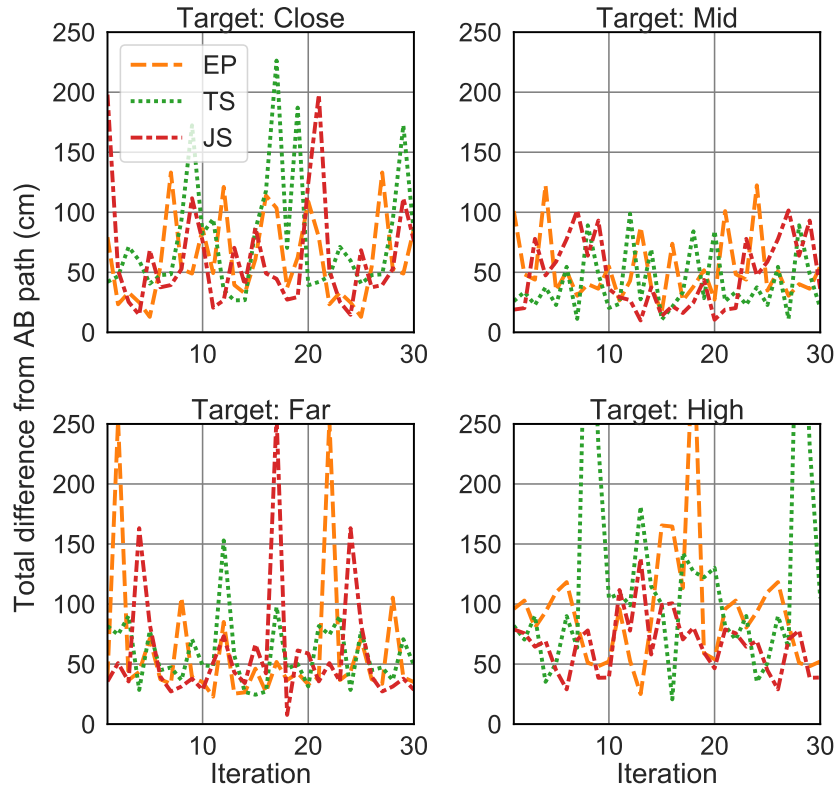


FIGURE 7.7: Case study experimental results for hand path difference from AB (Δ_μ) over iterations of the task for each target.

with his left arm, the duration of the experiment may not be sufficient to see significant improvement in his performance.

Similarly to the experimental results, the results for hand and joint paths are presented only for the Far target. Hand path results are presented in 7.9a while joint path results are presented in 7.9b. For this subject, the TS case is the one that observes the lowest hand path variability (Figure 7.9a), which is supported by the results in Figure 7.10a, except for the High target. However, in terms of the closeness to the AB hand path, all three prosthetic cases perform similarly. On the other hand, the experimental results suggested that the JS modality achieved the lowest variability.

Regarding the joint path, the case study results in Figure 7.9b are closer to the experimental results in Figure 7.5b in terms of their shape. While the amputee subject showed smaller joint-range utilisation, similar features highlighting the interface use strategy arise. For instance, the EP strategy shows the same straight line shapes characteristic of sequential motion, while both TS and JS show curves. In the TS case, it can be seen that the amputee subject also followed the aim-and-extend strategy as seen by the

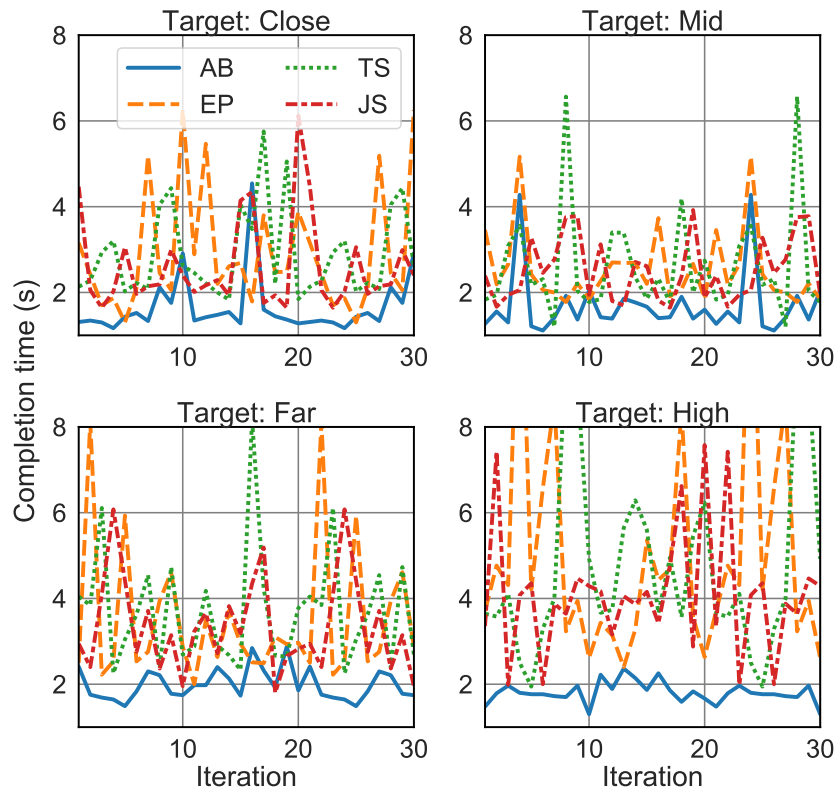
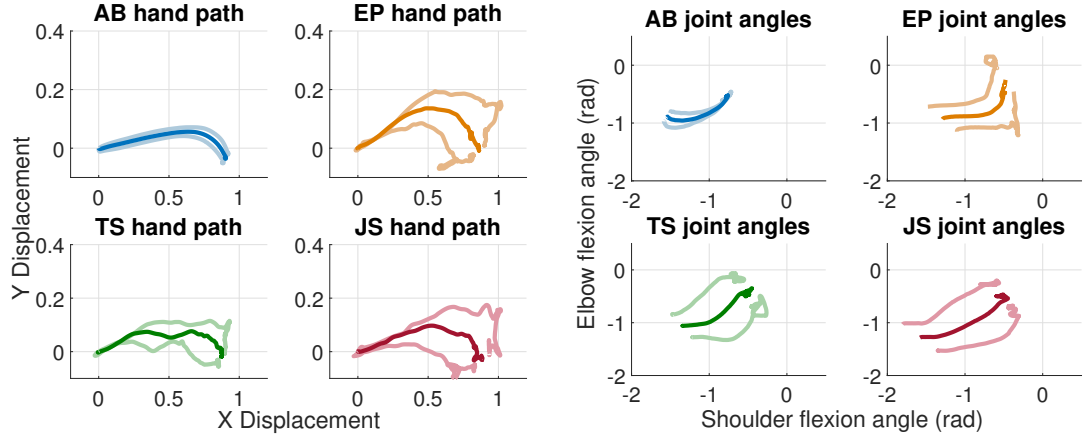


FIGURE 7.8: Case study experimental results for task completion time (t_f^μ) over iterations of the task for each target.

horizontal line segment with lower variability. In general, both TS and JS outperform EP in terms of joint path variability as shown in Figure 7.10b.

