Upper-body Motion Coordination after Stroke: Insights from Kinematic and Muscle Synergies

by

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Abstract

Several studies suggest that the human central nervous system controls groups of muscles and/or joints (synergies) rather than controlling each muscle or joint separately to reduce the dimensionality of motor planning and execution. Furthermore, recent studies with stroke survivors indicate that motor impairment after stroke is due to a disruption in the recruitment and the combination of the motor synergies.

The objective of the work in this thesis was to investigate human upper body motor coordination and to demonstrate the viability of synergistic motor control theory in describing the natural upper body movements, as well as quantifying the effects of stroke on motion generation.

A critique of previous studies on this topic is that the synergies they report are task-specific and reflect the biomechanical constraints of the task rather than the neural strategies of motor control. To address this, the studies covered in this dissertation were focused on quantification of motor synergies demonstrated during exploratory motor tasks. Exploratory motions have the potential to reveal individualized motion tendencies or motor deficits.

The first study compared the robustness of matrix factorization methods reported in literature to characterize motor synergies, and showed that non-negative matrix factorization is more suited for synergy analysis. The second study established how much exploratory motion data is needed to reliably extract motor synergies of healthy and stroke survivor individuals. A group of healthy adults were recruited for the third study. The results showed that motor synergies between the dominant and non-dominant hands of healthy adults are similar (within-subject similarities) and that healthy adults share a set of “healthy” motor synergies (between-subjects similarities). The fourth study explored how stroke changes motor synergies. The study showed that healthy motor synergies are preserved in the less-affected arm of stroke survivors. However, the motor synergies of the stroke-affected arm are altered through merging and fractionation of healthy synergies and these processes are a function of the individual’s impairment and time post-stroke.

These results offer a better understanding of motor synergies and can improve rehabilitation practices by identifying strengthening physical therapy exercises that utilize or promote the use of “healthy” synergies.
Lay Summary

This thesis explores the impacts of a stroke on motion coordination. Motion coordination can be defined as the way joints/muscles work together to generate movements. This thesis focused on motor synergies as a framework to study motion coordination. This framework states that the brain controls joints/muscles by grouping them together and activating these synergy groups, rather than controlling each joint/muscle individually.

The first two studies presented in this thesis explore the robustness of the state-of-the-art methodology in motor synergies research. The results of the third study showed that the motor synergies employed by the dominant and non-dominant arms in the healthy population are similar. These synergies are also similar between people with no prior neurological damage. The fourth study showed that stroke does not change the synergies of the non-affected arm. However, it causes the synergies of the affected arm to merge and fractionate to generate new altered synergies.
Preface

Studies and experiments described in this thesis were performed with the approval of the Clinical Research Ethics Board (CREB) at the University of British Columbia, under ethics application #H15-01450 “Kinematic and Muscle Synergies”.

The material presented in Chapter 2 was previously published as a conference paper and a journal paper in the International Conference on NeuroRehabilitation and Journal of Neurophysiology:


The work presented in Chapter 3 was published as a conference paper in the International Conference on Rehabilitation Robotics:


The results presented in Chapter 4 have been submitted as a journal manuscript entitled “Kinematic and muscle synergies in healthy exploratory upper-body motions”. The work presented in Chapter 5 has been submitted as a journal manuscript entitled “Post-stroke Kinematic and Muscle Synergies in Exploratory Upper-body Motions”. As of July 2017, the first manuscript is undergoing the first-round of revisions and the second manuscript is undergoing the first round of peer-review process.

For all of the aforementioned publications and manuscripts, the author of this thesis worked individually under the supervision of Dr. Van der Loos and was responsible for performing
literature review, developing the study design, collecting data, developing software and data analysis, and writing the manuscripts.

The author was directly involved in the design and development of the experiment setup and equipment used in the studies presented in this thesis. The different stages of the R&D process leading to the final design used in this thesis have been published in several journal and conference papers (for a list see Appendix D).
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Brachi: Brachioradialis

Biceps: Biceps brachii

CI: Confidence intervals

CNS: Central nervous system

DelAnt: Anterior fibres of deltoid

DelMed: Medial fibres of deltoid

DelPos: Posterior fibres of deltoid

Delta VAF: Change in variance accounted for

DOF VAF: Variance accounted for of a muscle or joint

D: Dominant

ElFlEx: Elbow flexion/extension

ElPrSu: Elbow pronation/supination

EMG: Electromyography

FMA: Fugl-Meyer assessment

ICA: Independent Component Analysis

N-D: Non-Dominant

NNMF: Non-negative matrix factorization

PCA: Principal Component Analysis

PectMaj: Clavicular fibres of pectoralis major

ROM: Range of motion

RPS: Reaching performance scale
ShAbAd: Shoulder abduction/adduction

ShFlEx: Shoulder flexion/extension

ShRot: Shoulder rotation

TriLat: Lateral heads of triceps

TriLong: Long heads of triceps

TrPit: Trunk pitch

TrRol: Trunk roll

TrYaw: Trunk yaw

UCM: Uncontrolled manifold

UE-FMA: Upper extremity portion of Fugl-Meyer assessment

VAF: Variance accounted for

WrDev: Wrist ulnar deviation

WrFlEx: Wrist flexion/extension
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To that last ray of light when all is dark,

To my Patronus Charm,

With all my love,

To Erika!
1 Introduction

1.1 Motor Coordination

Humans are capable of smooth and well-coordinated motor behaviours. The human central nervous system (CNS) plans and executes these motions with ease despite facing multiple levels of challenges such as redundancy in the human musculoskeletal system, noisy sensory input, and complexity (i.e., nonlinearity and time-dependency) of the biomechanics of the body. Understanding how the CNS overcomes the computational burden of motor control has been in the forefront of the human motor control and motor learning fields (Guigon 2010).

Human motor behaviour is highly goal-directed. This requires the CNS to coordinate different aspects of motion generation in order to achieve motion goals (Turvey 1990). For example, to open a jar, motions of two hands need to be coordinated so that one hand can stabilize the jar while the other hand exerts force on the jar lid. This requires bimanual coordination of the muscles, joint torques, and joint motions. Motor coordination is defined as the combination of body movements created with kinematic (such as spatial direction) and kinetic (force) parameters that result in intended actions (Diedrichsen et al. 2010). Motor coordination can be inter-limb, intra-limb, or on a higher level involving sensory information and motion execution at the same time (like hand-eye coordination tasks).

However, there are several unanswered questions on how the CNS handles motion coordination. Historically, motor coordination is assumed to be a simplifying strategy employed by the CNS in regards to the problem of redundancy and to reduce the dimensionality of available choices to execute the motion (Bernstein 1967; Turvey 1990; Latash 1996). Following Bernstein’s work (Bernstein 1967), motor coordination research was focused on studying tasks that would eliminate or isolate the redundant degrees of freedom. Then, the main idea would be to find computational rules and principles that would lead to the unique solutions observed in human motor behaviour (see (Rosenbaum et al. 1995) for a review).
A more recent view on motor coordination is reflected in the principle of abundance (Latash and Anson 2006). This principle states that the CNS views the human musculoskeletal system not as a redundant system but as an abundant one. This means that the CNS, instead of eliminating redundant degrees of freedom in motion effectors (muscles and joints), uses the abundance of available effectors to ensure the motion is both stable and flexible. The principle of abundance tightly connects to the concept of motor synergies and the uncontrolled manifold (UCM) hypothesis.

1.2 Theories of Motor Control to Explain Motor Coordination

The uncontrolled manifold hypothesis provides a way to articulate how the CNS utilizes the principle of abundance. Using the terminology introduced by Latash and Anson (Latash and Anson 2006), the CNS organizes the control of elemental variables to stabilize performance variables. For example, in studying reaching in three-dimensional space, the rotation of each of the arm joints (arm’s kinematic degrees of freedom) or activation of each of the arm muscles (arm’s muscle degrees of freedom) or joint torques (arm’s kinetic degrees of freedom) can be considered as an elemental variable. To this end, an elemental variable is the smallest unit that can describe the musculoskeletal system at the chosen level of analysis. Continuing with the example of three-dimensional reaching, the position of the tip of the index finger or the orientation of the hand can be a performance variable depending on the goal of reaching (pointing versus grabbing a glass of water). Performance variables are directly related to the task goal and present the important outcomes of the motion.

The uncontrolled manifold hypothesis states that although the role of each individual elemental variable is central to the generation of performance variables, the variability of the elemental variables is not necessarily reflected in the variability of the performance variables (Ting and Chvatal 2010). The UCM hypothesis proposes that the CNS divides the space into controlled and uncontrolled elemental variables. The uncontrolled variables (i.e., the uncontrolled manifold) are task-irrelevant and show more variability during the task (Scholz and Schöner 1999). On the other hand, the controlled variables are task-relevant and are controlled by the CNS to ensure their variation does not lead to deviation of the performance variable beyond a narrow allowable margin. This guarantees that the performance variable changes according to the task goal, while the variation in the uncontrolled manifold is to ensure flexibility and stability of the motion. Therefore, the UCM hypothesis does not treat variability in motor patterns as an error showing
poor planning by the CNS, but it considers it as a proof for efficient control (Tresch and Jarc 2009).

Building on the uncontrolled manifold hypothesis, the concept of motor synergies is a way to quantify the covariation of the elemental variables during a task. Using the UCM terminology, a motor synergy can be defined as a set of stable spatiotemporal patterns of activity shared across elemental variables that leads to a desirable performance variable (McMorland et al. 2015). Recent studies suggest that the CNS may generate motor commands through a linear combination of motor synergies, each controlling a group of elemental variables (Cheung et al. 2009). Such co-activation of elemental variables leads to a reduction in the dimensionality of the motor control problem. Based on this definition, by the scaling and time-shifting of a small set of covariation patterns, the entire set of muscle or joint variations during a task can be generated (d’Avella et al. 2003).

To quantify motor synergies, dimensionality reduction methods (Tresch et al. 2006) are readily available to analyse large sets of muscle activity or joint angle changes observed over the course of motor tasks. However, providing insight into the motor behaviour of healthy and motor impaired individuals based on these quantified synergies can be challenging.

1.3 Neural Origins of Motor Synergies

Motor synergies are an abstract, low-dimensional representation of motion coordination that is executed within a high-dimensional effector activation space. Motor synergies are discussed in the literature on two fundamentally different levels: functional and anatomical motor synergies (McMorland et al. 2015).

Functional motor synergies, the topic of this thesis, can be considered “soft” synergies that arise from the goal-directed coordination in the high-dimensional effector activation space during a functional task. The general approach in this area of research is to measure surface electromyography (EMG) of a large number of relevant muscles or kinematics of joint motions during a functional task. The collected data are then processed through a statistical or computational method of dimensionality reduction to identify sets of low-dimensional summaries of the data, called motor synergies. After verifying that these synergies can be combined to accurately reconstruct the observed behavioural data, the next step is relating the
motor synergies to the physiology of the functional task (Latash 2008). Functional motor synergies are discussed more in the following sections.

Soft synergies are identified by applying a computational method to functional co-activation of muscles and/or joints and therefore can be dynamic and context-dependent. However, the anatomical synergies hypothesis considers the possibility of hard synergies at the level of hardwired anatomical structures that control activation of muscles in groups. This would require indwelling finewire intramuscular EMG electrodes into study participants’ limbs and due to its intrusive nature, there has been little work directly studying the notion of anatomical synergies and their neural implementation.

The source of such hard synergies for upper limb movements is assumed to be along the corticospinal tract, which is known to be the main conveyor of the control and activation strategies to the upper limb (Lemon 2008). Studies on rats (Tresch and Bizzi 1999) and on frogs (Cheung et al. 2005; Bizzi et al. 2008) provide evidence for the existence of spinal structures that activate hard muscle synergies. These studies showed that activation of groups of muscles is dependent on the precise location of microstimulation in the spinal cord and that these hardwired activations can be combined to construct natural behaviours such as jumping in cats or swimming in frogs. In a study on primates, Overduin et al. (Overduin et al. 2012) examined the effects of microstimulation of the motor cortex on muscle activation patterns. This study showed that the muscle activations observed after microstimulation of the motor cortex can cover a range of synergies observed during different tasks (e.g., grasping, reaching, and transporting an object). The fact that activation of the motor cortex leads to activation of several synergies also suggests that hard synergies are generated downstream of the cortex (not in the cortex), supporting the findings of (Tresch and Bizzi 1999) and (Bizzi et al. 2008). In fact, McMorland et al. (McMorland et al. 2015) suggest that the spread of muscle representation across the motor cortex (Wickens et al. 1994; Rathelot and Strick 2006; Capaday et al. 2013), as well as the broad horizontal projections present in the motor cortex (Huntley and Jones 1991), provide a robust neural network allowing the CNS to control soft synergies.

The notion of functional kinematic synergies is common place as it is a way to quantify motor coordination without looking into the neural construct of motor coordination. However, the hypothesis of anatomical kinematic synergies (i.e., the CNS controls functional behaviours at the
joint level by combining joint synergies) is less popular and studies on this topic are scarce and non-conclusive (Saleh et al. 2010, 2012; Mollazadeh et al. 2014).

1.4 Stroke: Prevalence and Impacts

A cerebrovascular accident, or stroke, is a localized reduction in blood supply to a region of the brain and causes neurons in the affected area to die. Thus, a stroke typically causes loss of brain function. Ischemic strokes, which account for 80% of the total incidence, are caused by a blockage of vessels from a blood clot and interruption of blood flow. About 20% of strokes are hemorrhagic strokes that are caused by rupture of blood vessels in the brain (The Heart and Stroke Foundation of Canada 2017). The effects of a stroke mainly depend on the location and size of the blood flow disturbance. Strokes predominantly involve one of the cerebral hemispheres and can affect one’s ability to perform basic functions such as to move, see, remember, speak, reason, read and/or write.

In North America, approximately 610,000 people experience their first stroke each year (The American Heart Association 2012). In Canada, over 50,000 strokes are reported each year and 300,000 Canadians are living with the effects of stroke (The Heart and Stroke Foundation of Canada 2017). Hospital and physician services, lost wages, and decreased productivity associated with stroke cost the Canadian economy $3.6 billion per year. The healthcare cost for stroke survivors was estimated at $18.8 billion in the United States in 2008, while an additional cost of $15.5 billion was associated with lost productivity and premature mortality caused by stroke (Fang et al. 2012).

1.5 Effects of Stroke on Motion Coordination

Three out of four stroke survivors have an upper-limb impairment as a result of their stroke, mainly affecting one side of their body (Wolfe 2000; Veerbeek et al. 2011). Recovery of upper-limb function is key to success of a physical therapy program in returning stroke survivors back to their independent lives (Stinear 2010; Lam et al. 2015; Tatla et al. 2015). Fortunately, a considerable portion of the impairment resolves spontaneously within three months post-stroke (Kwakkel et al. 2004; Zarahn et al. 2011). This is also known as the proportional recovery rule and is reported to be around 30% of the initial impairment (measured on the Fugl-Meyer scale) for stroke survivors with a mild or moderate initial impairment (Prabhakaran et al. 2008). During
this spontaneous recovery period the structure of muscle synergies on the more-affected side of the body remains mostly intact (Tropea et al. 2013).

Stroke leads to a broad range of motor function disturbances that can be categorized under three main impairments: weakness because agonist muscles do not activate properly as their neural drive through the corticospinal tract reduces, spasticity because antagonist muscles show an altered regime of reflex activity, and impaired motor coordination (Twitchell 1951; Steenbergen et al. 1996; Roh et al. 2015). Impaired motor coordination remains severe even after weakness and spasticity are addressed by physical therapy in the chronic stroke population (Dewald et al. 2001). Therefore, quantification of motor coordination and co-activation of agonist and antagonist muscles can play an important role in setting up physical therapy exercises in the chronic stage of stroke.

Weakness, spasticity, and impaired motor coordination can all be considered a form of “abnormal” synergy. They all represent a spatiotemporal co-activation of the available effectors to generate motion. In the chronic stage, stroke survivors can develop and demonstrate these abnormal synergies (McMorland et al. 2015). There are several notable studies that identify how chronic muscle synergies evolve post-stroke (Cheung et al. 2009, 2012; Clark et al. 2010).

1.6 Purpose and Overview of This Thesis

This dissertation builds on the methods that have been developed in the past decade to further expand our understanding of motor synergies. In particular, I generated computational procedures to quantify upper-limb bimanual coordination on kinematic and muscle activation levels using the notion of motor synergies. These procedures were then used to study motion coordination in healthy and post-stroke populations. More precisely, the following research questions were answered:

1. What is the most robust dimensionality reduction method in quantifying motor synergies (see Chapter 2)?

2. How much joint motion and EMG time-series data (e.g., 10 seconds or 10 minutes) are required to precisely quantify motor synergies (see Chapter 3)?

3. What are the synergies that the healthy CNS uses to combine the activation of muscles and motion of joints? Does the healthy CNS use the same synergies to control the
dominant and the non-dominant sides of the body? Are these motor synergies shared in the healthy population (see Chapter 4)?

4. How do motor synergies change after stroke? Does the stroke-affected CNS employ two different sets of motor synergies in controlling the paretic and non-paretic sides of the body? How are post-stroke synergies related to healthy synergies (see Chapter 5)?

Several recent studies have demonstrated that a range of functional tasks can be explained by motor synergies. These studies have shown that between 75-90% of the variance in the measured EMG (Muceli et al. 2010; Torres-Oviedo and Ting 2010; d’Avella and Lacquaniti 2013; Gentner et al. 2013; Vinjamuri et al. 2014; Azaripasand et al. 2015; Hagio et al. 2015; Roh et al. 2015; Tagliabue et al. 2015) can be explained by combinations of muscle synergies. Similarly, studies have shown that a low-dimensional space accounts for a large portion of the kinematic variance in a range of tasks (Soechting and Flanders 1997; Braido and Zhang 2004; Jae et al. 2005; Tagliabue et al. 2015).

Although these studies support the motor synergies hypothesis, they have used several different computational methods to provide this support by identifying underlying synergies in human motor behaviour. A range of factorization methods has been used in these studies to reconstruct the experimental data by linearly combining a small set of basis vectors or motor synergies. To answer the first research question, in Chapter 2, I present a systematic comparison of the performance of the most reported factorization methods in literature to determine their robustness in identifying motor synergies, also published as (Lambert-Shirzad and Van der Loos 2017a, 2017b). The three considered factorization methods were: Non-Negative Matrix Factorization (NNMF) (Muceli et al. 2010), Principal Component Analysis (PCA) (Tagliabue et al. 2015), and Independent Component Analysis (ICA) (Hart and Giszter 2004). PCA and NNMF had comparable performance on both EMG and joint motion data, both outperforming ICA. However, NNMF’s non-negativity condition for activation of synergies helps in identifying physiologically meaningful synergies (i.e., muscle synergies have only non-negative EMG activations), making it a more appealing method for future studies.