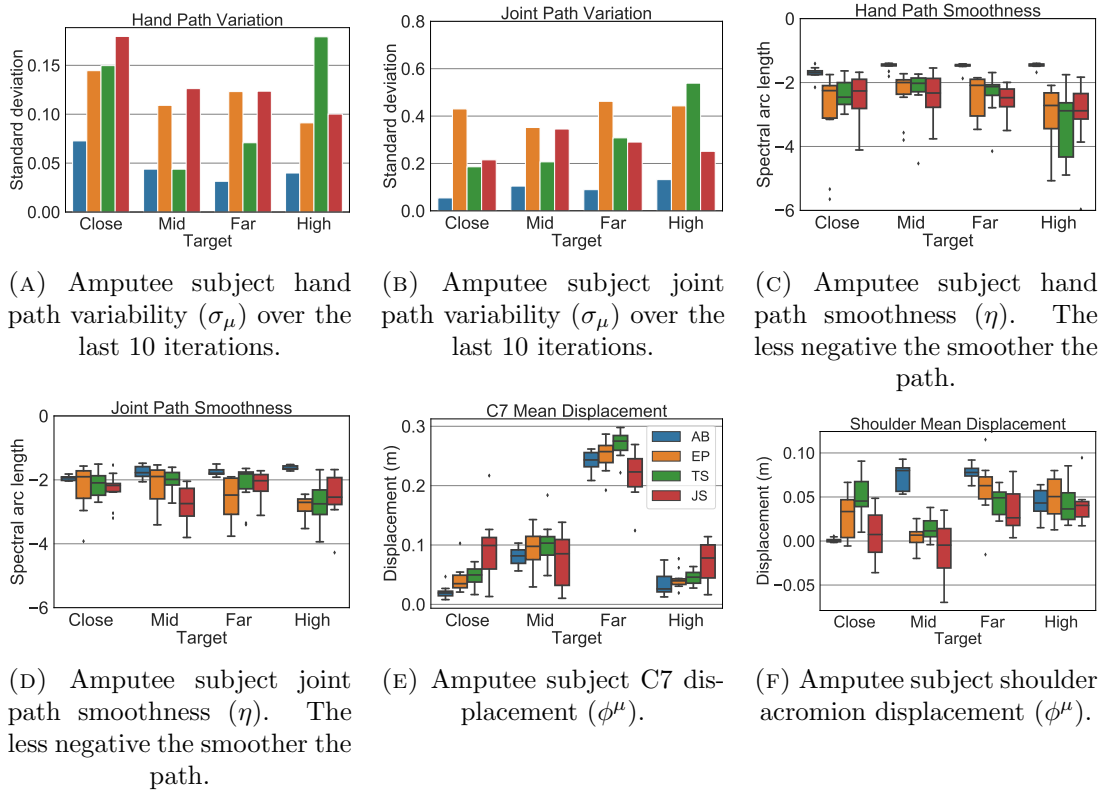
Lastly, results for hand and joint path smoothness (Figures 7.10c and 7.10d), and trunk and shoulder displacement (Figures 7.10e and 7.10f) show no significant difference between the three prosthetic cases.

These results highlight human-to-human variation, where preference to different interface modalities may arise. Moreover, the type of amputation, or in this case limb difference, may affect the subject's preference towards an interface modality. Anecdotally, the subject stated a preference towards the TS modality as he found it easier to use because of the point-and-extend strategy. This motivates further studies with subjects with different amputations and limb differences that focus on the human aspect of the human-prosthetic interface.



(A) Mean and standard deviation hand paths. (B) Mean and standard deviation joint paths.

FIGURE 7.9: Mean and standard deviation hand paths and joint angles of the last 10 iterations (steady-state) of the Far target for the amputee subject



(A) Amputee subject hand path variability (σ_μ) over the last 10 iterations. (B) Amputee subject joint path variability (σ_μ) over the last 10 iterations. (C) Amputee subject hand path smoothness (η). The less negative the smoother the path. (D) Amputee subject joint path smoothness (η). The less negative the smoother the path. (E) Amputee subject C7 displacement (ϕ^μ). (F) Amputee subject shoulder acromion displacement (ϕ^μ).

FIGURE 7.10: Case study experimental results for the Quality of Motion and Motor Behaviour metrics for the last 10 iterations per target.

7.5 Conclusion

In this chapter, a realisation of a task-space synergy for motion-based human-prosthetic interfaces was presented which allows the prosthesis to be controlled in task-space

through the anticipated path of the prosthetic hand. Such type of synergistic interface has the potential to be generalisable to any reaching task, is personalised through the use of a kinematic model of the user's arm, and may prove useful in complex tasks that require the coordination of multiple degrees of freedom. An experimental study with able-bodied subjects and a case study with an amputee subject showed that the proposed task-space synergy achieves comparable performance to joint-space synergistic interfaces in terms of the closeness to able-bodied motor behaviour and task performance. These results show that the proposed task-space synergy method provides the advantage of personalisation by the synergy being calibrated to its user through a set of constant parameters, instead of relying on time-consuming calibration processes or leaving it to the human to learn. However, the method relies on the availability of task-space information which, in the case of the study presented herein, was provided by the user through an additional step (targeting phase) in the reaching motion. Nevertheless, both joint-space and task-space methods are limited in the sense that task-space information is eventually going to be required in a real-life scenario.

Joint-space HPIs encode the task-space information of the task they were trained with, thus, in order to be able to produce motion for different tasks, it will be necessary to predict or determine what is the desired task to be executed. Therefore, additional information related to the task will be required. On the other hand, the task-space synergy approach explicitly encodes task information in its formulation, and so the design of a task-space synergy-based HPI will require the incorporation of task information through the desired hand path. This motivates further studies of these two types of synergies where the task information is no longer assumed but obtained through sensors. This will allow the study of the limitations and practicality of these methods, which will inform what method is most appropriate outside of a laboratory environment.

Chapter 8

Conclusions and Future Work

This chapter concludes the thesis. First, a summary of the research aims and contributions in this thesis are presented. Second, a discussion on potential avenues for future development are presented.

8.1 Summary

The goal of this thesis was to develop a method for personalising human-prosthetic interfaces in a minimally invasive and autonomous manner. The review of the literature in upper-limb prosthetic interfaces highlighted the advantages of using kinematic synergies to compliment other modalities of prosthetic interfaces. However, it was found that current methods did not consider personalisation of kinematic synergies and had issues generalising to individuals outside of the synergy training datasets. Moreover, kinematic synergies were found to be task-dependent, so they had to be trained for specific tasks. With this in consideration, the following research aims were identified:

- A. To determine the feasibility of using online optimisation methods in the personalisation of human-prosthetic interfaces.
- B. To determine the characteristics of human motor behaviour related to motor preference and learning in the use of upper-limb prosthetics.
- C. To develop a minimally invasive and autonomous method for the personalisation of human-prosthetic interfaces.

- D. To investigate methods to incorporate task information in kinematic synergies for human-prosthetic interfaces.

The contributions of this thesis pertaining these research aims are as follow. First, the feasibility of using an online optimisation method, Extremum Seeking, for the personalisation of human-prosthetic interfaces was performed experimentally in a virtual reality environment. The method utilises a measure of performance that is iteratively optimised as the prosthesis user performs a task. The feasibility study was performed under strong assumptions on human motor adaptation, requiring subject to undergo significant previous training with a virtual elbow prosthesis. The results from the study showed promise in the method as it allowed the personalisation algorithm to operate while subjects repeated a task. However, further studies showed how human motor adaptation affects the method. Due to the effects of human motor adaptation, the method required to be tuned for each individual and for the user to reach a steady-state in motor behaviour, which may take a long time. This motivated the study of human motor behaviour in the use of upper-limb prostheses and the development of a personalisation algorithm.

Second, an experimental study on the motor behaviour of individuals using a kinematic synergy-based prosthetic elbow revealed two major characteristics that affect their performance of a task: motor preference and motor adaptation. Motor preference relates to the relationship between a synergy value and a measure of task performance. It was found that within a synergy region of interest, there exists a synergy value that maximises the measure of performance. Moreover, that this synergy value differs across individuals. Motor adaptation relates to a transient increase in the measure of performance over multiple iterations of the task until reaching a steady-state. The rate at which the increase occurs, and the steady-state values were found to be individual dependent. The steady-state value is also dependent to the synergy value as determined by motor preference. The results of this study were used to develop a grey-box model of human motor behaviour in the context of upper-limb prostheses that characterises the common features of motor preference and adaptation in its structure, while capturing individual behaviour in the model parameters. This knowledge of human motor behaviour and developed model informed the development of an online personalisation algorithm for human-prosthetic interfaces.

Third, an online personalisation algorithm for human-prosthetic interfaces was developed based on the algorithm of Fast Extremum Seeking. The algorithm uses the grey-box model of human motor preference and adaptation discussed in the previous contribution to inform the design of the components of the algorithm. Similarly to the previously discussed algorithm, a measure of task performance is required. The personalisation algorithm was demonstrated in human experimental studies in both a virtual environment and a prosthetic prototype. The personalisation algorithm has the advantages that it can operate concurrently to the prosthesis user learning to use the prosthetic device and does not require to be tuned for each individual. These advantages allow for the personalisation process to occur during a traditional prosthesis training session in the clinic with minimal input from the clinician in the personalisation process. Further studies revealed compensation motion to be a promising candidate for a practical measure of task performance as it is observed among upper-limb prosthesis users while performing reaching tasks and can be measured with wearable inertial measurement units.

Finally, a novel “task-space synergy” was proposed to incorporate task information in the formulation of kinematic synergy-based human-prosthetic interfaces. The method uses desired hand path information, a kinematic model of the human-prosthesis arm, and the motion of the residual-limb to determine the motion of the prosthesis joints. The proposed task-space synergy was demonstrated in a simplified case where the task information is incorporated by introducing a constraint in the movement of the hand. This constraint means that when the task-space synergy-based HPI is activated the hand slides on a forward path where the progression along the path is controlled by the movement of the user’s residual-limb. Experimental results showed that the task-space synergy method performed equivalently to other kinematic synergy-based methods without the need for synergy training or personalisation.

8.2 Future Work

As a result of the novel methods presented in this thesis for the online personalisation of human-prosthetic interfaces a number of potential avenues for further development exist. These potential avenues for development are presented next according to the relevant method.

8.2.1 Online Personalisation

Further development of the online personalisation algorithm for human-prosthetic interfaces can be done in the following areas: generalisation, robustness, and practicality.

8.2.1.1 Generalisation

In terms of generalisation, studies could be performed on human behaviour with other modes of interfaces outside of the prosthetic application. Particularly, it would be of interest to determine whether human behaviour while using general forms of human-machine interfaces follow the characteristics of the grey-box model of human motor preference and adaptation. In the case that the same characteristics are identified, then it may be possible to implement the algorithm to other forms of human-machine interfaces. Such studies would also allow to determine whether further developments of the algorithm are necessary for more general applications.

The major challenges with generalisation will lie on the definition of the objective function and ensuring that this objective function is shared by the human and the machine. Defining an objective function for general human-machine interface applications may be unfeasible as there may not exist a shared objective function between the tasks that is of relevance to personalisation. This could be a shortcoming of the personalisation method, which may require task-specific definitions of the objective function. Similarly, methods for ensuring both the human and machine have the same objective function could be highly specific to the application. There could be instances where constant display of performance information to the human is admissible, such as in manufacturing.

8.2.1.2 Robustness

With respect to robustness, non-linearities were identified in human motor behaviour, particularly with motor adaptation. Two main features were observed: a forgetting factor and strategy changes. The forgetting factor is observed as a decrement in the measure of performance after a period of the prosthetic device not being used. While this can be mitigated by performing the personalisation procedure in a single session, it may be of interest to study the long-term changes in human motor behaviour after prolonged

prosthesis use. In such cases, it may be required to perform the personalisation procedure multiple times or over longer time-frames. Thus, it may be necessary to determine how such non-linear behaviour can be handled in the personalisation algorithm. In terms of the strategy changes, these are observed as sudden changes in the measure of performance within a personalisation session which occur from a change in human motor strategy. Such sudden changes can affect the estimation of the gradient used in the personalisation process. Theoretically, this makes the synergy-performance map piece-wise continuous which violates some of the assumptions required by the algorithm that could result in infinite gradients. In practice, these gradients are limited by the numerical computations and can be saturated; however, these still affect the performance of the algorithm. A possible improvement for the algorithm could be to include in the framework the handling of such non-linear behaviour.

8.2.1.3 Practicality

With respect to the practical application of the algorithm, it was shown that compensation motion was a promising candidate for the measure of task performance as it is prevalent in prosthesis users and it is measurable with wearable sensors. These studies were performed in a controlled environment where the task was controlled by a touch-screen. While such scenarios may be viable in a clinical training setting, they are too constrained for day-to-day settings. Further developments should centre around the use of the personalisation algorithms in unconstrained environments with more varied objectives. These developments are important as they will pave the way to clinical studies.

Multiple aspects will affect the performance of the personalisation algorithm in practical settings outside of virtual reality. For instance, the physical connection between the human and the prosthesis is typically done with a socket which is not rigidly attached to the human. This means that errors will be likely introduced to the estimations which cannot be accounted for. Similarly, humeral rotation is rarely included in above elbow prostheses which will limit the controllable degrees of freedom in the algorithm. This could be addressed by adding complexity to the prostheses; however, this may not address the more significant issues prosthesis users face with their devices [6]. Another

factor that will need to be considered is the long term learning of the human. The personalisation algorithm presented in this thesis addresses the short-term motor learning of prosthesis use. However, long term changes in human motor behaviour, e.g., optimising the metabolic cost of using the prosthesis, are expected to occur as amputees get more acquainted with their prosthesis. These long term changes need to first be understood so it is possible to propose an extension to the algorithm that may be able to handle these changes that occur at a long term time-scale.

The integration of the personalisation method to a clinical setting must consider two aspects: the hardware where it is going to be implemented, and the procedure to follow for the personalisation. In terms of the hardware, the personalisation procedure can be executed on a trial prosthesis or the final prosthesis of the user. Either way, the integration of motion sensors to the prosthesis would be required as none of the current prosthesis include these. To achieve this it would be possible to create an independent hardware module which adds synergistic functionality to the prosthesis which consists of a series of IMUs (an integrated one and additional external sensors for personalisation), a processor, and an interface to the prosthesis. In terms of the procedure, given the current state of the personalisation algorithm, the personalisation procedure would need to be done in the clinic as part of the prosthesis set-up. The prosthesis user would then need to attend the clinic for further tuning, as it is done with current prostheses. However, this can be alleviated by considering long-term human motor learning as discussed before. Moreover, the procedure could be performed with any objects by following the method in Chapter 6, only with the modification that the start and end of the task are indicated by the closing and opening of the terminal device, respectively.

8.2.2 Task-space Synergy

The proposed task-space synergy method was presented in a simplified setting as a proof-of-concept. Further developments could focus on generalising the method to hand motion and orientation in 3D space. Such developments should allow for the method to be used with arbitrary hand motion and poses within the workspace while retaining user control through motion coupling. With such capabilities in mind, one of the major challenges with the practicality of the task-space synergy method in prosthetics is the availability of the desired hand path. This includes determining the desired task, e.g. what object to

reach, the optimal hand path to perform the task, and the parameterisation of the path in terms of the residual-limb motion. Future work could initially use virtual environments where task information can easily be obtained to demonstrate the capabilities of the method followed by hardware solutions to obtain task information in a practical setting.