As mentioned, several studies have shown how the concept of motor synergies can be used to explain a major fraction of variation in EMG or joint motion data of a range of goal-directed motor tasks. One of the critiques of these studies is that the synergies they report are task-specific and might reflect the biomechanical constraints of the task rather than the underlying neural
strategies of motor control (Rearick et al. 2003; Todorov and Ghahramani 2004; Tresch and Jarc 2009; Steele et al. 2015). To address this main critique of motor synergies, my studies were focused on quantification of motor synergies demonstrated during exploratory motor tasks instead of goal-directed motor tasks with physical constraints.

The first logical step to consider exploratory motions in the study of motor synergies is to determine how much data is required to reliably and fully profile the motion patterns of an individual. Chapter 3 presents a study, also published as (Lambert-Shirzad and Van der Loos 2017c) on how the quality of motor synergies analysis depends on the amount of exploratory motion data to be included in the analysis. In this study, I recruited 10 healthy and 10 post-stroke participants and collected electromyography (EMG) and joint motion data of their arms as they completed a motor exploration task. The effects of clinical status and limb strength/dominance on the amount of data required to identify synergies were investigated. Clinical status had a significant effect on the required amount of data for both datasets. Limb strength had a significant effect only for kinematic data. Based on the results, I determined the upper-bound 95% confidence interval to set the amount of data required for synergy analysis in both populations.

Chapter 4 discusses the results of a study on the use of non-negative matrix factorization to identify muscle and kinematic synergies in healthy upper-limb exploratory motions. I recruited 15 healthy participants and collected EMG and joint motion data from both of their arms. Four muscle synergies and three kinematic synergies were sufficient to reliably reconstruct the motion data of each participant. This suggests that the healthy CNS uses a modular motion coordination scheme for arm motion control. Interestingly, the identified synergies were similar between the dominant and non-dominant limbs. Moreover, the results showed that healthy participants share the same muscle and kinematic synergies. Using the identified synergies, I introduce healthy templates for muscle/kinematic synergies.

In general, research concerning motor synergies has been focused on developing methods to characterize synergies using behavioural data from the healthy population. The number of studies using data from a clinical population is rising. Chapter 5 covers a study that explores upper-body motion coordination post-stroke from a motor synergies perspective. The templates for healthy motor synergies reported in Chapter 4 were used as a benchmark for healthy motion coordination to study how stroke alters motion coordination patterns and causes impairment. The results
showed that the motor synergies of the less-affected side of the body are preserved after stroke. Although a number of the more-affected arm synergies were similar to those of the healthy population, a considerable portion of them were altered. The majority of these altered synergies could be related to the synergies of the healthy population through merging and fractionation of healthy synergies. The alteration in the synergies of the weak arm was linearly related to each participant’s motor function and time post-stroke.

Chapter 6 summarizes the findings of this work and discusses its implications in understanding motion coordination post-stroke, as well as providing recommendations for future studies.
2 Comparison of Matrix Factorization Methods for Extracting Kinematic and Muscle Synergies

The central nervous system coordinates different aspects of motion generation in order to achieve motion goals. The concept of motor synergies provides an approach to quantify the covariation of joint motions and of muscle activations during a task. To analyse goal-directed movements, factorization methods can be used to reduce the high dimensionality of these variables while accounting for much of the variance in large datasets. Literature on comparing factorization methods in identifying motor synergies using numerically-generated, simulation, and muscle activation data from animal studies already exists. I present an empirical evaluation of the performance of three of these methods on muscle activation and joint angles data from human reaching motion.

The three factorization methods considered in this chapter are Principal Component Analysis (PCA), Non-Negative Matrix Factorization (NNMF), and Independent Component Analysis (ICA). Bilateral human reaching datasets are used to compare the methods, and the advantages of each are presented and discussed. PCA and NNMF had comparable performance on both EMG and joint motion data, and both outperformed ICA. However, NNMF’s non-negativity condition for activation of basis vectors is a useful attribute in identifying physiologically meaningful synergies, making it a more appealing method for future studies. A simulated dataset is introduced to clarify the approaches and interpretation of the synergy structures returned by the three factorization methods. The results can be used to unify approaches in identifying and interpreting motor synergies.

2.1 Introduction

The CNS plans and executes smooth and well-coordinated motor behaviours with ease, despite facing multiple levels of challenges such as redundancy in the musculoskeletal system, noisy sensory input, and nonlinearity and time-dependency of the biomechanics of the body. This
requires the CNS to coordinate different aspects of motion generation in order to achieve the motion goals (Turvey 1990). The CNS organizes the control of elemental variables to stabilize performance variables (Latash and Anson 2006). For example, in reaching in a three-dimensional space, the rotation of each of the arm joints (kinematic degrees of freedom) or activation of each of the arm muscles (muscular degrees of freedom) can be considered an elemental variable. An elemental variable is the smallest unit that can describe the musculoskeletal system at the chosen level of analysis. As an example in three-dimensional reaching, the position of the tip of the index finger or the orientation of the hand can be a performance variable depending on the goal of reaching (e.g., pointing vs. picking up an object). Performance variables are directly related to the task goal and present the most important outcomes of the motion.

The concept of motor synergies (i.e., muscle or kinematic synergies) provides an approach to quantify the covariation of the elemental variables during a task. A motor synergy can be defined as a set of stable spatiotemporal patterns of activity shared across elemental variables that leads to a desirable performance variable (McMorland et al. 2015). Recent studies, among different models of motion generation, suggest that the CNS may generate motor commands through a linear combination of motor synergies, each controlling a group of elemental variables (Santello 2002; Freitas et al. 2006; Cheung et al. 2012; Alessandro et al. 2013; Bizzi and Cheung 2013; Berger and d’Avella 2014; Tamei et al. 2015; Federolf 2016). Such co-activation of elemental variables leads to a reduction in the dimensionality of the motor control.

To quantify motor synergies, dimensionality reduction methods are used to analyse large sets of muscle activity or joint angle changes observed over the course of motor tasks. Several recent studies have demonstrated that a range of functional tasks can be explained by motor synergies. These studies have shown that between 75-90% of the variance in the EMG measured during unilateral reaching (Muceli et al. 2010; d’Avella and Lacquaniti 2013; Azaripasand et al. 2015), balance (Torres-Oviedo and Ting 2010), grasping (Vinjamuri et al. 2014; Tagliabue et al. 2015), gait (Hagio et al. 2015), visuomotor adaptation (Gentner et al. 2013), and unilateral isometric force generation (Roh et al. 2015) can be explained by combinations of muscle synergies. Similarly, studies have shown that a low-dimensional space combining joint motions accounts for a large portion of the kinematic variance in a range of tasks such as unilateral reaching.
(Braido and Zhang 2004), typing (Soechting and Flanders 1997), grasping (Tagliabue et al. 2015), and multi-digit force generation (Jae et al. 2005).

One of the critiques of these studies is that the synergies they report are task-specific and might be reflecting the biomechanical constraints of the task rather than the underlying neural strategies of motor control (Rearick et al. 2003; Todorov and Ghahramani 2004; Tresch and Jarc 2009; Steele et al. 2015). For example, a tabletop reaching task while the torso is restrained (Dipietro et al. 2007) reduces the redundancy of joint motion patterns that can be identified as a kinematic synergy.

To address this critique, the studies included in this thesis are focused on quantification of motor synergies demonstrated during exploratory motor tasks instead of goal-directed motor tasks with physical constraints. Specifically, I studied exploring a task space parallel to the frontal plane using symmetric bimanual reaching motions, i.e., the two hands move synchronously in horizontal and vertical directions. This task presents two main advantages. First, by removing constraints imposed by the task’s goal (reaching to specific targets), the apparent reduction in the redundancy of the joint space will be removed (Thakur et al. 2008). Moreover, the requirement to execute symmetric bimanual motions is a natural tendency in the activities of daily living (Kelso 1984; Steenbergen et al. 1996; Vinjamuri et al. 2008) and will not be viewed as a constraint imposed by the task. Second, the way humans execute an exploratory task is a function of their own biomechanical constraints (McDonald et al. 1995) and motor control strategies. This means that analyzing the motion patterns of an individual during an exploratory task has the potential to reveal individualized motor control strategies and deficits (Huang and Patton 2013; Lancaster et al. 2014; Valdés et al. 2015).

Although several studies support the motor synergies hypothesis, they have used several different computational methods to provide this support by identifying underlying synergies in human motor behaviour. A range of factorization methods has been used in these studies to reconstruct the experimental data by linearly combining a small set of basis vectors or motor synergies. Tresch et al. (Tresch et al. 2006) empirically compared performance of 6 matrix factorization methods using numerically-generated and experimental data from frogs. In a recent study, Steele et al. (Steele et al. 2015) compared the performance of the factorization methods in (Tresch et al. 2006) using muscle activation data generated from a musculoskeletal software model. Building on these works, I present an empirical evaluation of the performance and robustness of three
factorization methods on human reaching motion data (muscle electromyography and joint angles). The three methods considered in this chapter are Principal Component Analysis, Non-Negative Matrix Factorization, and Independent Component Analysis. Although similar in their general approach, these factorization methods return different synergy structures, as they utilize different algorithms. Using numerical simulation, I also studied the meaning of the synergy vectors returned by each of the factorization methods. This will inform how synergy vectors can be interpreted by motor coordination researchers.

The results presented in this chapter can be used to expand our understanding of the robustness and numerical interpretation of the methods used in motor synergy research, building a common ground for understanding “healthy” motor coordination. This knowledge can in turn lead to an understanding of the effects of different motor deficits on motor synergies and the nature of motor recovery, and ultimately, to creating individualized care for physical therapy clients.

2.2 Methods

2.2.1 Research Ethics and Study Participants
Fifteen healthy adults were recruited and provided written consent to take part in this study. The average age of the participants was 24.8 ± 3.5 years. The male to female ratio was 8/7. This study was approved by UBC’s Clinical Research Ethics Board. All of the participants had normal or corrected vision to eliminate any correlation between task performance and vision in the hand-eye coordination task used in this study.

2.2.2 Experiment Setup, Data Collection and Preprocessing
The motion-controlled gameplay system developed under the FEATHERS project (Functional Engagement in Assisted Therapy through Exercise Robotics) was used in this study. This project was aimed at providing an engaging solution for physical therapy for adults post-stroke or teens with cerebral palsy by combining bilateral movements with computer games on a social media platform (Valdés et al. 2014; Shirzad et al. 2015). The system uses data read from a Microsoft Kinect® to map the user’s bilateral hand motions in the frontal plane to the motion of a cursor on the screen. Specifically, at a 30 frames per second rate, the 3D displacements of both wrists are compared at every time step to ensure that the hand motion with the least movement in the user’s frontal plane is mapped into cursor motion (i.e., the cursor does not move if only one hand is moved or if the hands are moved in opposing directions). The user then can play simple video
games using the cursor’s motion. See Appendix A for more details on the FEATHERS project. In the study presented in this chapter, the participants were instructed to keep their hands at least 10 cm apart from each other as they used the system.

Each participant took part in one data collection session in which they were asked to complete a set of tasks to gain familiarity with the FEATHERS system and a game called “Lucky Pirate” (OUAT Entertainment). This game is set on a static background (Figure 2.1) and requires players to explore the entire game screen to select and click on treasure chests that may contain gold coins. To promote engagement, the game provides visual and auditory feedback when the user opens a new treasure chest or completes a level. In addition, the user can obtain special items from the chests to extend game play. Completion of a level does not carry a time restriction; as a result, users are able to progress at their own pace. Retrieval of different items did not lead to any external rewards for the participants. At the end of the data collection, each participant was given a $10 coffee shop gift card to thank them for their time.

![Figure 2.1: Lucky Pirate game provides an environment promoting space exploration that can be translated into motor exploration when the game is played using the FEATHERS system.](image)
The game and the system are designed to provide a virtual reality based motor exploration task (Valdés et al. 2015). In order to avoid recording task-specific synergies that reflect the task’s biomechanical constraints rather than the underlying neural strategies of motor control (Rearick et al. 2003; Todorov and Ghahramani 2004; Tresch and Jarc 2009; Steele et al. 2015), participants’ reaching motions were made exploratory by removing task space constraints. This includes: 1) presenting the participant with a variety of targets rather than presenting them with a goal-directed reaching toward a specific target, and 2) asking the participant to perform freehand reaching motions in a 3D task space rather than 2D table-top reaching and/or holding on to a manipulandum. The requirement to use both hands to move the cursor on the screen is not considered a limiting physical constraint as the participants are free to choose how they want to temporally and spatially synchronize the motion of their hands. Moreover, the use of both hands at the same time does not impose any constraints in the joint and muscle spaces, letting the participants demonstrate and use separate joint/muscle space strategies (kinematic and muscle synergies) to generate the motions.

The participants were asked to sit on a 70 cm tall stool without a back-support, two meters away from a flat screen monitor (Figure 2.2). The game and the FEATHERS system and how it can be used to control the cursor on the computer screen were introduced to the participants at the beginning of the session, followed by 10 minutes of familiarization with the motion control system and the game. The familiarization ended when both the participant and the experimenter felt that the participant had a complete grasp of the system. Then, the Lucky Pirate gameplay screen was projected on the monitor and participants played the game by controlling a magnified cursor on the screen. The motion of the participant’s wrists was captured via a Kinect camera and was used by the FEATHERS software to move the cursor on the screen. Participants were instructed to keep both their hands open during gameplay and close both hands at the same time in order to click on treasure chests in Lucky Pirate.

After gaining familiarity with the task, the participants were asked to play the game for at least 5 minutes while upper-body motion data and muscle electromyography data were collected. The Microsoft Kinect motion capture system was used to collect joint kinematics data. The Kinect returns an average accuracy of 10±10mm for proximal joints and 31±11mm for distal joints with a high correlation (>0.9). The capability of the camera is deemed sufficient to capture motion of both stroke survivors and healthy participants during motions used in physical therapy and
The Kinect tracked the Cartesian location of several anatomical landmarks by assigning markers to them: centre of hip, chest at the level of the shoulders, shoulders, elbows, wrists, and hands. A 16-channel Delsys (Natick, MA, USA) EMG system recorded muscle activation from eight muscles on each side of the body: the brachioradialis, biceps brachii, triceps brachii (long and lateral heads), deltoid (anterior, medial, and posterior fibres), and pectoralis major (clavicular fibres) (Muceli et al. 2010; Gentner et al. 2013; Steele et al. 2013; Roh et al. 2015). EMG electrodes were placed in accordance with the European recommendations for surface electromyography (Hermens et al. 1999). The collected raw EMG signals were amplified and band-pass filtered (20-450 Hz) (Roh et al. 2013, 2015). Each muscle’s EMG signal was normalized to the maximum observed value of the signal. The preprocessed EMG data were then stored in two sets, the dominant and non-dominant limb, each including data from eight muscles.

To calculate joint angles (i.e., motion effectors) from marker positions, a human upper body musculoskeletal model developed by Holzbaur (Holzbaur et al. 2005) for the OpenSim environment (Delp et al. 2007) was used. OpenSim is an open-source musculoskeletal simulation platform that provides a variety of human models and motion generation simulation algorithms.
The original model only includes the right extremity. This model was modified and expanded to include both extremities and to be compatible with Kinect data. Using OpenSim software and the modified musculoskeletal model, the inverse kinematics of the marker motions were solved to find the joint angles.

Solving the inverse kinematics problem provides the change in the following joint angles over time: trunk motions as measured by roll, pitch, and yaw angles, flexion-extension of both shoulders, abduction-adduction of both shoulders, medio-lateral rotation of both shoulders, flexion-extension of both elbows, pronation-supination of both elbows, radial-ulnar deviation of both wrists, flexion-extension of both wrists (17 DOFs). Using this procedure, the joint angle time series during a motor exploration task for all 15 participants were calculated at 30 Hz. These data were then bifurcated with each set containing the joint angle time series data of the dominant and non-dominant upper limbs of each participant (ten DOFs in each set; trunk motion data was shared). Only movements within two standard deviations of the mean speed of the entire session were kept for further analysis. This was to ensure that all periods of pause or no movement were filtered out. The joint motion data were low-pass filtered at 6 Hz (Enoka 2015; Valdés et al. 2015). Synergy analysis of kinematics and EMG data was performed independently for the dominant and non-dominant limb data sets (i.e., within-arm synergies, not between-arm synergies).

2.2.3 Quantifying Synergies by Linear Decomposition of Data

Following the common formulation in the literature (Cheung et al. 2009; Bizzi and Cheung 2013; Berger and d’Avella 2014; Roh et al. 2015), a \( t \times m \) matrix \( M \) containing the time-series of change in \( m \) motion effectors (muscle EMGs or joint angles) during a functional task can be measured (\( t \) is the number of data points). A factorization method (one of PCA, NNMF, and ICA in this study) will solve for a set of \( n \) synergy vectors \( w \) (\( 1 \times m \) dimensional) arranged in an \( n \times m \) synergy structure matrix \( W \) (\( n < m \)). Each synergy vector specifies a relative mode of activation/use of the motion effectors during the task. This synergy structure is found so that the error in reconstructing the motion elements in matrix \( M \) using a linear combination of the synergy vectors, \( M = C \times W + E \), is minimized. In this linear combination of the synergy vectors \( C \) is a \( t \times n \) activation matrix and \( E \) is the unexplained variation.

Although the three factorization methods considered in this study assume that the data can be reconstructed using a linear combination of a set of basis vectors \( (M = C \times W + E) \), they employ
different assumptions and algorithms to find such basis vectors. More specifically, PCA uses singular value decomposition (SVD) to find basis vectors that best describe the variance (objective function) of the data while minimizing the covariance of the basis vectors (constraint). This can be solved analytically using SVD, which returns the eigenvectors of the covariance matrix of the data as the PCA basis vectors. This means that the largest part of the variability (mean) in the data can be reconstructed along the first basis vector (the eigenvector with the highest eigenvalue). The next vectors describe the directions that contain the highest deviation from the mean value. PCA vectors are orthogonal (eigenvectors are orthogonal), and therefore independent. As PCA utilizes second-order statistics (variance and covariance) it works best on Gaussian data sets with minimal noise and non-linearity.

Like PCA, NNMF also utilizes second-order statistics and finds vectors that best describe the variance of the data (objective function). NNMF constrains both $C$ and $W$ matrices to be non-negative and iteratively improves a set of initial guess vectors. Non-negativity of $C$ and $W$ matrices makes the optimization problem convex, ensuring that the outcomes are true global minima and not a local minimum. In a non-negative space, the basis vectors cannot be orthogonal. Nevertheless, the basis vectors are required to be independent.

ICA was developed to deal with non-Gaussianity in data and therefore utilizes higher moments of the data. ICA finds basis vectors that maximize the absolute value of the fourth moment “kurtosis” of the data. Kurtosis is a measure of tailedness of the probability distribution of a real-valued random variable (indicating non-Gaussianity of data). This will generate basis vectors that are statistically independent. ICA works particularly well to separate a multivariate signal (one sensor recording multiple sources at the same time) into independent non-Gaussian signals (source signals), an example of which is the cocktail party problem: a partygoer hears the sum of people’s voices (sources) chatting at a party and can decompose the aggregate incoming signal into what each person is saying.

2.2.4 Analysis of Factorization Performance using Healthy Motion Data

The collected data were divided into muscle and kinematic sets, each set containing separate time series data for the dominant and non-dominant hands. After preprocessing the data, a k-fold cross validation ($k = 20$) was implemented to compare the performance of the factorization algorithms. Within each fold, data were divided into 5 s epochs. Within each epoch, 80% of the data was randomly assigned to the training set and the remaining 20% was assigned to the validation set of
that fold. Within each fold, the validation data set was used to assess the performance of the dimensionality reduction methods on the training data set.

Variance Accounted For (VAF) was used to determine the number of synergy vectors ensuring factorization methods sufficiently learned the training data (Tresch et al. 2006). The number of synergy vectors is the minimum number of synergies that achieves a global (across all training data points) VAF > 90%, with less than a 5% increase in global VAF upon addition of another synergy vector. As a local criterion, the VAF for each muscle or joint (DOF VAF) must exceed 50%. This procedure ensures that the estimated number of synergies could predict both the overall data set as well as each of the DOFs of the overall data set (Ting and Chvatal 2010; Roh et al. 2013, 2015). I started this study by considering four factorization methods, PCA, NNMF, ICA, and Factor Analysis (Tresch et al. 2006). Factor Analysis did not fulfill the training requirements and therefore was eliminated from the study.

Once the synergy structure of a fold of training data was extracted, six metrics were used to quantify the performance of the factorization methods: number of identified synergies, average reconstruction error of both training and validation data sets, average correlation coefficient between the original data and the reconstructed data for both training and validation data sets, and dimension of the common subspace between the training and validation data sets (number of synergy vectors of the two data sets that have a strong correlation $r > 0.9$). To determine the first four metrics, the synergy structure of the training data was used to reconstruct both training and validation data sets. The six goodness of fit metrics considered in this study can be divided into three categories: category 1) two metrics to study the structure of the data (synergy vectors), category 2) two metrics to quantify how well identified synergies can be used to reconstruct the data (reconstruction error) and category 3) two metrics to observe correlation of the original and reconstructed data sets.

The average performance of the factorization methods over the k folds for each participant was used to statistically compare the methods. Finally, a two-way ANOVA was conducted to quantify the effect of different factorization methods (3 levels each at $n = 2$ (number of limbs) $\times$ 15 (number of participants) = 30: PCA, NNMF, ICA) and hand dominance (2 levels each at $n = 3$ (number of factorization methods) $\times$ 15 (number of participants) = 45: dominant vs non-dominant limb) on factorization performance. This model is valid if the interaction between choice of factorization method and hand dominance is statistically non-significant.
2.2.5 Comparison of Identified Synergy Vectors using Simulated Data

Three sets of randomly-generated, two-dimensional data sets (three \( M \) matrices of size \( 500 \times 2 \), containing simulated muscle activations \( m_1 \) and \( m_2 \)) were created to demonstrate the differences in how PCA, NNMF, and ICA identify synergy vectors to decompose variability in data. Two vectors \( w_1 = (0.25, 1) \) and \( w_2 = (1, 0.25) \) were used as the original basis vectors (synergies) to create the three data sets. The first set was created by randomly assigning the activation signals \( c_1 \) and \( c_2 \) from a uniform distribution between 0 and 1 (unimodal data with equal importance between the two basis vectors). The second set was created by randomly assigning the activation signals \( c_1 \) from a uniform distribution between 0 and 0.3, and \( c_2 \) from a uniform distribution between 0 and 1 (unimodal data favouring \( w_2 \)). Finally, the third set was created by combining two unimodal data sets, one favouring \( w_1 \) and one favouring \( w_2 \), to create a bimodal data set. I then applied PCA, NNMF, and ICA to each of data sets to compare the synergy structure identified by each method.

2.3 Results

2.3.1 Comparison of Synergy Structures Identified by Each Method

I used three sets of simulated two-dimensional data sets (scattered dots on each row of Figure 2.3) to demonstrate the differences in how PCA, NNMF, and ICA identify basis vectors to decompose variability in data.

Two vectors \( w_1 = (0.25, 1) \) and \( w_2 = (1, 0.25) \) were used as the original basis vectors (synergies) to create all three data sets (muscle activations \( m_1 \) and \( m_2 \)). These two vectors are shown on Figure 2.3: A, E, I with solid lines. The three data sets created were: 1) unimodal data with equal weights between the two basis vectors, Figure 2.3 A-D; 2) unimodal data favoring variance along \( w_2 \), Figure 2.3 E-H; and 3) bimodal data, Figure 2.3 I-L. See Methods section for more details.

The solid lines in Figure 2.3 B, F, J demonstrate the basis vectors identified by PCA. The numbers indicated beside each of the basis vectors indicates what percentage of the variance in the data can be reconstructed using that vector. Neither of the PCA basis vectors were similar to the original basis vectors. The first PCA basis vector aligns with the “centre” of the data and explains most of the variance in the data, and the second vector is orthogonal to the first vector.
NNMF basis vectors are illustrated in Figure 2.3 C, G, K; and ICA basis vectors are illustrated in Figure 2.3 D, H, L. NNMF basis vectors consistently identify the edges of the data set. Moreover, ICA returns basis vectors that are similar to NNMF basis vectors on unimodal data, but returns basis vectors that are similar to those of PCA on bimodal data.

Figure 2.3: A 2-D example illustrating differences between synergy structures identified using PCA, NNMF, and ICA on three different data types. Figures A-D show uniformly distributed data, E-F show skewed unimodal data, I-L show bimodal data.

2.3.2 Goodness of Fit Comparison: Kinematic Synergies

Following the analysis procedures explained in the Methods section, a k-fold cross validation with 20 folds was implemented to study how well different factorization methods can reduce the kinematic dimensionality of exploratory reaching movements on the dominant and non-dominant side of the body. For each side of the body ten DOFs were included in this analysis (three at trunk, three at shoulder, two at elbow, and two at wrist). For each participant’s dominant and non-dominant side, using the created 20 folds of training and validation data sets, I quantified the kinematic synergy structure by applying PCA, NNMF, and ICA. Then, the performance of each factorization method was determined using the introduced six goodness of fit metrics (average of
the 20 folds), on each of the two sides of the body, for each of the 15 participants, for each of the three methods. I used these data in a two-way ANOVA to quantify the effect of different factorization methods (3 levels each at \( n = 30 \): PCA, NNMF, ICA) and hand dominance (2 levels each at \( n = 45 \): dominant vs. non-dominant limb) on factorization performance. The interaction between choice of factorization method and hand dominance was statistically non-significant. Table 2.1 shows a summary of all performance metrics and how they vary between the two limbs for each factorization method.

Table 2.1: Kinematic Synergies: Comparison of different goodness of fit metrics between the two sides of the body for each factorization method.

<table>
<thead>
<tr>
<th></th>
<th>PCA</th>
<th>NNMF</th>
<th>ICA</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Identified Synergies</td>
<td>Dominant limb</td>
<td>3.4 ± 0.7</td>
<td>4.1 ± 1.1</td>
</tr>
<tr>
<td></td>
<td>Non-dominant limb</td>
<td>3.7 ± 0.6</td>
<td>4.3 ± 1.1</td>
</tr>
<tr>
<td></td>
<td>Both limbs</td>
<td>3.5 ± 0.7</td>
<td>4.2 ± 1.1</td>
</tr>
<tr>
<td>Average Reconstruction Error (Validation Data) in Degrees</td>
<td>Dominant limb</td>
<td>8.7 ± 1.5°</td>
<td>9.8 ± 1.4°</td>
</tr>
<tr>
<td></td>
<td>Non-dominant limb</td>
<td>7.8 ± 1.3°</td>
<td>9.7 ± 1.2°</td>
</tr>
<tr>
<td></td>
<td>Both limbs</td>
<td>8.2 ± 1.5°</td>
<td>9.8 ± 1.3°</td>
</tr>
<tr>
<td>Average Reconstruction Error (Training Data) in Degrees</td>
<td>Dominant limb</td>
<td>8.8 ± 1.6°</td>
<td>7.8 ± 1.9°</td>
</tr>
<tr>
<td></td>
<td>Non-dominant limb</td>
<td>7.9 ± 1.3°</td>
<td>7.3 ± 1.8°</td>
</tr>
<tr>
<td></td>
<td>Both limbs</td>
<td>8.3 ± 1.5°</td>
<td>7.6 ± 1.8°</td>
</tr>
<tr>
<td>Correlation Coefficient of Training Data</td>
<td>Dominant limb</td>
<td>0.96 ± 0.01</td>
<td>0.98 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Non-dominant limb</td>
<td>0.96 ± 0.01</td>
<td>0.97 ± 0.01</td>
</tr>
<tr>
<td></td>
<td>Both limbs</td>
<td>0.96 ± 0.01</td>
<td>0.97 ± 0.02</td>
</tr>
<tr>
<td>Correlation Coefficient of Validation Data</td>
<td>Dominant limb</td>
<td>0.96 ± 0.01</td>
<td>0.97 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Non-dominant limb</td>
<td>0.96 ± 0.01</td>
<td>0.97 ± 0.02</td>
</tr>
<tr>
<td></td>
<td>Both limbs</td>
<td>0.96 ± 0.01</td>
<td>0.97 ± 0.02</td>
</tr>
<tr>
<td>% of Common Synergies (Training and Validation Data)</td>
<td>Dominant limb</td>
<td>95 ± 6%</td>
<td>96 ± 5%</td>
</tr>
<tr>
<td></td>
<td>Non-dominant limb</td>
<td>97 ± 4%</td>
<td>95 ± 5%</td>
</tr>
<tr>
<td></td>
<td>Both limbs</td>
<td>96 ± 5%</td>
<td>95 ± 5%</td>
</tr>
<tr>
<td>Training Time (s)</td>
<td>4 ± 0.2 s</td>
<td>15 ± 6 s</td>
<td>13 ± 3 s</td>
</tr>
</tbody>
</table>
The number of synergy vectors that satisfied the training criteria differed between the dominant and non-dominant limbs. On average, more synergy vectors were required to capture the variance in the motion data from the non-dominant limb across all factorization methods, although this difference was not statistically significant ($p = 0.32$). On the other hand, choice of factorization method had a statistically significant effect on the number of identified synergies. ICA required a lower number of synergy vectors to summarize the variance in the data compared to PCA (2.8 vs. 3.5 synergy vectors, $p < 0.01$) and NNMF (2.8 vs. 4.2 synergy vectors, $p < 0.001$). The difference between PCA and NNMF was not statistically significant. Figure 2.4 shows the effects and statistical significance of choice of factorization method as well as dominance of the limb on the performance metrics.

Dominance of the limb did not have any significant effect on the average reconstruction error (reconstruction of the non-dominant limb’s data returned a slightly lower reconstruction error, $p = 0.67$ for the training data set and $p = 0.21$ for the validation data set). However, choice of factorization method had a statistically significant effect on this performance metric. In reconstructing the training data sets from synergy vectors of the training data, PCA had the lowest reconstruction error compared to both NNMF (8.2 vs. 9.8 degrees, $p < 0.01$) and ICA (8.2 vs. 13.6 degrees, $p < 0.001$). In this case, the difference between NNMF and ICA was also significant (9.8 vs 13.6 degrees, $p < 0.01$). The same relationship was observed in reconstructing the validation data sets from synergy vectors of the training data. ICA had a significantly larger reconstruction error compared to PCA (10.7 vs. 8.3 degrees, $p < 0.001$) and NNMF (10.7 vs. 7.6 degrees, $p < 0.001$). However, the difference between PCA and NNMF’s ability to reconstruct the validation data was not significant.

The effect of dominance of the limb was not significant on the correlation coefficient of the original and reconstructed data ($p = 0.89$ for training and $p = 0.49$ for validation data set). However, the choice of factorization method had a statistically significant role in determining this performance metric. On training data sets, NNMF-based reconstructed training data had a larger correlation coefficient with the original training data compared to PCA (0.97 vs. 0.96, $p < 0.001$) and ICA (0.97 vs. 0.95, $p < 0.001$). Moreover, NNMF-based reconstructed validation data had a larger correlation coefficient with the original validation data compared to PCA (0.97 vs. 0.96, $p < 0.01$).
Similar to the other performance metrics, dominance of the limb did not have a statistically significant effect on the percentage of common synergy vectors between training and validation data ($p = 0.24$), whereas the effect of choice of factorization method was significant. Although the difference between PCA and NNMF was not significant on this metric, they both returned a significantly higher percentage of common synergies between training and validation data compared to ICA (PCA and NNMF vs. ICA: 96 and 95 vs. 73%, both at $p < 0.001$).

I also considered each method’s training time (i.e., time spent to factorize the 20 folds of data for each participant) as a measure of computational efficiency of the methods. PCA returned the synergy structure significantly faster than NNMF (4 vs. 15 seconds, $p < 0.001$) and ICA (4 vs. 13 seconds, $p < 0.001$).

**Figure 2.4:** Kinematic synergies’ goodness of fit: Effects and statistical significance of choice of factorization method and limb dominance on the performance metrics. Measures showing a significant difference between the factorization methods are indicated with the following suffix: * $p <0.05$, ** $p <0.01$, and *** $p <0.001$. 
2.3.3 Goodness of Fit Comparison: Muscle Synergies

Following the analysis procedures explained in the Methods section, a k-fold cross validation with 20 folds was implemented to study how well different factorization methods can reduce the dimensionality observed in the participants’ EMG data during exploratory reaching. For each side of the body, EMGs of eight muscles were included in this analysis. For each participant’s dominant side and non-dominant side, using the 20 folds of training and validation data sets, I quantified the muscle synergy structure by applying PCA, NNMF, and ICA. Performance of each factorization method was determined using the same goodness of fit metrics as for the kinematic data: six performance metrics (average of the 20 folds), on each of the two sides of the body, for each of the 15 participants, for each of the three methods. Table 2.2 shows a summary of all the performance metrics and how they vary between the two limbs for each factorization method.

I used these data in a two-way ANOVA to quantify the effect of different factorization methods (3 levels each at \( n = 30 \): PCA, NNMF, ICA) and hand dominance (2 levels each at \( n = 45 \): dominant vs. non-dominant limb) on factorization performance. The interaction between choice of factorization method and hand dominance was statistically non-significant.

On average, more synergy vectors were required to capture the variance in the data from the non-dominant limb, across all factorization methods. However, this difference was not statistically significant (\( p = 0.39 \)). On the other hand, choice of factorization method had a statistically significant effect on the number of identified synergies. ICA required a higher number of synergy vectors to summarize the variance in the data compared to PCA (5.4 vs. 3.4 synergy vectors, \( p < 0.001 \)) and NNMF (5.4 vs. 3.6 synergy vectors, \( p < 0.001 \)). The difference between PCA and NNMF was not statistically significant. Figure 2.5 shows the effects and statistical significance of choice of factorization method as well as dominance of the limb on the performance metrics.

Reconstruction of the non-dominant limb’s data returned a slightly lower error, however this difference was not statistically significant (\( p = 0.36 \) for training and \( p = 0.43 \) for validation data sets). On the other hand, choice of factorization method had a statistically significant effect on this performance metric. The three methods did not show any statistically significant differences in reconstructing the training data sets from the identified synergy vectors. However, ICA had significantly lower reconstruction error compared to PCA (2.0 vs. 2.9%, \( p < 0.01 \)) and NNMF...
(2.0 vs. 2.8%, \( p < 0.01 \)) in reconstructing the validation data sets. The difference between PCA and NNMF in their ability to reconstruct the validation data was not significant.