Appendix A

Ethics Documentation

A.1 Ethics Application Form



How To Use This Form

- 1. Consider and refer to relevant guidelines and regulations.**
References to specific guidelines are provided, with hyperlinks, throughout this form. The primary guide for human research ethics in Australia is the [National Statement on Ethical Conduct in Human Research \(2007\) - Updated May 2015](#). Human research ethics applications at the University of Melbourne are reviewed and approved under the warrant of the *National Statement*. References to the *National Statement* are abbreviated (e.g. [NS §2.1](#).)
- 2. Use plain English.**
Use clear, non-technical language in your application. Be concise. Spell out the first instances of acronyms and abbreviations. Avoid jargon. Do not repeat information. Following these directions ensures effective review of your application. It will avoid unnecessary delays which result if applications are not clear and concise.
- 3. Consider ethical principles.**
Your application will be reviewed according to the principles of ethical research outlined in the *National Statement*, namely:
 - **Research Merit and Integrity** ([NS §1.1 - §1.3](#))
 - **Justice** ([NS §1.4 - §1.5](#))
 - **Beneficence** ([NS §1.6 - §1.9](#))
 - **Respect** ([NS §1.10 - §1.13](#))
- 4. Use the current version of the application form.**
Ensure that you are using the current version by downloading [this form](#) each time you prepare a new application.
- 5. Detailed instructions for specific questions are available online.**
If you are unsure about how best to answer a particular question, consult the Human Research Ethics [Guidance Document](#). That document provides detailed guidance on how to answer specific questions in this form.
- 6. Where possible, avoid printing this form.**
Consult your HEAG to find out if they still require hard copies of your application. If you must print this form, consider printing double-sided and in grayscale (black and white).
- 7. Save your completed application as a PDF and upload it to Themis.**
Refer to your local Human Ethics Advisory Group ([HEAG](#)) for detailed instructions on how and when to submit your application.

ANSWER ALL OF THE QUESTIONS IN THIS FORM

Ethics ID number: (assigned by Themis)	1750711.1	
Project Title: (as recorded in Themis)	Online Synergy Identification for Personalized Neuroprostheses	
Responsible Researcher: (as recorded in Themis)	A/Prof. Denny Oetomo	
Application Type: (mark with an "X")	☒	Minimal Risk
	☐	Standard Project

1. Project Details

1.1 Project Summary

Summarise your research project in plain language.

[Limit: 300 words]

A) Aims and Objectives

The aim of this research is to investigate the properties of upper arm prosthetic synergies (a synergy is defined as the motion relationship between the joints of a limb), their relationship to measures of motor task performance, and their identification through continuous prosthesis use. Furthermore, to study the behaviour introduced by human learning and the effects this has on the identification of synergies through prosthesis use.

Definition: Synergy. A synergy is defined as the motion relationship between the joints of a limb.

B) Key Question(s)

- Does the relationship between upper arm synergies and standard measures of motor task performance have a single optimal value that varies across individuals?
- What are the effects of human learning on the synergy identification algorithms?
- What synergy model is best suited to describe a set of reaching motions related to activities of daily life?
- How do measures of performance affect the motor behaviour of individuals?

C) Research Design

Hardware Setup

- The experiments will be performed either in a virtual reality (VR) environment which will be displayed to the subjects on an Oculus Rift or HTC VIVE headset, or with a non-invasive wearable robotic elbow with low power output and back-drivability (i.e. subjects can physically move the arm even at the maximum motor torque).
- In order to measure upper arm motion and behaviour, motion sensors (such as VIVE Trackers) will be fastened to the subject's dominant upper arm using an immobilizing elbow brace with adjustable straps
- A small weight will be securely fastened to the elbow brace to simulate weight differences between a prosthetic and the subject's limb.
- In order to measure upper arm muscle activation, surface electromyography (sEMG) sensors (such as Myoware or Ottobock sensors) will be placed on the subject's skin on top of the relevant muscles with off-the-shelf sEMG pads.
- In the case of amputee participants, a personalized socket will be developed with the help of a prosthetist with all sensors and attachment points safely integrated.

Test Subjects

- The experiments will be performed on 10-15 able-bodied subjects and 1-2 above elbow amputee subjects.
- Able-bodied subjects are to use their dominant arm for experiment.

This is common practice in the field as it is possible to simulate prosthesis use on able-bodied subjects through the use of VR.

Protocol

An experiment session will last one hour. The subject is to learn the usage of a simulated synergistic prosthetic device by repeating a reaching task. Learning of the task is measured by the variability of the trajectory followed by the hand, with the condition of success for learning the task being reaching a variability under a predefined constant value. The forward reaching movement is to be repeated a minimum of 10 times and maximum of 50 times, with successful learning determined as stated previously. Each reaching motion has a time limit of 3 seconds.

Each session will be separated in 5 blocks:

1. Hardware calibration (5 minutes):

• Calibrate system to individual and sensor placement.
2. VR/device training (2 minutes):
• VR version: simple VR game consisting of grasping and interacting with objects in space. • Hardware version: simple reaching exercises with robotic elbow to familiarize with device. • Allow subjects to familiarize with VR environment or hardware device, and interface.
3. Experiment task block 1 (25 minutes):
• Perform task for 5 different synergy parameters. • Rest: 1 minute in between synergies.
4. Rest (5 minutes, VR version without headset).
5. Experiment task block 2 (25 minutes):
• Perform task for 5 different synergy parameters. • Rest: 1 minute in between synergies.

Specific Guidelines Checklist		
Type an "X" in the left-hand column beside all items that apply to your research project. Linked sections of the National Statement contain relevant guidelines and requirements that you need to address when completing your application.		
	Children and/or young people (< 18 years old) will be recruited as participants.	→ Refer to NS §4.2.
	People in dependent or unequal relationships will be recruited as participants. (There are pre-existing relationships between participants and researchers, or between participants and others involved in facilitating or implementing the research. E.g. student/teacher, patient/doctor, employee/employer.)	→ Refer to NS §4.3.
	People in countries other than Australia will be recruited as participants.	→ Refer to NS §4.8.
	One or more of the following describes the research project: • it will be about Aboriginal and/or Torres Strait Islander individuals or peoples, their health, or their culture(s), language(s) or histories; • it will be about the impact(s) or effect(s) of some phenomenon or phenomena on Aboriginal and/or Torres Strait Islander individuals or peoples; • it will <i>specifically target</i> Aboriginal and/or Torres Strait Islander people to be recruited as participants; • it will be conducted in a geographic location where a significant number of the population are likely to be Aboriginal and/or Torres Strait Islander.	→ Refer to NS §4.7. → Refer to Values and Ethics. → Refer to GERAIS. → This application is ineligible for minimal risk review.
	One or both of the following describes the research project: • it will <i>specifically target</i> women who are pregnant to be recruited as participants; • it will be focused on women who are pregnant and/or the human foetus (including human foetal tissue or human embryos).	→ Refer to NS §4.1. → This application is ineligible for minimal risk review.
	People who may be involved in illegal activities will be recruited as participants, <i>and the research project could potentially expose such activities.</i>	→ Refer to NS §4.6. → This application is <i>likely</i> ineligible for minimal risk review.
	People with cognitive impairment, intellectual disability, or mental illness will be recruited as participants.	→ Refer to NS §4.5. → This application is ineligible for minimal risk review.
	People who are highly dependent on medical care will be recruited as participants.	→ Refer to NS §4.4. → This application is ineligible for minimal risk review.

X	None of the above applies to this research project.	
Additional Modules Checklist		
Type an "X" in the left-hand column beside all items that apply to your research project. This checklist will help you determine if you need to complete any other modules in addition to this application form. Linked sections of the <i>National Statement</i> contain relevant guidelines and requirements that you need to address when completing this form and any applicable additional modules.		
	This research project will involve the creation of a databank (i.e. your stored data will be made available to other parties for secondary use in future research projects).	→ Refer to NS §3.2. → Complete and attach the Privacy and Databanks Module.
	This research project will involve the collection of information for a databank (i.e. your stored data will be made available to other parties for secondary use in future research projects).	→ Refer to NS §3.2. → Complete and attach the Privacy and Databanks Module.
	This research project will involve accessing information from an existing databank (i.e. you will be accessing and making use of stored data that was previously collected – not for this specific project – by other parties).	→ Refer to NS §3.2. → Complete and attach the Privacy and Databanks Module.
	This research project will involve obtaining identifiable (or potentially identifiable) personal information (including health information) about individuals without their consent .	→ Complete and attach the Privacy and Databanks Module.
	This research project will involve the collection and/or use of human tissue/biological samples or materials (e.g. blood, saliva, cheek swabs, hair, human embryonic or foetal tissue).	→ Refer to NS §3.4. → Complete and attach the Body Tissue and Genetic Research Module.
	This research project will involve human genetics .	→ Refer to NS §3.5. → This application is ineligible for minimal risk review. → Complete and attach the Body Tissue and Genetic Research Module.
	This research project will involve medical interventions, therapies or trials .	→ Refer to NS §3.3. → This application is ineligible for minimal risk review. → Complete and attach the Interventions, Therapies and Trials Module.
	This research project will involve administration of ionising radiation .	→ Complete and attach the Ionising Radiation Module.
X	None of the above applies to this research project.	

2. Background and Method

2.1 Background and Significance	Provide a summary of background information. Explain the significance of the proposed research in the context of this background. Refer to NS §5.2.5. [Limit: 500 words]
Definition: Synergy. A synergy is defined as the motion relationship between the joints of a limb. A) Background: The number of degrees of freedom in current prosthetic devices is greater than the number of available electromyographic signals from the residual limb. This potentially causes complex and unintuitive interfaces, which in turn have been cited as a leading cause of prosthetic device abandonment. Synergistic prosthesis interfaces allow for an intuitive way to provide additional information to command the motion of the prosthesis by	

coordinating the motion relationship between the prosthesis and the residual limb. There is a challenge in identifying effective synergies, especially as the motion of an amputee generally differs from the typical able-bodied subjects, from person to person, and along the time of prosthesis usage.

B) Significance of This Research:

The main assumption considered in the literature is that the best synergy parameter values for an amputee are equal or close enough to the averaged able-bodied synergy parameter values. However, results have shown that this is not the case as prosthesis motion estimation error w.r.t. actual desired motion can be significantly large. This results from the changed limb dynamics due to amputation, the prosthesis' physical properties and dynamics; and the limitations to motion arising from these. Furthermore, complementing synergies with other human interfaces was reported to worsen estimation error as these signals are also significantly different in able-bodied people and amputees. Thus it is hypothesized that optimal synergy parameters vary among individuals (human-to-human variation), and along the time of use of the prosthetic device (learning). In order for amputees to be able to use these prosthesis control methods adequately, personalization and adaptation is required of the interfaces. Therefore, we are investigating the development of automatic personalization through the data gathered by the usage of prosthesis in daily life.

2.2 Research Design and Method	Provide details of your research design and your proposed method. Refer to NS §5.2.5 - §5.2.6. Attach a copy of any measures, scales, questionnaires, survey instruments (including online surveys), interview questions/themes, and/or focus group topics/questions to be used.
A) Participants (or Recruitment Targets, such as medical records): The intended recruitment target is: • Group 1: 10-15 able-bodied people. Group 2: 1-2 above elbow amputees. • The desired age range for both groups is 18-65. This is common practice in the field as it is possible to simulate prosthesis use on able-bodied subjects through the use of VR, with amputee subjects assisting on corroborating findings. B) Recruitment: Recruitment of able-bodied volunteers will take place through digital media such as email, the university portal, and social networks by the student researcher. Recruitment of above elbow amputees will take place through the project's clinical advisor who is a prosthetist at the Alfred Hospital. Recruitment will be targeted to amputees whose level of amputation does not conflict with the range of motion necessary for the experiment or causes them discomfort. No dependents of the researchers will participate in the experiment. C) Participant Incentives: N/A. D) Participant Task(s): Participants will be required to perform a series of reaching and/or grasping tasks in either a Virtual Reality Environment (VRE) or with a wearable non-invasive robotic elbow in order to simulate the usage of upper limb prosthetic devices. The VRE will be displayed by an Oculus Rift or HTC VIVE headset. In order to measure upper arm movement, motion trackers will be fastened to the dominant upper arm with an elbow immobilizing brace with adjustable straps. To measure muscle activation, off-the-shelf sEMG sensors will be placed on the subject's skin on top of the relevant muscles. The total length of the experiment will not exceed one hour per session, with experiments typically requiring one or two sessions. The tasks performed during experiments requires to be repeated between 100 to 200 times, with each task taking less than 5 seconds. E) Data/Material Collection Technique(s): All data will be gathered through the developed VR application. • Subject's upper arm rotation and angular velocity for three degrees of freedom: flexion/extension, abduction/adduction, and humeral rotation.	

- Simulated prosthesis rotation and angular velocity for one degree of freedom: elbow flexion/extension.
- Simulated prosthesis controller reference and control input.
- Simulated hand position and velocity in 3D space.

All hardware data will be gathered a developed Arduino/Windows application with integration with the VR system.

- Subject's sEMG measurements for the duration of the experiment at the relevant muscles, e.g. biceps and triceps.

F) Data Analysis:

Trajectory variability

The trajectory is sampled and evaluated at fixed time steps. Trajectory mean and standard deviation is calculated for a sliding window of 10 task repetitions at each sampling time step. This can be used to generate a spheroid at each time step which centred at the mean position with radius given by the standard deviation at that time step. The set of spheroids represents the mean trajectory and standard deviation. The success condition is achieved when the radius of all spheroids is smaller or equal to a predefined constant value.

Performance/Synergy map

With the recorded performance data for each synergy value, a map of their relationship will be generated in order to observe its convexity and optimal.

Upper body and arm behaviour

Upper body and arm motion and sEMG measurements to be analysed to determine the compensation motion and metabolic effort of performing task. This is in order to compare the difference in motor behaviour with different prosthesis interface modalities.

3. Risks, Benefits and Monitoring

3.1 Potential Risks to Participants	Does your research project pose any potential risks to participants? What are those risks? How will they be negated, minimised or managed? Refer to NS §2.1. Note that the risks you identify here should also be described in your Plain Language Statement (PLS). Attach a copy of any distress protocol or adverse event protocol (if applicable).
A) Potential Risks The following risks have been identified: • Tiredness of the arm and/or shoulder from continuous movement. • Motion sickness from continuous use of VR hardware. • Tripping hazard from cables connected to the hardware device. • Strangling with cables connected to the hardware device. B) Risk Management Strategy The following strategies will be followed to minimize the identified risks: • Participants will be given 1 minute breaks in between repetition sets in order to reduce arm tiredness. • VR application will be designed following standard practices to reduce motion sickness, only the motion of the participant will reflect motion in the VR environment, and participants will be given a 5-10 minute break for every 30 minutes of VR use in order to minimize VR tiredness or discomfort. • A new wireless VR platform was acquired to remove cables to the VR headsets and sensors, completely removing cable related hazards from the VR experiments.	

• Adequate cable management of the hardware set-up will be performed to minimize the tripping hazards in the experiment area. The experimenter will continuously monitor and handle the cables connected to the device to ensure safe operation by participants, and will alert participants or stop the experiment if any hazard that can injure participants is detected. • Participants will be allowed to rest or stop the experiment at any time if needed due to discomfort introduced by the VR hardware. • A two-way dead-man switch will be implemented for the hardware device. Both experimenter and subject must continuously engage individual switches to enable the hardware device.

3.2 Potential Risks to Non-Participants	Does your research project pose any potential risks to non-participants? (This could possibly include risks to researchers or independent contractors.) If so, how will these risks be minimised? Refer to NS §2.1.
N/A	

3.3 Risks, Benefits and Justification	In light of the risks and expected benefits of the research project, explain how the expected benefits of the research justify any risks it may pose. Refer to NS §1.6 - §1.7 and NS §2.1.
A) Expected Benefits These experiments will allow to: • Improve our understanding of the optimization processes that take place in the central nervous system and are involved in upper limb human motor control and their involvement in developing synergies. • Develop novel learning algorithms that allow the personalization of upper limb prosthetic devices to their users. • Improve the functionality of upper limb prosthetic devices by adding the capability of complex coordinated motion, thus enabling prosthesis users to perform a wider range of task.	