The effect of dominance of the limb was not significant on the correlation coefficient of the original and reconstructed data (\( p = 0.62 \) for both training and validation sets). However, the choice of factorization method was statistically significant (validation set only). ICA-based reconstructed validation data had a larger correlation coefficient with the original validation data compared to PCA (0.92 vs. 0.89, \( p < 0.01 \)) and NNMF (0.92 vs. 0.90, \( p < 0.05 \)).

| Table 2.2: Muscle Synergies: Comparison of different goodness of fit metrics between the two sides of the body for each factorization method. |
|---------------------------------|-----------------|-----------------|-----------------|
|                                | PCA             | NNMF            | ICA             |
| # of Identified Synergies       |                 |                 |                 |
| Dominant limb                  | 3.2 ± 0.9       | 3.5 ± 1.3       | 5.4 ± 1.1       |
| Non-dominant limb              | 3.5 ± 0.9       | 3.7 ± 1.0       | 5.5 ± 1.2       |
| Both limbs                     | 3.4 ± 0.9       | 3.6 ± 1.1       | 5.4 ± 1.1       |
| Average Reconstruction Error (Training Data) |                |                 |                 |
| Dominant limb                  | 3.0 ± 0.9 %     | 2.9 ± 1.0 %     | 2.7 ± 1.0 %     |
| Non-dominant limb              | 2.8 ± 0.8 %     | 2.7 ± 0.9 %     | 2.4 ± 1.1 %     |
| Both limbs                     | 2.9 ± 0.8 %     | 2.8 ± 0.9 %     | 2.5 ± 1.0 %     |
| Average Reconstruction Error (Validation Data) |                |                 |                 |
| Dominant limb                  | 3.0 ± 0.9 %     | 2.9 ± 1.0 %     | 2.0 ± 1.0 %     |
| Non-dominant limb              | 2.8 ± 0.8 %     | 2.7 ± 0.9 %     | 1.9 ± 1.0 %     |
| Both limbs                     | 2.9 ± 0.8 %     | 2.8 ± 0.9 %     | 2.0 ± 1.0 %     |
| Correlation Coefficient of Training Data |                |                 |                 |
| Dominant limb                  | 0.89 ± 0.03     | 0.90 ± 0.02     | 0.89 ± 0.01     |
| Non-dominant limb              | 0.88 ± 0.05     | 0.90 ± 0.01     | 0.89 ± 0.01     |
| Both limbs                     | 0.89 ± 0.04     | 0.90 ± 0.02     | 0.89 ± 0.01     |
| Correlation Coefficient of Validation Data |                |                 |                 |
| Dominant limb                  | 0.89 ± 0.03     | 0.90 ± 0.03     | 0.92 ± 0.04     |
| Non-dominant limb              | 0.89 ± 0.04     | 0.90 ± 0.02     | 0.92 ± 0.04     |
| Both limbs                     | 0.89 ± 0.04     | 0.90 ± 0.02     | 0.92 ± 0.04     |
| % of Common Synergies (Training and Validation Data) |                |                 |                 |
| Dominant limb                  | 94 ± 6 %        | 95 ± 5 %        | 50 ± 9 %        |
| Non-dominant limb              | 94 ± 7 %        | 95 ± 6 %        | 58 ± 11 %       |
| Both limbs                     | 94 ± 6 %        | 95 ± 5 %        | 54 ± 11 %       |
| Training Time (s)              | 5 ± 1           | 33 ± 17         | 40 ± 20         |
Figure 2.5: Muscle synergies’ goodness of fit: Effects and statistical significance of choice of factorization method and limb dominance on the performance metrics. Measures showing a significant difference between the factorization methods are indicated with the following suffix: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Similar to the other performance metrics, dominance of the limb did not have a statistically significant effect on the percentage of common synergy vectors between training and validation data ($p = 0.14$), whereas the effect of choice of factorization method was significant. Although the difference between PCA and NNMF was not significant on this metric, they both returned a significantly higher percentage of common synergies between training and validation data compared to ICA (PCA and NNMF vs. ICA: 94 and 95 vs. 54%, both at $p < 0.001$).

Considering each method’s training time (i.e., time spent to factorize the 20 folds of data for each participant) as a measure of computational efficiency, PCA significantly outperformed NNMF (5 vs. 33 seconds, $p < 0.001$) and ICA (5 vs. 40 seconds, $p < 0.001$).
2.4 Discussion

2.4.1 Factorization Performance

Considering the kinematic synergies, hand dominance had no significant effect on the factorization performance. On average, ICA identified the lowest number of synergy vectors, followed by PCA and NNMF. Despite the compactness of ICA’s factorization, this method had the statistically significant largest reconstruction error. The difference between PCA and NNMF’s reconstruction errors was also statistically significant. All three algorithms returned a strong correlation coefficient between the original data and the reconstructed data for both training and validation data sets ($r > 0.95$). ICA had the statistically significant lowest dimension of common subspace between the training and validation data sets compared to PCA and NNMF. ICA had the worst factorization performance compared to PCA and NNMF. Although PCA and NNMF had comparable performance on goodness of fit measures, PCA had a statistically significant lower dimension of common subspace between the training and validation data sets (93.8%, 95.2%, and 54.0% for PCA, NNMF, & ICA. No statistical difference between PCA & NNMF). This means that ICA failed to identify the same synergy structure between the training and validation data sets, making it an unreliable factorization method. Similar to joint motion results, PCA had a statistically significant lower training time (4 s) compared to NNMF (13 s).

Considering the muscle synergies, hand dominance had no significant effect on the factorization performance. On average, PCA factorized the data with the lowest number of synergy vectors, followed by NNMF and ICA. There was no statistically significant difference between the three algorithms on reconstruction error of training and validation data sets. Similarly, there was no statistically significant difference between the three algorithms on correlation coefficient between the original training data and the reconstructed training data. ICA had a statistically significant better correlation coefficient between the original and the reconstructed validation data set compared to PCA and NNMF. However, PCA and NNMF significantly outperformed ICA in returning a higher value for the dimension of common subspace between the training and validation data sets (93.8%, 95.2%, and 54.0% for PCA, NNMF, & ICA. No statistical difference between PCA & NNMF). This means that ICA failed to identify the same synergy structure between the training and validation data sets, making it an unreliable factorization method. Similar to joint motion results, PCA had a statistically significant lower training time (5 s) compared to NNMF (33 s) and ICA (40 s) on the EMG data.

To compare these results with similar studies, consider Tresch et al. (Tresch et al. 2006) and Steele et al. (Steele et al. 2015), who empirically compared performance of six matrix factorization methods on simulated and animal EMG data: NNMF, PCA, Factor Analysis (FA), and different ICA algorithms. Although FA showed a relatively high performance in (Tresch et
al. 2006), it could not pass the training requirement of producing a factorization with a minimum VAF for each muscle or joint (DOF VAF) of 50%. This local criterion ensures that the identified synergies can predict both the overall data set as well as each of the DOFs of the overall data set. However, it was not included in (Tresch et al. 2006) as a training requirement. The reported performance of PCA, NNMF, and ICA on kinematic and EMG data from healthy participants is comparable to the performance of these methods as reported in (Tresch et al. 2006) and (Steele et al. 2015) on simulated and animal EMG data.

2.4.2 Goodness of Fit Metrics
The six goodness of fit metrics considered in this study can be divided into three categories: category 1) two metrics concerned the structure of the data (synergy vectors), category 2) two metrics concerned how well identified synergies can be used to reconstruct the data (reconstruction error) and category 3) two metrics concerned correlation of the original and reconstructed data sets. Of the two metrics of structure (category 1), “number of identified synergy vectors” provides an estimate of how well the factorization method can condense the data. From a numerical point of view, this is an important measure when the data size is big. However, in this study the focus is on functional synergies and interpretation of 3 vs 4 synergy vectors does not add any additional challenge. On the other hand, in the same category, “percentage of common synergy vectors between training and validation data sets” provides a much richer estimate of how well a factorization method can identify the underlying structure of the data (coordination of joints or muscles in this study).

It is beneficial to reflect on the meaning of statistical significance and whether statistical significance can be interpreted as a tangible difference. Accordingly, the statistically significant differences observed between the values of the category-3 metrics across the factorization methods need to be interpreted cautiously. Although statistical significance was observed, all three of the factorization methods produced reconstructed data sets that strongly correlated with the original data sets (strong correlation is considered $r > 0.7$, compared with the worst case in this study, $r = 0.88$, for PCA on EMG data). This makes the correlation coefficient metric a weak candidate for quantifying goodness of fit of the considered factorization methods.

2.4.3 Differences between the Mathematical Principles of the Factorization Models
Understanding the mathematical principles that are used in matrix factorization methods (see Methods for an overview) can assist in explaining the inferior performance of ICA compared to
PCA and NNMF. As observed in Figure 2.3, neither of the PCA basis vectors look like the original basis vectors used to create the data sets. The first PCA basis vector aligns with the “centre” of the data and explains most of the variance in the data (87-98%) depending on how wide/divergent from the centre (Figure 2.3 B and J) or thin (Figure 2.3 F) the data set is. The second PCA vector is orthogonal to the first one and explains a much lower variance in the data. The VAF of the second vector can be considered a measure of scatteredness. PCA basis vectors, resembling performance of a multiple regression line, capture the mean and (residual) variance from the mean. This means some data points might have a negative activation $c$ along the second basis vector, making interpretation of activation matrix $C$ in functional tasks hard (e.g., a muscle can be negatively activated).

NNMF identifies vectors that describe a subspace within which all data points will lie. The non-negativity constraint dictates that only the points between the identified vectors can be reconstructed. So, NNMF basis vectors identify the edges of the data set. This means that the importance of the original basis vectors and uni/bimodality of the data do not play a role in identifying the basis vectors, whereas PCA basis vectors change based on the importance of the original basis vectors as this changes the major direction of the data (i.e., mean). NNMF’s non-negativity condition for activation of basis vectors is a useful attribute in identifying physiologically meaningful synergies as it prevents outputs containing negative activation of the muscles. In summary, researchers utilizing motor synergies need to be cognizant of the differences in the nature of the basis vectors returned by PCA and NNMF and interpret them accordingly. This means, one cannot compare the synergy structures of a PCA-based and an NNMF-based study.

Considering the results presented in Figure 2.3, ICA performs well on unimodal data sets and similar to NNMF, it can identify the original basis vectors that define the edges of the data. However, NNMF can identify the importance of the vectors better than ICA. Data in Figure 2.3 E-H (black dots) were created by randomly assigning the activation signals $c_1$ from a uniform distribution between 0 and 0.3, and $c_2$ from a uniform distribution between 0 and 1 (unimodal data favoring $w_2$ over $w_1$ with a 3.3 to 1 ratio). The VAF ratio between NNMF basis vectors is 75% to 25%, closer to the weighting of the original basis vectors, compared to ICA’s 67% to 33%. Moreover, on the bimodal data set, ICA identifies basis vectors that are similar to those found by PCA, describing mean and variance from the mean. This shift from describing the edge
of the data to the major direction of the data can cause confusion in interpreting the results of the decomposition if the nature of the data is unknown.

It is worthwhile to repeat that ICA was developed for decomposition of non-Gaussian data, specifically data with a flat distribution (as opposed to a bell curve). On the other hand, PCA and NNMF use second-order statistics (mean and variance, both Gaussian features) to decompose data. Joint motion and EMG data have a low level of non-Gaussianity and have a skewed bell curve distribution. As an example, consider the involvement of elbow extension-flexion in a task. Only a portion of the elbow extension-flexion range of motion (ROM) is used to do a specific task and moving away from that zone of the ROM makes completion of the task hard, thus reducing the chances of the elbow being moved to those zones. Naturally, on the relatively Gaussian joint motion and EMG data presented in this study, PCA and NNMF outperform ICA. Also, PCA is a faster method as it returns an analytic solution whereas NNMF and ICA find the basis vectors numerically and through iterations. However, NNMF can identify non-negative synergy vectors and activation signals, making interpretation of the synergy structure easier and physiologically more meaningful, and ultimately, making NNMF a preferable method to PCA.

2.4.4 Interpretation of the Synergy Vectors: Example from One Participant

To provide an example of synergy vectors, I used NNMF to extract kinematic (Figure 2.6) and muscle (Figure 2.7) synergies from motion data of participant Y20 (healthy female, right handed, 27 years old). These two figures show the kinematic and muscle synergy vectors for both dominant and non-dominant limbs of this participant, extracted with the training criteria introduced previously. Each synergy vector shows how different degrees of freedom (joints or muscles) are activated relative to the other DOFs. The three synergy vectors presented in Figure 2.6 sufficed to return a VAF value over 98% for the kinematic data. The number of muscle synergies that fulfilled the training criteria was four.

Within kinematic and EMG data sets, synergy vectors of the two limbs were matched based on their similarity as measured by the dot product of the synergy vectors of the two limbs. Interestingly, the synergy structure of the dominant and non-dominant limbs are similar for this participant (dot products of the synergy vectors are greater or equal to 0.95, very close to being parallel).
Figure 2.6: Kinematic synergies of the dominant and non-dominant limbs of participant Y20.

Figure 2.7: Muscle synergies of the dominant and non-dominant limbs of participant Y20.
The bimanual task required similar motions in the task space (i.e., moving the two hands toward the same target without requiring the participant to match the motion generation (EMG) and the joint space variations between the two limbs). However, as shown by the similarity of the synergy vectors, the synergies controlled by the CNS to create the spatially and temporally unsynchronized motions of the two limbs in the task space are similar. This suggests that the CNS uses the same control strategy to coordinate the motion of the two limbs. Chapter 4 presents a study to explore whether within limb synergies are similar across all healthy participants. That study also investigates whether or not healthy adults utilize the same synergy set to generate reaching motions (between-participants similarities).

### 2.5 Conclusion

Systematic comparisons of factorization methods for motor synergy identification were previously done using numerically-generated and experimental data from frogs (Tresch et al. 2006) and simulated data from a musculoskeletal model (Steele et al. 2015). This chapter presented a comparison of three factorization methods on identifying kinematic and muscle synergies in human data. PCA and NNMF had a comparable performance on both EMG and joint motion data, and both outperformed ICA. However, NNMF’s non-negativity condition for activation of basis vectors leads to identifying physiologically meaningful synergies, making it a more appealing method for future studies. Through a simple 2D example, I demonstrated the nature of the synergy vectors identified by each of the three methods, highlighting that PCA vectors describe the major direction of the data (mean and standard deviation) and NNMF vectors describe the edges of the data. This difference needs to be considered in interpreting the functional meaning of the synergy vectors.

The results presented here can be used to unify the methods in motor synergy research, building common ground for understanding motor synergies. An understanding of the factorization algorithms provides researchers with a means to select the most robust algorithm to characterize the synergies observed during a functional task performed by healthy participants. This will define a “healthy” profile of motor synergies employed during arm motions (Chapter 4 of this thesis). These healthy synergies can be used to study how neural injuries, for example stroke, can change motor synergies (Chapter 5 of this thesis). This knowledge can be used in quantifying motor deficits and designing individualized care for physical therapy clients.
3 Data Sample Size Needed for Analysis of Kinematic and Muscle Synergies in Healthy and Stroke Populations

In the past decade, multiple studies have focused on the idea that the central nervous system (CNS) controls human motions using a set of modules to synergistically activate groups of muscles to control joints. However, the synergies reported by these studies are task-dependent and might not reflect the true motion control strategies adopted by the CNS. Studying exploratory motions has the potential to reveal biomechanical constraints and motor control strategies in healthy and clinical populations. A logical prerequisite to considering exploratory motions in the study of motor synergies is to determine how much data is required to reliably and fully profile the motion patterns of an individual. This chapter presents how the quality of motor synergies analysis depends on the amount of exploratory motion data included in the analysis.

I recruited 10 healthy and 10 post-stroke survivors and collected electromyography and joint motion data from each of their limbs as they completed a motor exploration task. The main outcome was a comparison of the effects of clinical status (healthy vs. stroke) and limb strength/dominance on the amount of data required to identify synergies. Considering electromyography data, clinical status had a significant effect on the required amount of data. For kinematic data, both clinical status and limb strength had a significant effect. Based on the results of this study, I determined the upper bound of the 95% confidence interval to set the minimum amount of data required for characterizing synergies in healthy and stroke populations: 235 sec for electromyography data and 265 sec for kinematic data. These results provide an important step toward using motor exploration in the study of motor synergies to understand healthy motor coordination and how stroke alters it.

3.1 Introduction

The control of upper-body reaching motions is a complex task for the central nervous system, as the dynamic relationships between activation of muscles, joint torques, and joint motions are
non-linear and time-dependent. The redundancy in the human musculoskeletal system also adds to the complexity of this task. An extensive set of experimental evidence suggests that the CNS coordinates the muscular and kinematic elements of motion using modular control of muscle activations or joint motions (Soechting and Flanders 1997; Braido and Zhang 2004; Torres-Oviedo and Ting 2010; Vinjamuri et al. 2014; Azaripasand et al. 2015; Hagio et al. 2015; Tagliabue et al. 2015). Motor synergies (i.e., muscle or kinematic synergies) are the underlying concept of the suggested modular control of motions.

Study of motor synergies in the stroke-survivor population can provide additional insights to complement clinical assessments such as the Fugl-Meyer and Wolf Motor Function. The recovery of upper-limb function following stroke is characterized by the emergence of abnormal movement coordination and patterns. These patterns can be quantified as altered motor synergies. Clinical assessments used by therapists are focused on the ability to perform different activities (i.e., functional assessments). However, analysis of motor synergies can offer an insight into what is causing the inability to complete functional tasks. Motor synergy characterization can complement functional assessments and provide an opportunity to formulate individualized exercises that focus on the roots of the motor impairment of each patient (d’Avella et al. 2015).

A main critique of motor synergies studies is that the synergies they report are task-specific and might be reflecting the biomechanical constraints of the task rather than the underlying neural strategies of motor control (Rearick et al. 2003; Todorov and Ghahramani 2004; Tresch and Jarc 2009; Steele et al. 2015). The previous chapter proposed a setup to quantify motor synergies demonstrated during exploratory motor tasks instead of goal-directed motor tasks with physical constraints (Lambert-Shirzad and Van der Loos 2017a). The way humans execute an exploratory task is a function of their own biomechanical constraints (McDonald et al. 1995) and motor control strategies. Therefore, analyzing the motion patterns of an individual during an exploratory task has the potential to reveal individualized motion tendencies or motor deficits (Huang and Patton 2013; Lancaster et al. 2014; Valdés et al. 2015).

An important initial step to use exploratory motions for motor synergy analysis is to systematically determine the duration of data required to fully capture the motion patterns of an individual. It is possible that each person may require a different amount of data to be fully profiled. In this chapter I explore whether a fairly consistent amount of data can reliably quantify motor synergies of any person. I will also present the effects of clinical status (stroke vs.
healthy), type of data (muscle activation vs. joint motion), and limb strength (limb dominance for the healthy population, stroke-affected vs. less-affected limb for the clinical population) on the required data sample size. The results can be used to ensure enough data is collected to reliably extract motor synergies for different individuals.

3.2 Methods

3.2.1 Research Ethics and Study Participants

This study was approved by University of British Columbia's Clinical Research Ethics Board. Ten healthy adults and ten stroke survivors were recruited and provided written consent to take part in this study.\(^1\)

The average age was 24.3 years for the healthy participants and 60.5 years for the stroke survivors, with a standard deviation of 3.3 and 9.9 years, respectively. The male to female ratio was 7/3 for both participant groups. All stroke-survivor participants had a moderate impairment as measured by the upper-extremity portion of the Fugl-Meyer (FM) scale: range of scores between 21 to 50 is considered as moderate impairment (Kwakkel et al. 2004). Participants in the stroke-survivor group had an average score of 37.2 with a standard deviation of 9.5.

3.2.2 Experimental Setup and Study Protocol

This study employed the same experimental setup as the one presented in the previous chapter. I used a system that utilizes skeleton data read from a Microsoft Kinect® to map the user’s bilateral hand motions to the motion of a cursor on a computer screen. In order to control the cursor’s motion, the user was required to move both hands at the same time in the same direction. The participant then played a simple video game using cursor motion.