3.4 Management and Monitoring	How will researchers manage and monitor conduct of the research project? Refer to NS §5.5.
A) Management Ricardo Garcia Rosas will manage and conduct the experiments. All team members will contribute to the analysis of data. B) Monitoring Ricardo Garcia Rosas will instruct participants on safety measures to be considered during the experiment. Visual contact with participants, the VR hardware, and the VR environment will be continuously followed. Participants will be asked about their comfort level throughout the duration of the experiment. C) Independent Contractors N/A	

4. Consent

4.1 Obtaining Informed Consent		Type an "X" in the left-hand column beside as many of the following options as apply to your research project. Use the space provided below to explain how you will obtain informed consent from participants. If you seek a waiver of consent, or the use of opt-out consent, use the space provided to justify your request. Refer to NS §2.2 , NS §2.3 .
X	Written consent will be sought from (or on behalf of) participants.	→ Refer to NS §2.2.6 . → Attach a copy of your consent form(s).
	Verbal consent will be sought from (or on behalf of) participants.	→ Refer to NS §2.2.5 - §2.2.6 . → Explain why you have chosen this form of consent, and how an individual's consent to participate will be recorded. → Attach a copy of your consent script(s).
	Consent will be implied, rather than explicitly obtained.	→ Refer to NS §2.2.5 - §2.2.6 . → Explain why you have chosen this form of consent.
	Third parties (e.g. parents/guardians of minors) will provide consent on behalf of participants.	→ Refer to NS §2.2.12 . → Explain who will be providing consent on behalf of participants and why.
	Third parties (e.g. community elders, school boards) will be involved in whole of community participation decisions.	→ Refer to NS §2.2.13 . → Provide details of which third parties will be involved, why they will be involved, and how this will be accomplished.
	This application seeks a waiver of consent.	→ Explain why you are seeking this option. Justify your request by referring to the conditions described in NS §2.3.10 - §2.3.11 .
	This application proposes to use opt-out consent.	→ Explain why you are seeking this option. Justify your request by referring to the conditions described in NS §2.3.6 .
[Write your responses here. If you will be obtaining consent from participants, describe who will obtain consent. Explain how it will be established that potential participants are competent to understand the research and to participate voluntarily, particularly if they are in a dependent relationship with the researcher(s). If you will not be obtaining consent from individual participants, justify your request for a waiver of consent, or for use of opt-out consent.]		

4.2 Limited Disclosure	Do you propose to use limited disclosure, concealment or deception for this research project? (Answer Yes or No. If Yes, use the space below to explain.) Refer to NS §2.3 .	
	YES or NO:	NO
[If NO, you may leave this space blank. If YES, provide a justification for the limited disclosure, concealment or deception. Comment on the special considerations discussed in NS §2.3 . Indicate whether you intend to debrief participants, and justify that position. If you are seeking a waiver of consent for all participants, select NO.]		

4.3 Future Use of Data, Materials, or Tissues	Do you intend for the data and/or materials and/or tissues collected for this research project to be reused in future research? Type an "X" in the left-hand column beside as many of the following options as apply to your research. Use the space provided to specify which data/materials/tissues will be reused, if any. Refer to NS §2.2.14 .	
X	Consent (or waiver of consent) will be specific.	→ Data/materials/tissues will be used <i>only</i> for this research project (i.e. no future use).

	Consent (or waiver of consent) will be extended .	→ Data/materials/tissues used in this research project may also be used in future projects that are <i>closely related</i> to this project, or <i>in the same general area</i> of research as this project.
	Consent (or waiver of consent) will be unspecified .	→ Data/materials/tissues used in this project may also be used in <i>any</i> future research.
<i>[If data/materials/tissues from this research project will not be reused, select "specific" above and state "N/A" here. If data/materials/tissues will be reused, describe which of them will be reused explain and how such future use will occur. If different conditions of consent apply to different data/materials/tissues, explain which conditions apply to which data/materials/tissues. If you will also be completing the Privacy and Databanks Module, you may simply write "Refer to Privacy and Databanks Module" here.]</i>		

4.4 Conflict of Interest	Does your research present or involve any conflict of interest, whether potential, real, or perceived; or will the researcher(s) have dual roles in relation to the participants? (Answer Yes or No. If Yes, use the space below to explain.) Refer to NS §5.4 , University of Melbourne Code of Conduct for Research §2.5 , and Australian Code for the Responsible Conduct of Research §7.2 .	
	YES or NO:	NO
<i>[If YES, explain what the potential conflict of interest is and how it will be managed. If applicable, you may also need to include a comment on the Plain Language Statement and Consent form declaring that potential conflict of interest. If NO, you may leave this space blank.]</i>		

4.5 Information for Participants	How will relevant information about the research project be provided to potential participants? Attach a copy of any advertisement (print or online), Plain Language Statement (PLS), consent form, letter, email, telephone script, and/or debriefing statement to be used. Refer to NS §5.2.23 .
PLS and consent forms will be provided.	

Plain Language Statement (PLS): Your PLS must satisfy the requirements set out in the *National Statement* ([NS §2.2.1 - §2.2.3, §2.2.6](#)). The Research Ethics and Integrity's website has [guidance on composing your plain language statement](#), as well as an [example PLS template](#). A list of PLS requirements is also provided at the end of this form. **Ensure that your PLS is written in plain language. Ensure that the information contained in your PLS is consistent with the information in your application.**

Consent Form: Your consent form must satisfy the requirements set out in the *National Statement* ([NS §2.2](#)). The Research Ethics and Integrity's website has [guidance on composing your consent form](#), as well as an [example consent form](#). A list of consent form requirements is also provided at the end of this form. **Ensure that your consent form is written in plain language. Ensure that the information contained in your consent form is consistent with the information in your application.**

5. Dissemination and Data Management

5.1 Providing Results to Participants	How will the results of the research project be provided to participants in an accessible format? Refer to NS §1.5 .
Participants interested in receiving the results can subscribe to an email list such that the results can be sent to them as a summary of findings.	

5.2 Reporting Project Outcomes	How will outcomes of the research project be made public? Refer to NS §1.3 .
---------------------------------------	--

Results of this project are intended to be published in scientific journals and/or presented in conferences related to robotics and biomedical engineering.

5.3 Data Management

How do you propose to manage the data collected in this research project? Specify what types of data will be collected, how they will be stored and in what format. How will access to the data be controlled and by whom? Discuss retention, security, and data sharing plans. What measures will be taken to protect participants' privacy, and their data?

Refer to [NS §1.11](#), the [Australian Code for Responsible Conduct of Research §2](#), and the [University of Melbourne Code of Conduct for Research §2.1](#).

A) Privacy and Confidentiality

Data storage for this project complies with the University policy. No personal information will be obtained from volunteers. The outcomes of the project will be made public and also available to the participants.

B) Security and Storage of Data

All the data and codes will be kept in a password locked laptop and the laptop will be kept in locked filing cabinet. Access to computer files to be available by password only.

C) Retention

Data will be kept for 5 years by the University after last publication of results. After this period, all data and copies are to be deleted.