After providing consent to participate in the study, each participant took part in one data collection session. After becoming familiar with the system and controlling the computer cursor with their hand motions, participants were introduced to the game called “Lucky Pirate” (OUAT Entertainment). This game provides a virtual reality based motor exploration task (Valdés et al. 2015) set on a static background and requires players to explore the entire game screen to select

\(^1\) 10 participants from the 15 healthy participants included in the study presented in the previous chapter were randomly selected and the data collected from them for the previous study was used in this study.
and click on treasure chests that may contain gold coins or other treasures. Completion of a level in the game does not carry a time restriction and as a result, participants were able to progress at their own pace.

The participants were asked to play the game for five periods, with each period covering three minutes of gameplay. During each gameplay period, joint motion data and EMG data were collected. I used a Microsoft Kinect to record joint angles of the following upper limb joints: shoulders (6 DOF), elbows (4 DOF), wrists (4 DOF), and trunk rotations (3 DOF). A 16-channel Delsys EMG system was used to record muscle activation from 8 muscles on each side of the body: the brachioradialis, biceps brachii, triceps brachii (long and lateral heads), deltoid (anterior, medial, and posterior fibers), and pectoralis major (clavicular fibres) (Muceli et al. 2010; Gentner et al. 2013; Steele et al. 2013; Roh et al. 2015). EMG electrodes were placed in accordance with the European recommendations for surface electromyography (Hermens et al. 1999).

3.2.3 Data Preprocessing

Before extracting muscle synergies, the EMG signals were amplified (×1000) and band-pass filtered (20-450 Hz) (Roh et al. 2013, 2015). Each muscle’s EMG signals were normalized to the maximum observed value of the signal. The preprocessed EMG data for each participant were then stored in two files, the dominant and non-dominant limb for healthy participants and the stroke-affected and less-affected limbs for the stroke-survivors, each including data from eight muscles.

The Microsoft Kinect motion capture system was used to collect joint kinematics data (Choppin and Wheat 2013; Webster and Celik 2014). The Kinect tracked the Cartesian locations of several anatomical landmarks by assigning markers to them: centre of hip, chest at the level of shoulders, shoulders, elbows, wrists, and hands (i.e., centre of palms). To calculate joint angles from marker positions, a human upper-body musculoskeletal model developed by Holzbaur (Holzbaur et al. 2005) for the OpenSim environment (Delp et al. 2007) was used. The original model only includes the right extremity and was modified and expanded to include both extremities and to be compatible with Kinect data. Using OpenSim software and the modified musculoskeletal model, the inverse kinematics of the marker motions were solved to find the change in the following joint angles over time: trunk motions as measured by roll, pitch, and yaw angles, flexion-extension of both shoulders, abduction-adduction of both shoulders, medio-lateral rotation of
both shoulders, flexion-extension of both elbows, pronation-supination of both elbows, radial-ulnar deviation of both wrists, flexion-extension of both wrists (17 DOFs).

Using this procedure, the joint angle time series during a motor exploration task for all participants were calculated at 30 Hz. These data were then bifurcated with each set containing the joint angle time series data of the dominant/non-dominant or affected/less-affected upper limbs of each participant (ten DOFs in each set; trunk motion data was shared). Only movements within two standard deviations of the mean speed of the entire session were kept for further analysis. This was to ensure that all periods of pause or no movement were filtered out. The joint motion data were low-pass filtered at 6 Hz (Enoka 2015; Valdés et al. 2015) to remove motion artefacts.

3.2.4 Quantifying Motor Synergies

Synergy analysis of kinematics and EMG data was performed independently for each limb (i.e., within arm synergies, not between arm synergies). Following the common formulation in the literature (Cheung et al. 2009; Bizzi and Cheung 2013; Berger and d’Avella 2014; Roh et al. 2015), a $t \times m$ matrix $M$ containing the time-series of change in $m$ motion effectors (muscle EMGs or joint angles) was formed ($t$ is the number of data points). Non-Negative Matrix Factorization (NNMF) was used to solve for a set of $n$ synergy vectors $w$ ($1 \times m$ dimensional) arranged in an $n \times m$ synergy structure matrix $W$ ($n<m$). This synergy structure is found so that the error in reconstructing the motion elements in matrix $M$ using a linear combination of the synergy vectors is minimized. This linear combination of the synergy vectors is expressed as $M = C \times W + E$, where $C$ is a $t \times n$ activation matrix and $E$ is the unexplained variation.

The collected data were divided into muscle and kinematic sets, each set containing separate time series data for the two limbs. Variance Accounted For (VAF) was used to determine the number of synergy vectors ensuring sufficient factorization of the data by NNMF method (Lambert-Shirzad and Van der Loos 2017a). The number of synergy vectors is the minimum number of synergies that achieves a global (across all training data points) VAF $> 90\%$, with less than a 5% increase in global VAF upon addition of another synergy vector. As a local criterion, the VAF for each muscle or joint (DOF VAF) is required to exceed 50%. This procedure ensures that the estimated number of synergies can predict both the overall data set as well as each of the DOFs of the overall data set.
3.2.5 Data Analysis

The collected data were divided into muscle and kinematic sets, each set containing separate time series data for the strong and weak limbs (dominant and non-dominant for healthy participants, stroke-affected and less-affected for stroke-survivors). To obtain a view of how movement patterns changed throughout motor exploration practice, I quantified motor synergies of movement data cumulated over time. To this end, participants’ motor exploration datasets were divided into 5 sec epochs. Starting with considering one epoch and then adding one more epoch in each step, I studied how adding more data changes the quantified synergies.

In each step $x$ epochs were chosen randomly ($x$ changes between 1 to the maximum number of available epochs for each participant). Then 50% of the data within each epoch was chosen randomly and assigned into a training set and the other 50% was put into a validation set. This was followed by combining all $x$ of the training and validation sets into one aggregated training set and one validation set. I extracted the synergy vectors of the aggregated training and validation sets. Dot product value was used as a measure to quantify how parallel the two sets of vectors were. Therefore, the dot product is a way to calculate the similarity in the synergy structure by identifying the shared (i.e., parallel) vectors of the two data sets (Torres-Oviedo and Ting 2010). I matched the synergy vectors of the training and validation sets to find the combination that produces the highest total sum of dot products. The total sum of dot products divided by the number of identified synergies in the training set was used as a metric to calculate the similarity between the identified synergy vectors of the training and validation data sets. A value of 1 for this measure signifies a perfect match between training and validation data sets and lower values mean a worse match between the two data sets. This procedure was repeated 45 times for each $x$ (a 45-fold resampling). The mean of the similarity scores generated for the 45 repetitions was used as a measure for the quality of synergy characterization.

These calculations were done for all participants (strong and weak limbs were considered separately; the participants were grouped by their clinical status). By adding more epochs to the analysis, the quality of synergy characterization should progressively get closer to one. Figure 3.1 shows how quality of synergy characterization changed as more epochs were included for the EMG data of the strong limb of stroke participant #8 (blue dots). This indicates that the synergy vectors of the training sets and the validation sets become more and more parallel and thus, similar. I define the time to characterization (i.e., the amount of data needed to fully capture
the motion patterns of an individual) as the time in which the quality of synergy characterization plateaus.

To determine the time to characterization, a function as in Equation 3.1 was fitted to the quality of synergy characterization data needed for each case:

\[ y = a \times e^{x/b} - c / x + d \]  

(Equation 3.1)

In Equation 3.1, \( y \) is the quality of synergy characterization and \( x \) is the epoch number. As the number of epochs \( x \) increases, \( y \) approaches the asymptote value \( d \). I consider the time (number of epochs included multiplied by 5 sec) to reach 95% of the asymptote value as the time to characterization.

![Figure 3.1: Quality of synergy characterization changes as more epochs are included in the analysis. Blue dots show the calculated quality measure for the strong limb’s EMG data of stroke participant #8. The red line is the curve fitted to the blue dots. Each epoch includes 5 sec of data.](image)

With this procedure, I calculated the time to characterization for the two limbs of each participant in the two population groups. This was done separately for the kinematic and EMG datasets. For each of these data sets, I compared the time to characterization between the two limbs and the two populations using a 2×2 Analysis of Variance, with population (2 levels) and limb strength (2 levels) as factors. Differences with a probability of less than 0.05 (adjusted with Bonferroni's correction for multiple comparisons) were considered significant.

### 3.3 Results

#### 3.3.1 Quality of Synergy Characterization Increases as More Data Are Included

For each participant's motor exploration datasets, I quantified how characterization of motor synergies evolved over cumulative epochs. This was done using a 45-fold resampling technique
to generate training and validation datasets to study the effects of arm strength and clinical status on the amount of data required to reliably profile an individual’s kinematic and muscle synergies.

Increasing the amount of data included in motor synergy analysis gradually increased the quality of synergy characterization. Figure 3.2 shows this general trend for all participants (lines on the graphs) divided by the data type (EMG on top row and kinematic data on the bottom), and clinical status and arm strength (columns). This trend indicates synergy vectors extracted from the training and validation datasets became more similar with the addition of more data, suggesting a more reliable synergy extraction.

![Figure 3.2: Increasing the amount of data included in motor synergy analysis gradually increased the quality of synergy characterization. This trend is shown for all 10 participants (lines on the graphs) divided by the data type (EMG on top row and kinematic data on the bottom), and clinical status and arm strength (columns).](image)

### 3.3.2 Amount of Data Required for Reliable Extraction of Motor Synergies

This trend in the quality of synergy characterization was used to calculate the time to characterization for each of the four conditions (columns of Figure 3.2) on the two datasets (rows of Figure 3.2). For each data type I performed a repeated–measures 2×2 ANOVA (arm strength and clinical status as the two factors, each having two levels at \( n = 10 \)). There was no statistically significant interaction between arm strength and clinical status. Table 3.1 and Table 3.2 show a summary of how the time to characterization varies between the mentioned conditions.
On average, more data was required to characterize both muscle and kinematic synergies of the stroke survivors compared to healthy adults. However, the strength of the limb (hand dominance for healthy adults and side less affected by stroke for the clinical group) had different effects on the time to characterization depending on data type.

Table 3.1: Time to Characterization of Muscle Synergies in Number of Epochs. Each Epoch Includes 5 sec of EMG Data.

<table>
<thead>
<tr>
<th>EMG Data</th>
<th>Healthy Adults</th>
<th>Stroke Survivors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong Arm</td>
<td>40.5 ± 6.6</td>
<td>47.5 ± 8.3</td>
</tr>
<tr>
<td>Weak Arm</td>
<td>40.8 ± 8.1</td>
<td>45.2 ± 9.8</td>
</tr>
</tbody>
</table>

Table 3.2: Time to Characterization of Kinematic Synergies in Number of Epochs. Each Epoch Includes 5 sec of Joint Motion Data.

<table>
<thead>
<tr>
<th>Joint Motion Data</th>
<th>Healthy Adults</th>
<th>Stroke Survivors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong Arm</td>
<td>35.3 ± 8.2</td>
<td>42.8 ± 9.3</td>
</tr>
<tr>
<td>Weak Arm</td>
<td>41.3 ± 4.6</td>
<td>48.2 ± 7.41</td>
</tr>
</tbody>
</table>

Considering muscle synergies, clinical status of the individuals had a statistically significant effect on the time to characterization (healthy adults 40.6 epochs and stroke survivors 46.3 epochs, \( p < 0.05 \)). Arm strength did not have a significant effect on time to characterization.

Both arm strength and clinical status had a statistically significant effect on time to characterization of kinematic synergies. Significantly more epochs (\( p < 0.01 \)) were required to reliably quantify kinematic synergies of the stroke survivors (45.5 epochs) compared to the healthy adults (38.3 epochs). Similarly, significantly more epochs (\( p < 0.05 \)) were required to quantify the kinematic synergies of the weak arm (44.8 epochs) compared to the strong arm (39.0 epochs) of the participants.

Based on the samples analysed in this study, 95% confidence intervals (CI) of time-to-synergy characterization were built. The upper bound of these CIs can be treated as the minimum amount of data required to reliably quantify motor synergies. The upper bound of the time-to-characterization CIs for the stroke survivors was higher than for the healthy participants for both muscle synergies (52.8 vs. 46.1 epochs) and kinematic synergies (53.1 vs. 47.6 epochs).
3.4 Discussion

In order to use motor exploration in the study of motor synergies, it is necessary to determine the amount of data required to fully capture the motion patterns of healthy and stroke-survivor individuals. In this study I used a statistical approach to build a model of how the outcome of motor synergy analysis becomes more complete and reliable as more motor exploration data are included in the analysis.

There was no significant effect observed when time-to-characterization of muscle synergies was compared between the two limbs. However, the difference was significant between the two limbs when considering kinematic synergies. Moreover, the results illustrate that more data are required to quantify both muscle and kinematic synergies of the stroke population compared to healthy adults. Post-stroke motor deficits cause changes in patterns of movement, making them generally more spastic and slower. It is possible that this changes the quality and richness of the electromyography and joint motion data that were collected during the study from the stroke-survivors. It would be interesting to study if a stroke-survivor’s Fugl-Meyer score is correlated with the calculated time to characterization. In that case, the difference between time to characterization between the healthy and clinical population can be used as a way to track the improvement of the stroke survivors as they complete their physical therapy regimens.

To answer how much data are required to fully capture the motion patterns of an individual for motor synergy analysis, 95% confidence intervals (CI) of time-to-synergy characterization were calculated. The upper bound of the CI for the stroke survivors was 53 epochs, and 47 epochs for the healthy adults. This means that to study post-stroke muscle or kinematic synergies, at least $53 \times 5 = 265$ sec of “active” motor exploration data are required to be able to reliably profile a stroke-survivor’s motion patterns. This number is $47 \times 5 = 235$ sec for healthy adult participants. Here preprocessed data (see Section 3.2.3 Data Preprocessing) is considered as active motor exploration data.

This study is the only one that has considered the relationship between the quality of motor synergy analysis and the size of data included in the analysis. The common practice in the field of motor synergies is to collect data during multiple repetitions of a simple task like reaching between two specific points or walking on a treadmill. As these tasks are cyclic or biomechanically constrained, the motion data are highly repeatable for each individual. Therefore, a reliable and complete motion dataset can be collected by simply sampling from
multiple trials of the task. However, in an exploratory reaching motion task, by removing the biomechanical constraints imposed by reaching between two points, the collected data will not be repeatable from one trial to another. This makes it a necessity to determine how much data should be collected to identify motor synergies from exploratory motions. The methods presented in this chapter are closely related to those used by Wright et al. in (Wright et al. 2014) to study how much table-top exploratory reaching motion data is required to study movement (position, velocity, acceleration) distributions in healthy and stroke populations. In their study, exploration was considered complete after the participants’ hand had traveled 25 meters. Unlike the results presented in this chapter, Wright reports a shorter time to characterization for the stroke population. However, they showed that stroke survivors completed the 25 meters of the exploration task faster and that time to characterization was confounded by the amount of data available. In this study, this confounding effect was alleviated by marking the end of an exploration trial based on the duration of exploratory motion (5 episodes of 3 minutes of exploration) rather than the length covered during exploration.

3.5 Conclusion

As the use of sensors to collect data about different aspects of motion in different clinical populations becomes more mainstream, it becomes easier to build statistical models of motor behaviour as a way to assess motor deficits. The work presented in this chapter is a first step toward generating procedures to remove bias in collection of motion data for building such statistical models. Collecting “enough” motor exploration data to analyse motor synergies can help build a model of healthy motor synergies (Chapter 4) and can lead to better understanding of how stroke causes motor deficits in each individual post-stroke (Chapter 5). This in turn can be used to design data-driven and individualized physical therapy exercises.
4 Kinematic and Muscle Synergies in Healthy Exploratory Upper-body Motions

Previous studies suggest that the central nervous system (CNS) may generate motions by using modular control of muscles and joints (synergies) as they identified existence of motor synergies in a variety of human motions. However, in order to provide a holistic and task-independent view of modular motion coordination, motor synergy analysis needs to shift from the study of specific tasks to the study of exploratory motions. Studying exploratory motions can reveal biomechanical constraints and motor control strategies employed by healthy and clinical populations. The previous two chapters were focused on answering two basic questions to set a standard for synergy analysis using exploratory motions. Chapter 2 identified Non-Negative Matrix Factorization as the top dimensionality reduction method for motor synergy analysis. Chapter 3 covered a study to set the lower bound for exploratory motion data required for reliable extraction of motor synergies.

Building on the findings of the previous chapters, in this chapter I present a study to identify muscle and kinematic synergies in healthy upper-limb exploratory motions using non-negative matrix factorization. The study involved recruitment of 15 healthy participants and collection of electromyography and joint motion data from their arms as they completed an exploratory motion task. Four muscle synergies and three kinematic synergies were sufficient to reliably reconstruct the motion data of each participant. The identified synergies were similar between the dominant and non-dominant limbs. Moreover, the results show that healthy participants share the same muscle and kinematic synergies. This suggests that the healthy CNS uses a modular motion coordination scheme for arm motion control. Using the identified synergies, I introduce healthy templates for muscle/kinematic synergies. These templates can be used as a benchmark for healthy motion coordination to study how neurological injuries alter motion coordination patterns and cause impairment.
4.1 Introduction

Understanding how the CNS overcomes the computational burden of motor control has been on the forefront of human motor control and motor learning fields (Guigon 2010). There is a growing body of work that supports the existence of a synergistic motor control mechanism utilized by the CNS to facilitate motor coordination. The theory of motor synergies suggests that the CNS controls groups of muscles and/or joints (elemental variables) rather than controlling each muscle or joint separately, effectively reducing the high dimensionality of motor planning and execution variables (Santello 2002; Freitas et al. 2006; Cheung et al. 2012; Alessandro et al. 2013; Bizzi and Cheung 2013; Berger and d’Avella 2014; Tamei et al. 2015; Federolf 2016).

Historically, motor coordination is assumed to be a simplifying strategy employed by the CNS to handle redundancy and to reduce the dimensionality of available choices to execute the motion (Bernstein 1967; Turvey 1990; Latash 1996). A more recent view on motor coordination is grounded in the principle of abundance (Latash and Anson 2006): the CNS, instead of eliminating the redundant degrees of freedom in motion effectors (muscles and joints), uses the abundance of available effectors to ensure the motion is both stable and flexible. The principle of abundance tightly connects to the concept of motor synergies and the uncontrolled manifold (UCM) hypothesis.

Latash and Anson (Latash and Anson 2006) argue that the CNS organizes the control of elemental variables (joint rotations or activation of muscles) to stabilize performance variables (e.g., the position of the index finger during pointing). Performance variables are directly related to the task goal and present the important outcomes of the motion. The UCM hypothesis proposes that the CNS divides the space into controlled and uncontrolled elemental variables. The uncontrolled variables, i.e., the uncontrolled manifold, are task-irrelevant and show more variability during the task (Scholz and Schöner 1999). On the other hand, the controlled variables are task-relevant and are controlled by the CNS to ensure their variation does not lead to deviation of the performance variable beyond a narrow allowable margin. This guarantees that the performance variable changes according to the task goal, while the variation in the uncontrolled manifold is to ensure flexibility and stability of the motion. The UCM hypothesis does not treat variability in motor patterns as an error showing poor planning by the CNS, but it considers variability as proof of efficient control (Tresch and Jarc 2009): the CNS only corrects
the variability that prevents realisation of the motor behaviour goal. The uncontrolled manifold, i.e., the task-irrelevant variability, is not controlled, as it would be a waste of effort.

Building on the UMC hypothesis, the concept of motor synergies is a way to quantify the covariation of the elemental variables during a task. Using the UCM terminology, a motor synergy can be defined as a set of stable spatiotemporal patterns of activity shared across elemental variables that leads to a desirable performance variable (McMorland et al. 2015).

Following Bernstein’s work (Bernstein 1967), motor coordination research, including studies of motor synergies, has been conventionally focused on studying tasks that would eliminate or isolate the redundant degrees of freedom. Different linear dimensionality reduction methods have been used to quantify kinematic or muscle synergies in a variety of such tasks in both animals and humans (Soechting and Flanders 1997; Braido and Zhang 2004; Jae et al. 2005; Tresch et al. 2006; Torres-Oviedo and Ting 2010; Muceli et al. 2010; Roh et al. 2012; d’Avella and Lacquaniti 2013; Gentner et al. 2013; Vinjamuri et al. 2014; Azaripasand et al. 2015; Tagliabue et al. 2015; Hagio et al. 2015; Lambert-Shirzad and Van der Loos 2017b). These studies cover a range of functions including balance, gait, reaching, grasping, isometric force generation, typing, etc. However, a serious critique of these studies is that the synergies they report are task-specific and might reflect the biomechanical constraints of the task rather than the underlying neural strategies of motor control (Rearick et al. 2003; Todorov and Ghahramani 2004; Tresch and Jarc 2009; Steele et al. 2015). For example, the reduction in the redundancy of joint motion patterns during a tabletop reaching at shoulders height as the torso is restrained (Dipietro et al. 2007) can be identified as a kinematic synergy, but is only valid with the torso restrained.

In order to address this critique of motor synergies research, in the previous chapters I introduced the idea of motor synergy analysis using motion data from an exploratory motor task instead of a task with physical constraints. This chapter covers a study in which participants were asked to play a simple video game that allowed them to explore a task space parallel to the frontal plane using bimanual reaching motions. This task does not put any constraints on the joint motions or the activation of arm muscles, therefore it does not remove the redundancy in muscle activation and joint space. My hypothesis was that the healthy population uses the same “healthy” muscle/kinematic synergies to move both arms. Consequently, the goal of this study was to examine: 1) the similarity of the motor synergies between the dominant and non-dominant limbs of the healthy population, 2) the between-subjects similarity of synergies, and 3) whether a set of
synergies (i.e., healthy synergies template) can be defined to reconstruct the muscle activation or joint motion data of healthy participants.

4.2 Methods

4.2.1 Research Ethics and Study Participants
This study was approved by UBC’s Clinical Research Ethics Board. Fifteen neurologically healthy adults without muscular or orthopaedic impairment were recruited and provided written consent to take part in this study\(^2\). The average age of the participants was 24.8 ± 3.5 years and two of the participants were left-hand dominant. The male to female ratio was 8/7.

4.2.2 Experiment Setup
Similar to the studies presented in the previous chapters, the motion-controlled gameplay system developed under the FEATHERS project (Functional Engagement in Assisted Therapy through Exercise Robotics) was used in this study. The FEATHERS project aims to provide an engaging solution for physical therapy for adults post-stroke or teens with cerebral palsy by combining bilateral movements with computer games on a social media platform (Valdés et al. 2014; Shirzad et al. 2015). The system uses data read from a Microsoft Kinect® (Choppin and Wheat 2013; Webster and Celik 2014; Tamei et al. 2015) to map the user’s bilateral hand motions in the frontal plane to the motion of a cursor on a computer screen. Specifically, at a rate of 30 frames per second, the 3D displacements of both wrists are compared at every time step to find the mutual direction of motion of both hands in the user’s frontal plane. Then the hand motion with the shortest movement along this mutual direction of motion is mapped into a cursor’s motion on a 17” flat screen. The user can then play simple video games using cursor motion. During game play, participants were required to keep their hands at least 10 cm apart from each other to remove the possibility of relying on only one hand to move the cursor.

Participants were asked to play a game called “Lucky Pirate” (OUAT Entertainment, apps.facebook.com/luckypirate). This game is set on a static background and requires players to explore the entire game screen to select and click on treasure chests that may contain gold coins or other treasures. Completion of a level did not carry a time restriction; as a result, participants

\(^2\) The data used for the analysis presented in Chapter 2 was also used for the analysis presented in this chapter.
were able to progress at their own pace. Retrieval of different items did not lead to any external rewards for the participants. However, at the end of the data collection, each participant was given a $10 coffee shop gift card in appreciation.

The game and the system are designed to provide a virtual reality based motor exploration task (Valdés et al. 2015). Participants’ reaching motions were made exploratory by removing task space constraints to avoid recording task-specific synergies. This includes: 1) asking the participant to perform freehand reaching motions in a 3D task space rather than 2D table-top reaching and/or holding on to a manipulandum during the reach, and 2) asking the participants to choose the target of their reaching motions by presenting them with a variety of possible targets rather than presenting them with one pre-defined target.

The requirement to use both hands to move the cursor on the screen is not considered a limiting physical constraint as the participants are free to choose how they want to temporally and spatially synchronize the motion of their hands. Moreover, the use of both hands at the same time does not impose any constraints in the joint and muscle spaces, letting the participants demonstrate and use separate joint/muscle space strategies (kinematic and muscle synergies) to generate the motion. As an example, the biomechanics of a reaching motion by the right arm does not change when only the right hand is moved toward a target compared to when the right and left hands are moved together toward the target.

4.2.3 Data Collection Procedure

Each participant took part in one data collection session. After becoming familiar with the FEATHERS system and “Lucky Pirate” game, the participants were asked to sit on a 70 cm tall stool without a back-support, two meters away from a flat screen monitor (see Figure 2.2). The Lucky Pirate gameplay screen was projected on the monitor and participants played the game by controlling a magnified cursor on the screen. The motion of the participants’ wrists was captured via a Kinect camera and was used by the FEATHERS software to move the cursor on the screen. After the participants expressed that they were comfortable with using the FEATHERS system to play the game, they were asked to play the game for at least five minutes while whole-body motion data and muscle electromyography data were collected.

A 16-channel Delsys (Natick, MA, USA) EMG system was used to record muscle activation from eight muscles on each side of the body at 2000 Hz: the brachioradialis (Brachi), biceps
brachii (Biceps), long and lateral heads of triceps brachii (TriLong and TriLat), anterior, medial, and posterior fibres of deltoid (DeltAnt, DeltMed, and DeltPos), and clavicular fibres of pectoralis major (PectMaj) (Muceli et al. 2010; Gentner et al. 2013; Steele et al. 2013; Roh et al. 2015). EMG electrodes were placed in accordance with the European recommendations for surface electromyography (Hermens et al. 1999). Prior to data collection, maximum voluntary contractions were performed to ensure electrodes were placed properly.

4.2.4 Electromyography and Kinematic Data Preprocessing

Before extracting muscle synergies, the EMG signals were amplified (×1000) and band-pass filtered (20-450 Hz) (Roh et al. 2013, 2015). Each muscle’s EMG signal was normalized to the maximum observed value of the signal. The preprocessed EMG data were then stored in two files, the dominant and non-dominant limb, each including data from eight muscles.

The Kinect tracked the Cartesian location of several anatomical landmarks by assigning markers to them: centre of hip, chest at the level of shoulders, shoulders, elbows, wrists, and hands (i.e., centre of palms). To calculate joint angles from marker positions, a human upper-body musculoskeletal model developed by Holzbaur (Holzbaur et al. 2005) for the OpenSim environment (Delp et al. 2007) was used. The original model only includes the right extremity and was modified and expanded to include both extremities and to be compatible with Kinect data. Using OpenSim software and the modified musculoskeletal model, the inverse kinematics of the marker motions were solved to find the change in the following joint angles (17 DOFs) over time: trunk motions as measured by roll, pitch, and yaw angles (TrRol, TrPit, and TrYaw), flexion-extension of both shoulders (ShFlEx), abduction-adduction of both shoulders (ShAbAd), medio-lateral rotation of both shoulders (ShRot), flexion-extension of both elbows (ElFlEx), pronation-supination of both elbows (ElPrSu), radial-ulnar deviation of both wrists (WrDev), and flexion-extension of both wrists (WrFlEx).

Using this procedure, the joint angle time series during a motor exploration task for all 15 participants were calculated at 30 Hz. These data were then bifurcated with each set containing the joint angle time series data of the dominant and non-dominant upper limbs of each participant (10 DOFs in each set; trunk motion data were shared). Only movements within two standard deviations of the mean speed of the entire session were kept for further analysis. This was to ensure that all periods of pause or no movement were filtered out. The joint motion data were low-pass filtered at 6 Hz (Enoka 2015; Valdés et al. 2015) to remove motion artefacts.
4.2.5 Quantifying the Number of Synergy Vectors

The collected data were divided into muscle and kinematic sets, each set containing separate time series data for the dominant and non-dominant hands. After preprocessing the data, Variance Accounted For (VAF) was used to determine the number of synergy vectors ensuring sufficient factorization of the data by non-negative matrix factorization method (Tresch et al. 2006). The number of synergy vectors is the minimum number of synergies that achieves a global (across all training data points) VAF > 90%, with less than a 5% increase in global VAF upon addition of another synergy vector (Delta VAF). As a local criterion, the VAF for each muscle or joint (DOF VAF) was required to exceed 65%. This procedure ensures that the estimated number of synergies can predict both the overall data set as well as each of the DOFs of the overall data set (Ting and Chvatal 2010; Roh et al. 2013, 2015; Lambert-Shirzad and Van der Loos 2017a).

To define the number of synergy vectors, in the first step I factorized the data with the criteria mentioned in the previous paragraph. This resulted in 2 or 3 kinematic synergy and 3 or 4 muscle synergy vectors for each participant (more details in Section 4.3: Results). To facilitate comparison of synergy sets between participants, I chose the higher number for each set as the number of synergy vectors (3 for kinematic and 4 for muscle synergies) and re-extracted the motor synergies for each participant (Roh et al. 2012, 2015).

4.2.6 Quantifying Similarity of Synergy Vectors

Three metrics were used to quantify the similarity between sets of synergies extracted from different data sets (data from two participants or data from the two sides of the body for one participant): dot product of synergy vectors, global VAF of reconstructed data, and DOF VAF of reconstructed data (Cheung et al. 2005; Torres-Oviedo and Ting 2010). Each of these metrics reflects a different aspect of synergy similarity analysis between two data sets and as a group, helps build a thorough image of the similarity of motor synergies in the healthy population.

To quantify how aligned two vectors are, the dot product of the two vectors can be used (ranging from zero for orthogonal vectors to one for parallel vectors). Therefore, the dot product of synergy vectors can be used as a way to quantify the similarity in the synergy structure by identifying the shared (i.e., parallel) vectors of the two data sets.

A Monte Carlo simulation was carried out to determine the similarity cut-off threshold for dot product values. I identified synergy vectors for each limb of each participant. A set of 250
random vectors was constructed by sampling from indices of the identified synergy vectors. This was followed by calculating the scalar product values of all possible random vector pairs (250×250 = 62,500 values) to generate a sampled distribution of possible scalar product values. The 95th percentile of this distribution was then used as a cut-off threshold with any dot product value above this threshold considered statistically significant \( (p\text{-value} < 0.05) \). With this procedure, a pair of synergy vectors with a statistically significant dot product value are considered statistically similar, or in short, similar (Roh et al. 2012; Gentner et al. 2013).

To calculate the dot product similarity of two synergy sets, the synergy vectors of the first set were compared against each of the synergy vectors of the second set to create a matrix containing dot product values of any choice of two synergy vectors from the two synergy sets. Using this matrix, the synergy vectors of the two sets were matched to maximize the sum of dot products of the matched synergy vectors.

VAF is defined as a percentage and is calculated as \( \text{VAF} = 1 – \frac{\text{SSE}}{\text{SST}} \), where sum of squared errors SSE is the unexplained variation and total sum of squares SST is the total variation of the data. With this definition, VAF is sensitive to both shape and magnitude of the original measured data and reconstructed (factorized) data (compare with Pearson correlation coefficient, which only considers the shape of data). Therefore, VAF can be used as a measure to quantify how well synergy vectors of one data set can be used in reconstructing (i.e., explaining the variation in) another data set.

A second Monte Carlo simulation was carried out to set the similarity cut-off thresholds for global VAF and DOF VAF values. A set of 250 random vectors was constructed by sampling from indices of the identified synergy vectors. Starting with the first participant’s data, a set of synergy vectors (4 for EMG data and 3 for kinematic data) was selected from the random vectors and used to reconstruct the data from each limb. A global VAF value and an average DOF VAF value were then calculated based on the differences between the original data and the reconstructed date. This procedure was done 200 times for each of the two limbs of the 15 participants to generate a sampled distribution of global VAF and DOF VAF values \( (200 \times 15 \times 2 = 6000 \text{ sampled values for each VAF measure}) \). The 95th percentile of this distribution was used as a cut-off threshold with any VAF value above these thresholds considered statistically significant \( (p\text{-value} < 0.05) \). Therefore, a set of synergy vectors producing reconstruction VAF measures above these thresholds are considered significantly similar.
4.3 Results
The primary aim of the present study was to identify the motor synergies underlying exploratory reaching motions. To this end, EMG and joint motion data were collected as each of the participants completed a five-minute data collection session. During the session, participants played Lucky Pirate by moving their hands to move a cursor on the screen to different treasure chests. Participants were able to set their own pace and open as many chests as they wanted as long as they continuously moved their hands and played the game without any extended pauses.

Using the collected data, I examined the similarity of the motor synergies between the dominant and non-dominant limbs of the healthy population, whether these synergies are similar for all participants (between-subjects similarity of synergies), and finally, whether a set of synergies (i.e., healthy synergies template) can be defined to reconstruct the muscle activation or joint motion data of the healthy participants.

4.3.1 Variation in the Data (Behaviour, Joint Kinematics, EMG) During the Task
Figure 4.1 shows the collected data from participant H05 (male, right-handed, 29 years old) as an example. Figure 4.1.A shows the distribution of the wrist positions in workspace (top two plots). The wrist positions were translated by the FEATHERS software into the motion of the cursor on the computer screen (Figure 4.1.A, bottom plot). The contours in Figure 4.1.A show the minimum observed time spent at each point in the workspace in the frontal plane. The points that are surrounded by a contour line have appeared in the position data for at least the amount of time that corresponds with the colour of the contour line. The origin of the workspace in the top two plots was set to the lowest leftmost point that the participant’s left hand visited during game play.

Panels B and C of Figure 4.1 show the recorded joint motion (degrees) and EMG (normalized to maximum observed in the channel) data for the participant. All the joints and muscles considered in this study were actively involved during the task. However, their activity did not follow any specific pattern as the participant explored the workspace without any inputs from the experimenters.

It is interesting to notice that the recorded activity of some joints and muscles recorded from the two arms was very similar (e.g., shoulder abduction/adduction, elbow flexion/extension, deltoid posterior, and brachioradialis). These joints and muscles are mainly involved in up and down
motions of the hands, which were required to be synchronous, as dictated by the FEATHERS software.

For other joints and muscles, the recorded activities from the two arms were asynchronous and dissimilar since they largely control right-left motions of the hands, which were not symmetric during the task. For example, to move the hands rightward, the right arm extends away from the body and the left arm flexes toward the midpoint of the body. This caused the asymmetry in the motion of joints and activation of muscles between the two arms.

4.3.2 Four Muscle Synergies Reliably Reconstruct Muscle Activation Data for All Healthy Participants

After preprocessing the muscle activation data, the data for the dominant and non-dominant arms were saved and analysed separately. Figure 4.2 shows global VAF (top row), Delta VAF (middle row), and DOF VAF (bottom row) as a function of the number of synergies extracted from the muscle activation data of the dominant (left column) and the non-dominant (right column) limbs, for all participants. As expected, global VAF and DOF VAF increase and Delta VAF decreases
as the number of synergies increases. Figure 4.3 shows the minimum number of synergies that satisfied the training criteria.

Figure 4.2: Muscle activation global VAF, Delta VAF, and DOF VAF as a function of number of synergies extracted for each of the two arms. Muscle names are abbreviated.

Figure 4.3: Summary of analysis to determine number of muscle synergies that satisfy the training criteria. Muscle names are abbreviated.

To define the number of synergy vectors, in the first step the data sets were factorized with the training criteria mentioned in the methods section. This returned 3- or 4-muscle synergy vectors for each participant (Figure 4.3, top row). Most of the collected muscle activation data required 4
synergy vectors for sufficient factorization (~60%). This percentage was slightly higher for the non-dominant limb. These synergy vectors reconstructed more than 94% of the global VAF and at least 65% of the DOF VAF in the data for both limbs (Figure 4.3, bottom row).

To facilitate comparison of synergy sets between participants and within participants (between dominant and non-dominant limbs), the higher number, i.e., four, was chosen as the universal number of synergy vectors (Roh et al. 2013, 2015) and four muscle synergies were extracted for each arm of the participants.

### 4.3.3 Three Kinematic Synergies Reliably Reconstruct Joint Motion Data for All Healthy Participants

As in the muscle synergy analysis, a set of training criteria based on VAF was used for extracting kinematic synergies. The analysis showed a similar relationship between number of synergies and global VAF, Delta VAF, and DOF VAF, compared to observations in the previous section (Figure 4.4).