6. Other Issues

6.1 Other Ethical Issues

Are there any other issues, not addressed above or in additional modules, which are relevant to the ethical review of your research project? **Refer to the relevant sections of the *National Statement* identified in the *Specific Guidelines Checklist*, if applicable.**

N/A

Attachments Checklist	
Review your answers above to determine which attachments (if any) are required for your application. Type an "X" in the left-hand column beside all items that apply to your research project. Attach a copy of the items you have selected.	
X	Plain Language Statement (PLS) for Participants
X	Consent Form for Participants
	Additional PLS(s) (e.g. for parents, teachers, schools)
	Additional Consent Form(s) (e.g. for parents, teachers, schools; or assent forms for children)
	Recruitment Materials (e.g. advertisement(s), posters, letter(s) or email(s) of invitation)
	Questionnaire(s) and/or Survey Instrument(s)
	Measure(s) and/or Scale(s)
	List of Interview Questions and/or Themes
	List of Focus Group Questions and/or Themes
	Participant Distress Protocol
	Adverse Event Protocol
	Debriefing Statement
	Approval(s) of research by an HREC external to the University of Melbourne
	Other External Approval(s) (e.g. schools, communities)
	Full Protocol (for Medical Research)
	Translations and/or Back-Translations (where languages other than English used)
	Privacy and Databanks Module
	Body Tissue and Genetic Research Module
	Ionising Radiation Module
	Interventions, Therapies and Trials Module
	Other Documents (e.g. contracts, agreements) – specify which:

Plain Language Statement (PLS) Requirements:

1. Clearly identify the University of Melbourne (i.e. by prominent placement of the University's logo) and the department(s)/ school(s)/faculty(-ies) involved. If printed, the PLS should be on University of Melbourne letterhead.
2. Clearly identify the title of the project, and the name(s) and contact details of the Principal Researcher and Other Researchers. For student projects, specify the student's level of study.
3. Clearly explain the purpose of the research project.
4. Clearly explain what participants will be asked to do, and provide an estimated time commitment.
5. If participants will be photographed, audio- or video-recorded, clearly state as much.
6. Clearly explain any risks arising from participation, as well as any procedures or measures in place to minimise such risks.
7. Describe any expected benefits to the wider community. If applicable, also describe any expected benefits to participants.
8. List any payments, incentives or reimbursements to be made to participants.
9. State that involvement in the project is voluntary and that participants are free to withdraw from participation at any time. Explain any implications of withdrawal, including whether it will be possible for participants to withdraw any data already collected from or about them.
10. Describe the likelihood and form of dissemination of the research results, including publication.
11. Describe the arrangements in place to protect the confidentiality of participants' data, and advise participants of any legal limitations to such confidentiality. If the sample size for the project is small, advise participants that this may make them identifiable.
12. The project HREC number (which is the ethics ID number assigned by Themis) and the date and version number of the PLS must appear on the PLS. If the PLS is printed, put this information in the footer.
13. Explain what will happen to participants' data after the research project ends (i.e. how long it will be retained, whether it might be used again for future research and if so who would have access.)
14. Include the following statement: "This research project has been approved by the Human Research Ethics Committee of The University of Melbourne. If you have any concerns or complaints about the conduct of this research project, which you do not wish to discuss with the research team, you should contact the Manager, Human Research Ethics, Research Ethics and Integrity, University of Melbourne, VIC 3010. Tel: +61 3 8344 2073 or Email: humanethics-complaints@unimelb.edu.au All complaints will be treated confidentially. In any correspondence please provide the name of the research team or the name or ethics ID number of the research project."
15. If the research is externally funded, state the amount(s) and source(s) of funding for the research.
16. If there are any potential conflicts of interest for any of the researchers, sponsors (if applicable) or institutions, disclose these potential conflicts of interest.
17. If any participants will be in a dependent relationship with any of the researchers, state that decisions about participation will not affect the dependent relationship. (E.g. students' grades will not be affected if they decline to participate or withdraw from the project at any stage).

Consent Form Requirements:

1. Clearly identify the University of Melbourne (i.e. by prominent placement of the University's logo) and the department(s)/ school(s)/faculty(-ies) involved. If printed, the consent form should be on University of Melbourne letterhead.
2. Clearly identify the title of the project, the name(s) and contact details of the Principal Researcher and Other Researchers. For student projects, specify the student's level of study.
3. If participants will be photographed, audio- or video-recorded, clearly state as much.
4. State that involvement in the project is voluntary and that participants are free to withdraw consent at any time, and to withdraw any unprocessed data previously supplied. Also state that the purpose of the project is research.
5. Describe the arrangements in place to protect the confidentiality of participants' data, and advise participants of any legal limitations to such confidentiality. If the sample size for the project is small, advise participants that this may make them identifiable.

Declaration by the Responsible Researcher

The information contained in this application is, to the best of my knowledge and belief, accurate.

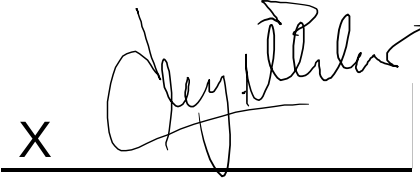
I have read the University's current human ethics guidelines. I accept responsibility for the conduct of the procedures set out in the attached application in accordance with: those guidelines, with the [University's Code of Conduct for Research](#), and with any other condition laid down by the University of Melbourne's Central Human Research Ethics Committee (CHREC), its Human Ethics Sub-Committees (HESCs), or by the Human Ethics Advisory Group (HEAG) which will review this application. I have attempted to identify all risks related to the research that may arise in conducting this research. I acknowledge our obligations as researchers and the rights of the participants stipulated in the [National Statement on Ethical Conduct in Human Research \(2007\) - Updated May 2015](#). I certify that the research team has the appropriate qualifications, experience and facilities to conduct the research described in the attached application, and to deal with any emergencies and contingencies related to research that may arise throughout the life of the project.

If approval is granted, the project will be undertaken in strict accordance with the approved protocol and relevant laws, regulations and guidelines.

I, the Responsible Researcher, agree to:

- start this research project only after obtaining final approval from the HESC (if this is a standard project), or the HEAG (if this is a minimal risk project);
- carry out this research only where adequate funding is available to enable the research to be carried out according to good research practice and in an ethical manner;
- provide additional information as requested by the CHREC, HESC, or HEAG;
- provide progress reports to the CHREC, HESC, or HEAG as requested, including annual and final reports;
- maintain the confidentiality of all data collected from, or about, research participants and maintain security procedures for the protection of their privacy;
- submit an amendment if any modification to the research design or protocol is proposed (including any change of researchers) and to proceed with the research only after the amendment has been approved by the HESC (if this is a standard project) or by the HEAG (if this is a minimal risk project);
- notify the HESC (if this is a standard project) or the HEAG (if this is a minimal risk project) in writing immediately if any adverse event occurs during the course of the research;
- notify the HESC (if this is a standard project) or the HEAG (if this is a minimal risk project) in writing immediately if any complaints are received about the research;
- comply with an audit of the research undertaken, if requested by the CHREC, HESC, or HEAG;
- use only the data/tissue samples collected for this research, and for which HESC/HEAG approval has been given.

I certify that all members of the research team have read this application and the [National Statement on Ethical Conduct in Human Research \(2007\) - Updated May 2015](#) and that they have agreed to comply with the provisions of the latter.

Responsible Researcher Name	Signature	Date
A/Prof. Denny Oetomo	 X	02/11/2018

Declaration by Human Ethics Advisory Group (HEAG)

For HEAG use only.		
Enter the date the application was received, then type an "X" in the left-hand column beside each item as applicable.		
Date Application Received:		
	Technical review has been completed by the HEAG.	The merit of the proposed research project set out in this application has been reviewed on technical grounds. Refer to NS §1.1.
	Ethical review has been completed by the HEAG.	The HEAG has reviewed the proposed research project set out in this application for compliance with the principles of Human Research Ethics.
	The Minimal Risk review process is appropriate for the proposed research project set out in this application.	→ Complete Declaration A (below)
	The Standard Project review process is appropriate for the proposed research project set out in this application	→ Complete Declaration B (below)

Declaration A (Minimal Risk):	The HEAG has reviewed this project. The HEAG considers the methodological/technical and ethical aspects of the proposal to be appropriate to the tasks proposed. The HEAG grants approval for this research project to commence. The HEAG considers that the researcher(s) has/have the necessary qualifications, experience and facilities to conduct the research described in the attached application in a manner that complies with the University's policy on the management of research data and records, and to deal with any emergencies and contingencies that may arise. <i>[Note: If the HEAG Chair is also a researcher in this project, the declaration should be signed by another authorised member of the HEAG.]</i>	
Name of HEAG Chair/Authorised Member	Signature	Date

Declaration B (Standard Project):	The HEAG has reviewed this project and considers the methodological/technical and ethical aspects of the proposal to be appropriate to the tasks proposed. The HEAG regards this project as ready to submit to the HESC. The HEAG considers that the researcher(s) has/have the necessary qualifications, experience and facilities to conduct the research described in the attached application in a manner that complies with the University's policy on the management of research data and records, and to deal with any emergencies and contingencies that may arise. <i>[Note: If the HEAG Chair is also a researcher in this project, the declaration should be signed by another authorised member of the HEAG.]</i>	
Name of HEAG Chair/Authorised Member	Signature	Date

A.2 Ethics Approval

07 December 2018

A/Prof D.N. Oetomo
Mechanical Engineering
The University of Melbourne

Dear A/Prof Oetomo

Project title: **Online Synergy Identification for Personalized Neuroprostheses**
Researchers: **A/Prof Y Tan, A/Prof D N Oetomo, Prof C G Manzie, Mr R Garcia Rosas**
Ethics ID: **1750711**

I am pleased to advise that the amendment to this Project was approved by the Engineering Human Ethics Advisory Group on .

Please note it is your responsibility to ensure that all people associated with the Project are made aware of the amendment.

Yours sincerely



A/Prof George Buchanan
Chair Engineering - Human Ethics Advisory Group

cc:
HEAG Administrator - Engineering
HEAG Chair - Engineering

A.3 Plan Language Statement

Plain Language Statement

Melbourne School of Engineering
Department of Mechanical Engineering



Project: Online Synergy Identification for Personalized Neuroprostheses

Ricardo Garcia-Rosas (Student Researcher).
Tel: +61 403 462 078. Email: ricardog@student.unimelb.edu.au
(Responsible Researchers)
A/Prof. Denny Oetomo. Email: doetomo@unimelb.edu.au
(Additional Researchers)
A/Prof. Ying Tan. Email: yingt@unimelb.edu.au
Prof. Chris Manzie. Email: manziec@unimelb.edu.au

Introduction

Thank you for your interest in participating in this research project. The following few pages will provide you with further information about the project, so that you can decide if you would like to take part in this research.

Please take the time to read this information carefully. You may ask questions about anything you don't understand or want to know more about.

Your participation is voluntary. If you don't wish to take part, you don't have to. If you begin participating, you can also stop at any time.

What is this research about?

The aim of this research is to investigate the properties of the relationship that occurs between the motion of the joints in the upper arm and upper limb prosthetic devices during coordinated motion. How these properties are related to measures of upper limb motion performance. And to the identification of residual limb and prosthesis joint relationships through continuous prosthesis use. Furthermore, to study the behaviour introduced by human learning and the effects this has on the identification algorithms through prosthesis use.

What will I be asked to do?

Should you agree to participate you will be required to perform a series of reaching and/or grasping tasks in a Virtual Reality Environment (VRE) or with a wearable non-invasive robotic elbow that simulates the usage of upper limb prosthetic devices. The VRE will be displayed by an Oculus Rift or HTC VIVE headset. In order to measure your upper arm movement, a motion tracker will be fastened to your dominant upper arm with an elbow immobilizing brace with adjustable straps. In the case of amputee participants, a personalized socket will be developed with the help of a prosthetist with all sensors and

attachment points safely integrated. In order to measure upper arm muscle activation, surface electromyography (sEMG) will be placed on your skin on top of the relevant muscles with off-the-shelf sEMG pads. The total length of the experiment will be one hour per session, with experiments requiring four to five sessions. The tasks performed during experiments require to be repeated between a maximum of 200 times, with each task taking less than 5 seconds. You will be given 1 minute rest in between every 25 repetition sets and a 5-10 minute break every 30 minutes.

What are the possible benefits?

Your participation in this research will assist in the development of more capable and intuitive upper limb prosthetic devices.

What are the possible risks?

The risks involved in participating in the experiment are tiredness of the arm and/or shoulder from continuous movement, motion sickness from continuous use of VR hardware, tripping hazard and strangling from the cables connected to the hardware device. Careful consideration has been taken to account for these risks and reduce discomfort. Regular breaks and rest will be given in order to minimize tiredness and discomfort. While the VR application is designed to avoid motion sickness, some people can still be subject to motion sickness in VR. You are allowed to rest or stop the experiment at any time if needed due to discomfort introduced by the VR hardware. The experimenter will monitor cables around you to reduce hazards and will instruct you if any action or stopping the experiment is required to ensure your safety.

Do I have to take part?

Your participation in this study is completely voluntary. Should you wish to withdraw at any stage, or to withdraw any unprocessed data you have supplied, you are free to do so without prejudice.

Will I hear about the results of this project?

Results of this project are intended to be published in scientific journals and/or presented in conferences related to robotics and biomedical engineering. Results can be provided to participants after publication upon request.

What will happen to information about me?

All sensor data will be stored anonymously with only information relevant to statistical data, such as age and gender, included; however, given the small number of participants involved in the study, it may not be possible to guarantee my anonymity. Data gathered from the experiments will be safeguarded subject to any legal requirements; your data will be password protected and accessible only by the named researchers. The data from this research will be stored at the University of Melbourne and will be destroyed 5 years after the last publication of results.

Where can I get further information?

If you would like more information about the project, please contact the responsible researcher; A/Prof. Denny Oetomo (doetomo@unimelb.edu.au). If you would like to participate, please indicate that you have read and understood this information by signing the accompanying consent form and return it to the researchers. The researchers will then contact you to arrange a mutually convenient time for you participate in the different sessions.

Who can I contact if I have any concerns about the project?

This research project has been approved by the Human Research Ethics Committee of The University of Melbourne. If you have any concerns or complaints about the conduct of this research project, which you do not wish to discuss with the research team, you should contact the Manager, Human Research Ethics, Research Ethics and Integrity, University of Melbourne, VIC 3010. Tel: +61 3 8344 2073 or Email: HumanEthics-complaints@unimelb.edu.au. All complaints will be treated confidentially. In any correspondence please provide the name of the research team or the name or ethics ID number of the research project.

A.4 Consent Form

Consent Form

Melbourne School of Engineering
Department of Mechanical Engineering



Project: Online Synergy Identification for Personalized Neuroprostheses

Responsible Researcher: A/Prof. Denny Oetomo

Student Researcher: Ricardo Garcia-Rosas

Additional Researchers: A/Prof. Ying Tan, Prof. Chris Manzie.

Name of Participant: _____

1. I consent to participate in this project, the details of which have been explained to me, and I have been provided with a written plain language statement to keep.
2. I understand that the aim of this research is to investigate the properties of the relationship that occurs between the motion of the joints in the upper arm and upper limb prosthetic devices during coordinated motion. How these properties are related to measures of upper limb motion performance. And to the identification of residual limb and prosthesis joint relationships through continuous prosthesis use. Furthermore, to study the behaviour introduced by human learning and the effects this has on the identification algorithms through prosthesis use.
3. I understand that my participation in this project is for research purposes only.
4. I acknowledge that the possible effects of participating in this research project have been explained to my satisfaction.
5. I understand that my interviews will involve recording of my movement in the VRE as recorded by the VR headset, motion and sEMG sensors, which will measure the motion of my head, body and upper arm, and relevant muscle activation.
6. I understand that my participation is voluntary and that I am free to withdraw from this project anytime without explanation or prejudice and to withdraw any unprocessed data that I have provided.
7. I understand that the data from this research will be stored at the University of Melbourne and will be destroyed 5 years after the last publication of results.
8. I have been informed that the confidentiality of the information I provide will be safeguarded subject to any legal requirements; my data will be password protected and accessible only by the named researchers.
9. I understand that given the small number of participants involved in the study, it may not be possible to guarantee my anonymity.
10. I understand that after I sign and return this consent form, it will be retained by the researcher.

Participant Signature: _____ **Date:** _____

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