![Figure 4.4: Joint motion global VAF, Delta VAF, and DOF VAF as a function of number of synergies extracted for each of the two arms. Joint names are abbreviated.](image)

Typically, 2 or 3 kinematic synergy vectors were enough to satisfy the training criteria (Figure 4.5, top row). Most of the joint motion data required two synergy vectors for sufficient factorization (~55%). This percentage was slightly higher for the dominant limb. These extracted
synergy vectors reconstructed more than 97% of the global VAF and at least 65% of the DOF VAF in the data for both limbs (Figure 4.5, bottom row).

Similar to muscle synergy analysis, to facilitate comparison of kinematic synergy sets between participants and within participants (between dominant and non-dominant limbs), I chose the higher number as the universal number of synergy vectors (three kinematic synergies) and re-extracted the kinematic synergies of each of the arms of the participants.

Figure 4.5: Summary of analysis to determine number of kinematic synergies that satisfy the training criteria. Joint names are abbreviated.

4.3.4 Quantifying Similarity of Synergies

Three metrics were used to quantify the similarity between sets of synergies within or between participants: dot product of synergy vectors, global VAF of reconstructed data, and mean DOF VAF of reconstructed data. Three Monte Carlo simulations were carried out to generate a sample distribution of possible values for the similarity metrics. The 95th percentile of these distributions was then used as a cut-off threshold for statistically significant similarity.

Figure 4.6 shows distribution of the similarity metrics for the muscle activation and the joint motion data derived from the Monte Carlo simulations. Based on this, muscle synergy vectors that have a dot product value greater than 0.81, reconstruction VAF greater than 84.8%, and mean reconstruction DOF VAF greater than 80.5% are statistically similar. Also, kinematic synergy vectors that have a dot product value greater than 0.91, reconstruction VAF greater than
89.7%, and mean reconstruction DOF VAF greater than 85.4% are similar with statistical significance.

Figure 4.6: Monte Carlo simulations were carried out to generate sample distributions of possible values for the synergy vector similarity metrics using each of the muscle activation and joint motion data sets. The 95th percentile of these distributions is used as a cut-off threshold for statistically significant similarity of synergy vectors.

4.3.5 Muscle and Kinematic Synergies are Similar within Participants (between Dominant and Non-dominant Arms)

After extracting four muscle synergies and three kinematic synergies for each arm of all of the participants, I examined the within-participant similarity of synergies. This comparison was done separately for muscle and kinematic synergies using the metrics introduced in the previous section.

*Within-participant similarity of muscle synergies:* Figure 4.7 details global VAF and DOF VAF measures of similarity for muscle synergies. The two leftmost boxplots in each subplot in this figure shows the two VAF measures when the synergies of the non-dominant limb were used to reconstruct the muscle activation data of the dominant limb, and compares them to when the original synergies of the dominant limb were used to reconstruct the data. The distribution of global VAF and average DOF VAF are much more compact when the original synergy set is used to reconstruct the data compared to when the synergies of the other limb are used. However,
all the values in these distributions are above the similarity limit. This is also observed when the synergies of the dominant limb are used to reconstruct the muscle activation data of the non-dominant limb (the two rightmost boxplots in each subplot of Figure 4.7).

The original muscle synergies of each limb, on average, returned a global VAF of 96.7 ± 0.5 for the dominant limb and 96.3 ± 0.6 for the non-dominant limb. When the synergies of the other limb were used to reconstruct the data of a limb, a global VAF of 95.7 ± 1.3 for the dominant limb and 95.2 ± 1.6 for the non-dominant limb was observed. The synergies of each limb accounted for 95.2 ± 0.7 of DOF VAF in the dominant limb and 94.9 ± 1.0 in the non-dominant limb. These numbers changed to 94.2 ± 1.8 for the dominant limb and 93.7 ± 2.2 for the non-dominant limb when the synergy vectors of the other limb were used to reconstruct the data.

Figure 4.7: Global VAF and DOF VAF measures of similarity comparing the muscle synergies of the dominant and the non-dominant limbs.

Figure 4.8 shows the distribution of dot product similarity measures for muscle synergies of the two limbs of participants. For each participant, the muscle synergies were matched between the two limbs to maximize the sum of dot products of the matched synergy vectors. The matched synergies with the highest dot product (i.e., the most parallel synergy vectors) returned a dot product that was very close to 1 (“1st pair” in Figure 4.8). Considering all of the participants, the variability in the dot product values increases moving from the more parallel pair to the less parallel pair: 0.993 ± 0.006, 0.981 ± 0.017, 0.967 ± 0.027, 0.926 ± 0.112. Out of the 60 pairs of synergy vectors (4 pairs per each of the 15 participants), 59 pairs had a dot product value above the similarity limit.
Figure 4.8: Distribution of dot product similarity measures for the muscle synergies within participants.

Figure 4.9 shows muscle synergies of participants H01 and H18 as the worst and best cases of dot product similarity (similarity in the structure of the synergies). Muscle synergies of the dominant and non-dominant limbs of H18 are almost identical (dot product values of the 1st to the 4th pair are 0.998, 0.995, 0.986, and 0.983). Although the first three pairs of muscle synergies are similar between the two limbs of H01, the last pair of extracted synergies had a dot product value of 0.538, which was below the similarity limit.

Figure 4.9: Muscle synergies of participants H01 and H18 as the worst and best cases of dot product similarity within participants. Muscle names are abbreviated.
**Within-participant similarity of kinematic synergies:** Figure 4.10 shows kinematic synergies of participant H02. H02 was chosen as the best-case scenario demonstrating similarity of the synergy vectors between dominant and non-dominant limbs based on dot product values of the synergy vectors.

![Kinematic Synergy Vectors, Participant H02](image)

**Figure 4.10:** Kinematic synergies of a typical participant (H02) showing similarity of the synergy vectors between two limbs. Joint names are abbreviated.

Figure 4.11 shows the distribution of dot product similarity measures for kinematic synergies within participants. For each participant, the muscle synergies were matched between the two limbs to maximize the sum of dot products of the matched synergy vectors. Considering all of the participants, a similar trend to what was observed for muscle synergies was detected. The variability in the dot product values for the three pairs of kinematic synergies were: 0.986 ± 0.010, 0.970 ± 0.021, 0.952 ± 0.023. All pairs of synergy vectors had a dot product value above the similarity limit.

Figure 4.12 shows global VAF and DOF VAF measures of similarity. Similar to Figure 4.7, the two leftmost boxplots in each subplot of Figure 4.12 shows the two measures when the synergies of the non-dominant limb were used to reconstruct the joint motion data of the dominant limb, and compares them to when the original synergies of the dominant limb were used to reconstruct the data. The two rightmost boxplots in each subplot shows these values when the synergies of the dominant limb are used to reconstruct the joint motion data of the non-dominant limb. All the values of global VAF and DOF VAF were above the similarity limit.
The original kinematic synergies, on average, reconstructed a global VAF of 98.4 ± 0.3 for the dominant limb and 98.3 ± 0.4 for the non-dominant limb. When synergy vectors of the other limb were used to reconstruct the data of a limb, a global VAF of 98.1 ± 0.5 for the dominant limb and 98.0 ± 0.5 for the non-dominant limb was observed. The synergies of each limb accounted for 97.0 ± 0.8 of DOF VAF in the dominant limb and 96.9 ± 0.6 in the non-dominant limb. These numbers changed to 96.4 ± 0.7 for the dominant limb and 96.1 ± 0.8 for the non-dominant limb when the synergy vectors of the other limb were used to reconstruct the data.

Figure 4.11: Distribution of dot product similarity measures for the kinematic synergies within participants.

Figure 4.12: Global VAF and DOF VAF measures of similarity comparing the kinematic synergies of the dominant and the non-dominant limbs.
4.3.6 Muscle and Kinematic Synergies are Similar across Participants

For each individual, motor (muscle and kinematic) synergies of the two limbs are similar. To facilitate comparison of motor synergies between participants, I calculated each participant’s average motor synergy set by finding the mean of the matched synergy vectors between his/her two limbs. The mean synergies were then normalized. This procedure was done separately for muscle and kinematic synergies. The dot product values of these average synergy vectors and those of their corresponding dominant and non-dominant limbs were greater than the similarity limit. This indicates dot product similarity of each individual’s mean synergy set to his/her synergy sets of each limb. I used all individuals’ average synergy sets to study the similarity of motor synergies between participants using the similarity metrics introduced previously.

Between-participants similarity of muscle synergies: To understand the similarity in the structure of individual synergy sets, I matched individual muscle synergies across participants to achieve the highest sum of dot products of the matched synergy vectors over all participants. This process was repeated 15 times, each time starting with the individual synergies of one of the participants as the matching template, and each time led to the same matching of synergies across participants shown in Figure 4.13.

**Figure 4.13:** Muscle synergies were matched between all participants in order to create a healthy template for muscle synergies. Muscle names are replaced with numbers: 1, 2, and 3 are anterior, medial, and posterior fibres of deltoid. 4 is biceps brachii. 5 and 6 are long and lateral heads of triceps. 7 is brachioradialis, and 8 is clavicular fibres of pectoralis major.
In Figure 4.13, each column shows synergy vectors of a participant and each row shows the matched synergies between participants. The DP value reported on top of each of the synergy vectors (i.e., bar graphs) is the mean dot product of that synergy vector with its matched synergies. All DP values exceeded the similarity level except for one of the synergy vectors of participant H01 (Synergy #3 of H01 in Figure 4.13, which is the same synergy that was not similar between the two limbs for this participant in Figure 4.9). The variability in the DP values, moving from Synergy #1 to #4, was as follows: 0.918 ± 0.046, 0.853 ± 0.021, 0.944 ± 0.073, and 0.898 ± 0.029.

I used this matching of synergies to calculate the synergy set of an average healthy participant (i.e., the healthy template for muscle synergies) which is presented in the left column of Figure 4.14. These vectors are the normalized mean of the synergies in each row of Figure 4.13. The contribution of each template synergy vector to reconstructing global VAF of muscle activation data of all participants is shown in the right column of Figure 4.14.

Figure 4.14: The healthy template for muscle synergies and their contribution to reconstructing global VAF of muscle activation data of all participants. Muscle names are abbreviated.
The muscle synergy vectors in the healthy template synergy set were similar to all of the average synergy vectors of individuals (including all of H01’s synergies). The variability in the dot product values between each of the template synergy vectors and the average individual synergies, moving from Synergy #1 to #4, was as follows: 0.949 ± 0.033, 0.896 ± 0.074, 0.963 ± 0.044, and 0.942 ± 0.033. Note that the mean dot product values are higher when individual synergies are compared to the template synergies rather than being compared to each other.

I also compared the similarity of each individual’s mean synergy set to those of other participants as well as the healthy synergy template using global VAF and DOF VAF metrics. To calculate global VAF and DOF VAF values, I reconstructed the muscle activation data for each participant (separately for each limb) using the average synergy vectors of that individual, the average synergy vectors of each of the other participants, and the healthy synergy template. Figure 4.15 shows that these values were above the similarity limit, which demonstrates similarity of each person’s mean synergies to his/her dominant and non-dominant limb synergies, to individual mean synergy vectors of other participants, and to the healthy muscle synergy template.

![Figure 4.15: Global VAF and DOF VAF measures of similarity comparing the individual muscle synergies to individual synergies of dominant/non-dominant limbs (Self), to individual muscle synergies of others (Others), and to the healthy template synergies. Muscle names are abbreviated.](image)

**Between-participants similarity of kinematic synergies:** Individual kinematic synergies across participants were matched to achieve the highest sum of dot products of the matched synergy
vectors over all participants. I repeated this process 15 times, each time starting with the individual synergies of one of the participants as the matching template, and each time found the same matching of synergies (Figure 4.16). In this figure, each column shows synergy vectors of a participant and each row shows the matched synergies between participants. The DP value reported on top of each of the synergy vectors (i.e., bar graphs) is the mean dot product of that synergy vector with its matched synergies. All DP values exceeded the similarity level. The variability in the DP values, moving from Synergy #1 to #3, was as follows: 0.980 ± 0.012, 0.977 ± 0.011, and 0.968 ± 0.013.

Figure 4.16: Kinematic synergies were matched between all participants in order to create a healthy template for kinematic synergies. Joint names are replaced with numbers: 1, 2, and 3 are Trunk Roll, Yaw, and Pitch. 4, 5, and 6 are shoulder flexion/extension, abduction/adduction, and rotation. 7 and 8 are elbow flexion/extension and pronation/supination. 9 and 10 are wrist ulnar deviation and flexion/extension.

I used this matching of synergies to calculate the synergy set of an average healthy participant (i.e., the healthy template for kinematic synergies) which is presented in the left column of Figure 4.17. These vectors are the normalized mean of the synergies in each row of Figure 4.16. The contribution of each template synergy vector to reconstructing global VAF of muscle activation data of all participants is shown in the right column of Figure 4.17.

The kinematic synergy vectors in the healthy template set were similar to all of the average synergy vectors of individuals. The variability in the dot product values between each of the template synergy vectors in Figure 4.17 and the average individual synergies, moving from
Synergy #1 to #3, was as follows: 0.988 ± 0.012, 0.980 ± 0.009, and 0.973 ± 0.017. Note that the mean dot product values are higher when individual synergies are compared to the healthy template synergies rather than being compared to each other.

To calculate global VAF and DOF VAF values for similarity analysis, I reconstructed the joint motion data for each participant (separately for each limb) using the average synergy vectors of that individual, the average synergy vectors of each of the other participants, and the healthy synergy template. Figure 4.18 shows that these values were all above the similarity limit. This demonstrates similarity of each person’s mean synergies to his/her dominant and non-dominant limb synergies, to individual mean synergy vectors of other participants, and to the healthy muscle synergy template.

Figure 4.17: The healthy template for kinematic synergies and their contribution to reconstructing global VAF of joint motion data of all participants. Joint names are abbreviated.
4.4 Discussion

The primary goal of this study was to understand healthy motion coordination using the concept of motor synergies. I applied NNMF algorithm to identify muscle and kinematic synergies of 15 healthy adults as they completed a motor exploration task. The results showed that four muscle synergies and three kinematic synergies account for, on average, more than 94% of variance in the muscle activation and joint motion data sets of the participants. I compared the motion coordination between the two limbs of the participants and between all participants using the identified synergy vectors. Synergy structures, both at the muscle activation and the joint motion levels, are statistically similar between the two limbs of the healthy participants. This finding was used to determine each participant’s average synergy structure by calculating the normalized mean of his/her two limbs’ synergy structures. By comparing these individual average synergy structures, I was able to show that muscle and kinematic synergies are also similar between participants. Healthy templates for muscle/kinematic synergies were calculated by computing the normalized mean of all individual average synergy structures and showed that the healthy synergy templates are similar to each individual’s limb synergy vectors and can be used to reconstruct the collected exploration motion data.
4.4.1 Similarity of Muscle and Kinematic Synergies

Three metrics were used to quantify the similarity between sets of synergy vectors. Each metric reflects a different aspect of motion coordination similarity. Dot product values between synergy vectors can be used as a way to quantify the similarity in the synergy structure by identifying the shared (i.e., parallel) vectors of the two data sets. Variance accounted for (VAF) is sensitive to both shape and magnitude of the original measured data and reconstructed data. Therefore, global and DOF VAF can be used as a measure to quantify how well synergy vectors of one data set can be used in reconstructing another data set, on both holistic and element-by-element levels. Monte Carlo simulations were used to derive cut-off values for the three metrics, signifying a level of statistically significant similarity. The cut-off values found in this study are comparable to those found in other studies (Cheung et al. 2005; Torres-Oviedo and Ting 2010; Roh et al. 2012).

I observed that a reconstructed motion data set captures most of the original variance in the data when the synergy vectors identified from the same data set are used for reconstruction. The captured variance decreases when the person’s average synergy set is used in reconstructing the data. It further decreases when the healthy template for synergies is used for reconstruction. The lowest VAF was observed when the average synergies of the other participants were used to reconstruct a person’s motion data. This decrease in the VAF when moving away from reconstructing motion data of a participant using his/her original limb’s synergies to another participant’s synergies was expected.

As discussed in Section 4.1, Introduction, according to the uncontrolled manifold (UCM) hypothesis the CNS divides the space into controlled and uncontrolled elemental variables (manifolds). The variation of controlled variables ensures achieving the task goal. While the variation in the uncontrolled manifold ensures flexibility and stability of the motion and varies from person-to-person or day-to-day for a person.

Since the goal of synergistic study of motions is to separate the two manifolds and capture most of the controlled variability while filtering most of the uncontrolled manifold, I formed the following hypothesis: the healthy CNS employs a unique division of the two manifolds, and this can be shown by similarity of synergy vectors across participants. Quantification of synergy vectors using matrix factorization methods captures the majority of the controlled manifold. That is why reconstructing a data set based on its own original synergy vectors returns the highest
VAF. As synergy vectors of the two arms are aggregated to calculate a person’s average synergies, or the healthy template, we increase the weight of the uncontrolled (and therefore, not shared/similar between limbs or individuals) variability captured in the synergy vectors of other participants or the other limb. This can be considered as decreasing the signal-to-noise ratio captured by the calculated average and template synergies. Reconstructing the data based on these synergy vectors therefore returns a lower level of the original variance in the data. However, this reduction is not big enough to shift the VAF and DOF VAF of the reconstruction below the similarity levels.

4.4.2 Modular Coordination of Muscles and Joints in Healthy Arm Motions

There is strong evidence supporting a modular control of muscles and joints during arm motions covering a range of functional tasks (see Section 4.1 Introduction, for examples). Similar to the findings of this study, d’Avella et al. showed that four or five synergies can reconstruct the muscle activation patterns during point-to-point reaching movements (d’Avella et al. 2006), and Bockemühl et al. showed that three synergies are enough to reconstruct multi-joint arm movements in a vertical plane (Bockemühl et al. 2010). The muscle synergies identified in the study presented in this chapter are similar to those identified in studies of point-to-point reaching and isometric force generation (d’Avella et al. 2006; Roh et al. 2012). It is hard to directly compare the kinematic synergies reported by Bockemühl et al. with the findings of this study as they used principal component analysis (PCA) to quantify synergies, whereas I used non-negative matrix factorization for that purpose. In the study covered in Chapter 2, I looked into the structural differences in synergy sets identified by these two methods. There, I showed that PCA synergy vectors capture the major direction of the data (mean and standard deviation of the data) and NNMF synergy vectors describe the edges of the data. Therefore, factorizing a data set by PCA and NNMF will return two different and non-comparable synergy sets.

In the bimanual task considered in this study, the two hands moved toward the same target (chosen by the participant for each reach while playing the Lucky Pirate game) without requiring the participant to match the motion generation (EMG) and the joint space variations between the two limbs (e.g., inward rotation of one limb and outward rotation of the other during a left-to-right reaching motion). In other words, although the motions of the two hands are synchronized, the motion generation and DOFs involved in the motions are not necessarily the same. Even so, the results show that the two sides of the body exhibit the same muscle/kinematic synergy
vectors to generate these motions. Moreover, the similarity of motor synergies between limbs and participants suggests that the healthy CNS uses the same control strategy to coordinate the motion of the two limbs across participants.

4.4.3 Biomechanical Interpretation of Healthy Motor Synergies

I focus on the identified healthy template synergy vectors shown in Figure 4.14 and Figure 4.17 to discuss the modular motion coordination of arms during exploratory motions. Each synergy vector shows how different DOFs (elemental variables, either joints or muscles) are activated relative to the other DOFs.

The three synergy vectors presented as the healthy synergy template in Figure 4.17 suffice to return a VAF value over 95% for the kinematic data of all participants. Motion of the trunk, as measured by roll, pitch, and yaw angles, is represented by a similar relative activation in all three kinematic synergies. This consistency across synergies suggests that trunk motion is not involved in the modular control of reaching motions. This means healthy participants do not use their trunk degrees of freedom to change the position of their hand in a reaching task (also known as not compensating with the trunk).

Reaching motions involve both moving the hand in a task space to place it at the desired position and adjusting the hands’ orientation. The three degrees of freedom in the shoulder and flexion and extension of the elbow are used to place the hand at the desired location, and the wrist degrees of freedom and supination and pronation of the elbow are used to adjust the orientation of the hand. Intriguingly, the placement of the hand is captured by a fairly consistent relative activation of the shoulder DOFs and elbow flexion/extension captured in all three synergies. However, the wrist DOFs and elbow supination/pronation are controlled with a high degree of independence to adjust the hand’s orientation.

Figure 4.14 shows the four healthy template muscle synergies that reconstruct more than 90% of the variance in the muscle activation data of all participants. Synergy #1 suggests a synergistic activation of biceps brachii and triceps brachii (long and lateral heads), which can generate elbow flexion and extension during reaching motions. Synergy #2 activates anterior fibres of the deltoid and pectoralis major simultaneously, causing flexion and rotation in the shoulders. Synergy #3 activates the brachioradialis, which can flex and extend the wrist and can also
generate fast elbow flexion. Synergy #4 indicates co-activation of deltoid muscles and triceps brachii (lateral head), which can lead to shoulder abduction and flexion.

4.5 Conclusion

This chapter presented the results of a study showing that synergy structures, both at the muscle activation and at the joint motion levels, are statistically similar between the two limbs of healthy participants. This finding was used to exhibit that muscle and kinematic synergies are also similar between participants. The healthy templates of muscle and kinematic synergies identified in this study can be used to better understand how different neurological injuries change motion coordination and cause impairments. Specifically, the next chapter will present a study on how stroke alters motor synergies in the paretic and non-paretic sides of the body. The goal will be to understand whether the motion of the non-paretic sides of the body shows the healthy muscle/kinematic synergies.
While motor synergies are well established in the healthy population, our understanding of how healthy synergies change after a cortical brain injury is limited. The study presented in this chapter was aimed at gaining insight into how a stroke changes the synergy structure in both the affected and less-affected limb. I recruited 14 stroke-survivor participants and collected electromyography and joint motion data of their arms as they completed an exploratory reaching motion task. The non-negative matrix factorization algorithm was used to extract muscle and kinematic synergies from the collected data for both arms. This study is the first one to expand the literature on analysis of synergies post-stroke to include kinematic synergies as well as muscle synergies.

The results showed that both the muscle and kinematic synergies of the less-affected arm are preserved and not altered by stroke. Although a number of the more-affected arm motor synergies were similar to those of the healthy population, a considerable portion of them were altered post-stroke. Moreover, the majority of these altered synergies could be related to the synergies of the healthy population through two distinct mechanisms: the merging and fractionation of healthy synergies. The alteration in the synergies of the weak arm was linearly related to each participant's motor function and time post-stroke. The results presented here can provide a better understanding of the physiological processes behind impairment after stroke and can be used to develop more effective and individualized therapy programs.

5.1 Introduction

The central nervous system combines the degrees of freedom available in the human musculoskeletal system to generate coordinated motor behaviour. The theory of motor synergies suggests that the CNS controls groups of muscles and/or joints (elemental variables) rather than
controlling each muscle or joint separately. Studies of motor synergies have conventionally been focused on studying tasks that would eliminate or isolate the redundant degrees of freedom.

The way humans execute an exploratory task is a function of their own biomechanical constraints (McDonald et al. 1995) and motor control strategies. This means that analyzing the motion patterns of an individual during an exploratory task has the potential to reveal individualized motor control strategies and deficits (Huang and Patton 2013; Lancaster et al. 2014; Valdés et al. 2015) and, ultimately, fulfill the need for more objective clinical assessments (Lam et al. 2015; Tatla et al. 2015). Chapter 4 presented a study of motor synergies in the healthy population during an exploratory motor task instead of a motor task with physical constraints and showed that the healthy population shares a set of “healthy” muscle/kinematic synergies to move both arms.

In general, research concerning motor synergies has been focused on developing methods to characterize synergies. Naturally, this has been done using behavioural data from the healthy population. The number of studies using data from different clinical populations is rising. Neurologic injuries such as stroke disrupt the way the CNS coordinates motor behaviour. Three out of four stroke survivors have an upper-limb impairment as a result of their stroke, mainly affecting one side of their body (Wolfe 2000; Veerbeek et al. 2011). Recovery of upper-limb function is key to the success of a physical therapy program in returning stroke survivors back to their independent lives (Stinear 2010; Lam et al. 2015; Tatla et al. 2015). Fortunately, a considerable portion of the impairment resolves spontaneously within three months post-stroke (Kwakkel et al. 2004; Zarahn et al. 2011). During this spontaneous recovery period the structure of muscle synergies remains mostly intact (Tropea et al. 2013).

Stroke leads to a broad range of motor function disturbances that can be categorized under three main impairments: weakness because agonist muscles do not activate properly as their neural drive through the corticospinal tract reduces, spasticity because antagonist muscles show an altered regime of reflex activity, and impaired motor coordination (Twitchell 1951; Steenbergen et al. 1996; Roh et al. 2015). Weakness, spasticity, and impaired motor coordination can all be considered a form of “abnormal” synergy as they all represent a spatiotemporal co-activation of the available effectors to generate motion. In the chronic stage of stroke recovery, people develop and demonstrate these abnormal synergies (McMorland et al. 2015). There are several
notable studies that identify how chronic muscle synergies evolve post-stroke (Cheung et al. 2009, 2012; Clark et al. 2010).

In their first study, Cheung et al. (Cheung et al. 2009) observed that the spatial structure of the muscle synergies (i.e., their relative activation with respect to each other) for unimanual point-to-point reaching motions is not altered in the chronic stroke population with mild impairment. However, they showed that the recruitment and activation of these synergy structures (i.e., the temporal aspect of muscle activation) with respect to each other was altered in the experimental population. A follow-up study involving participants with a wider range of impairments (Cheung et al. 2012) uncovered evidence of merging and fractionation of the synergies of the strong side in forming abnormal synergies of the weak side of the body for more severely impaired participants. In a similar study, Clark et al. also showed that a fewer number of muscle synergy structures are required to reconstruct the muscle activation patterns during locomotion in severely impaired participants (Clark et al. 2010). These abnormal muscle synergies can be built by merging normal healthy synergies. Similar results have been reported for isometric force generation at the hand (Roh et al. 2015).

The results reported in these studies focus primarily on the differences between post-stroke muscle synergies of the strong and weak sides of the body. Moreover, kinematic synergies post-stroke have not been studied extensively. In this chapter, I focus on characterizing kinematic and muscle synergies of both limbs in a chronic stroke-survivor population and investigate how the post-stroke synergies differ from the healthy synergy template reported in the previous chapter. My hypothesis was that the post-stroke motor synergies of the less-affected (i.e., strong) side of the body will be similar to the healthy synergy templates. I also hypothesized that the post-stroke motor synergies of the more-affected (i.e., weak) side of the body will cover synergies similar to the healthy template, altered (merged and fractionated) healthy synergies, and new synergies.

5.2 Methods

5.2.1 Research Ethics and Study Participants

This study was approved by UBC’s Clinical Research Ethics Board. Fourteen stroke-survivor adults were recruited and provided written consent to take part in this study. Inclusion criteria for the stroke survivors were: 1) the occurrence of a single unilateral stroke at least 1 year before participation in the study; 2) absence of cognitive dysfunction precluding comprehension of the
experimental task; 3) the ability to lift and move hands against gravity for 15 minutes; 4) capacity to provide written informed consent³. Demographic and clinical data for each of the stroke-survivor participants are provided in Table 5.1.

Prior to the start of the experiment, participants completed two clinical assessments, the upper-extremity subsection of Fugl-Meyer Assessment (FMA) and the Reaching Performance Scale (RPS) (Levin et al. 2004), both administered by an experienced occupational therapist. The scores were used as a measure of upper-body motor function post-stroke with lower scores indicating a more severe impairment and a decreased functional ability in daily activities (Sullivan et al. 2011).

The average age of the participants was 59.3 ± 10.7 years and the male to female ratio was 9/5. Participants had an average Fugl-Meyer Assessment score (out of 66) of 34.1 ± 11.2 and a

³ Data collected from the first 10 participants (SS-01 to SS-10) was used in the analysis presented in Chapter 3.
Reaching Performance Scale score (out of 36) of 22.5 ± 9.1. The time elapsed after stroke for the participants ranged from 16 to 302 months.

5.2.2 Experiment Setup

Similar to the previous studies, the motion-controlled gameplay system developed under the FEATHERS project was used in this study (Valdés et al. 2014; Shirzad et al. 2015). The system uses data read from a Microsoft Kinect® (Choppin and Wheat 2013; Webster and Celik 2014; Tamei et al. 2015) to map the user’s bilateral hand motions in the frontal plane to the motion of a cursor on a computer screen. Specifically, the 3D displacements of both wrists are compared at 30Hz to find the mutual direction of motion of both hands in the user’s frontal plane. Then the hand motion with the shortest movement along this mutual direction of motion is mapped into a cursor’s motion on a 17” flat screen. The user can then play simple video games using cursor motion. During game play, participants were required to keep their hands at least 10 cm apart from each other to remove the possibility of bracing the weaker hand against the stronger and relying on the stronger arm to move the cursor (shifting the synergies from within-arm to between-arms synergies).

In this study, participants were asked to play a game called “Lucky Pirate” (OUAT Entertainment, apps.facebook.com/luckypirate). This game is set on a static background and requires players to explore the entire game screen to select and click on treasure chests that may contain gold coins. Completion of a level does not carry a time restriction; as a result, participants were able to progress at their own pace. As explained in the previous chapters, the game and the system are designed to provide a virtual reality based motor exploration task (Valdés et al. 2015). The requirement to use both hands to move the cursor on the screen was not considered a limiting physical constraint as the participants were free to choose how they wanted to temporally and spatially synchronize the motion of their hands.

5.2.3 Data Collection Procedure

Each participant took part in one data collection session. After becoming familiar with the FEATHERS system and “Lucky Pirate” game, the participants were asked to sit on a 70 cm high stool without a back-support, two metres away from a flat screen monitor (see Figure 2.2). The Lucky Pirate gameplay screen was projected on the monitor, and participants played the game by controlling a magnified cursor on the screen. The motion of the participants’ wrists was captured via a Kinect camera and was used by the FEATHERS software to move the cursor on the screen.
After the participants expressed that they were comfortable with using the FEATHERS system to play the game, they were asked to play the game for five intervals of three minutes each. The participants were given time to rest between intervals. During each of the gameplay intervals, upper-body motion data and muscle electromyography (EMG) data were collected. Each participant was given a $10 coffee shop gift card in appreciation at the end of the experiment.

A 16-channel Delsys (Natick, MA, USA) EMG system was used to record muscle activation from eight muscles on each side of the body at 2000 Hz: the brachioradialis (Brachi), biceps brachii (Biceps), long and lateral heads of triceps brachii (TriLong and TriLat), anterior, medial, and posterior fibres of deltoid (DeltAnt, DeltMed, and DeltPos), and clavicular fibres of pectoralis major (PectMaj) (Muceli et al. 2010; Gentner et al. 2013; Steele et al. 2013; Roh et al. 2015). EMG electrodes were placed in accordance with the European recommendations for surface electromyography (Hermens et al. 1999). Prior to data collection, maximum voluntary contractions were performed to ensure electrodes were placed properly.

The Microsoft Kinect motion capture system was used to collect joint kinematics data (Choppin and Wheat 2013; Webster and Celik 2014). The Kinect tracked the Cartesian location of several anatomical landmarks by assigning markers to them: centre of hip, chest at the level of shoulders, shoulders, elbows, wrists, and hands (i.e., centre of palms).

5.2.4 Electromyography and Kinematic Data Preprocessing

Before extracting muscle synergies, the EMG signals were amplified (×1000) and band-pass filtered (20-450 Hz) (Roh et al. 2013, 2015). Each muscle’s EMG signal was normalized to the maximum observed value of the signal. The preprocessed EMG data were then stored in two files, the dominant and non-dominant limb, each including data from eight muscles.

To calculate joint angles from marker positions, a human upper-body musculoskeletal model developed by Holzbaur (Holzbaur et al. 2005) for the OpenSim environment (Delp et al. 2007) was used. Using OpenSim software and the modified musculoskeletal model, the inverse kinematics of the marker motions were solved to find the change in the following joint angles (17 DOFs) over time: trunk motions as measured by roll, pitch, and yaw angles (TrRol, TrPit, and TrYaw), flexion-extension of both shoulders (ShFlEx), abduction-adduction of both shoulders (ShAbAd), medio-lateral rotation of both shoulders (ShRot), flexion-extension of both
elbows (ElFlEx), pronation-supination of both elbows (ElPrSu), radial-ulnar deviation of both wrists (WrDev), and flexion-extension of both wrists (WrFlEx).

Using this procedure, the joint angle time series during a motor exploration task for all 14 participants were calculated at 30 Hz. These data were then bifurcated, with each subset containing the joint angle time series data of the dominant and non-dominant upper limbs of each participant (10 DOFs in each set; trunk motion data were shared). Only movements within two standard deviations of the mean speed of the entire session were kept for further analysis. This was to ensure that all periods of pause or no movement were filtered out. The joint motion data were low-pass filtered at 6 Hz (Enoka 2015; Valdés et al. 2015) to remove motion artefacts.

5.2.5 Quantifying the Number of Synergy Vectors
The collected data were divided into muscle and kinematic sets, each set containing separate time series data for the dominant and non-dominant hands. After preprocessing the data, Variance Accounted For (VAF) was used to determine the number of synergy vectors ensuring sufficient factorization of the data by the NNMF method (Tresch et al. 2006). Similar to the study presented in Chapter 4, the number of synergy vectors is the minimum number of synergies that achieves a global (across all training data points) VAF > 90%, with less than a 5% increase in global VAF upon addition of another synergy vector (Delta VAF). As a local criterion, the VAF for each muscle or joint (DOF VAF) is required to exceed 65%. This procedure ensures that the estimated number of synergies can predict both the overall data set as well as each of the DOFs of the overall data set (Ting and Chvatal 2010; Roh et al. 2013, 2015; Lambert-Shirzad and Van der Loos 2017a).

5.2.6 Quantifying Similarity between Motor Synergy Vectors
The dot product of the two vectors can be used to quantify how aligned two vectors are (ranging from zero for orthogonal vectors to one for parallel vectors). Therefore, the dot product of synergy vectors can be used as a way to quantify one-on-one similarity between synergy vectors (i.e., structure of the synergy) (Cheung et al. 2005; Torres-Oviedo and Ting 2010).

In the previous chapter, I used a Monte Carlo simulation to generate a sampled distribution of the possible values of dot products between two synergy vectors. The 95th percentile of this distribution was then used as a cut-off threshold with any dot product value above this threshold considered statistically significant (p-value < 0.05). With this procedure, two synergy vectors
with a statistically significant dot product value are considered statistically similar, or in short, similar (Roh et al. 2012; Gentner et al. 2013). To calculate the dot product similarity of two synergy sets, the synergy vectors of the first set were compared against each of the synergy vectors of the second set to create a matrix containing dot product values of any choice of two synergy vectors from the two synergy sets. Using this matrix, the synergy vectors of the two sets were matched to maximize the sum of dot products of the matched synergy vectors.

In addition to dot product, VAF and DOF VAF can be used as complementary measures to quantify how well synergy vectors of one data set can be used in reconstructing (i.e., explaining the variation in) another data set (Roh et al. 2012). Therefore, these measures can be used to expand one-on-one similarity comparison of synergy vectors to comparing the similarity of a set of synergy vectors against another set. Specifically, this will be used to establish that the motor synergies of the less-affected side of body are preserved post-stroke and are similar to the healthy synergy templates introduced in the previous chapter. As explained in the previous chapter, a Monte Carlo simulation was carried out to set the similarity cut-off thresholds for global VAF and DOF VAF values. A set of synergy vectors producing reconstruction VAF measures above these thresholds are considered significantly similar.

Based on these Monte Carlo simulations, two sets of muscle synergy vectors that have a dot product value greater than 0.81, reconstruction VAF greater than 84.8%, and mean reconstruction DOF VAF greater than 80.5% are statistically similar. Also, sets of kinematic synergy vectors that have a dot product value greater than 0.91, reconstruction VAF greater than 89.7%, and mean reconstruction DOF VAF greater than 85.4% are similar with statistical significance.

### 5.2.7 Merging and Fractionation of Motor Synergy Vectors

It is possible that some of the motor synergy vectors of the affected limb remain similar to the healthy synergy vectors (i.e., preservation of synergy vectors). Merging and factorization of muscle synergies have been proposed as mechanisms to describe how the muscle synergies of the stroke-affected limb are altered compared to those of the less-affected limb (Clark et al. 2010; Cheung et al. 2012; Hashiguchi et al. 2016). In this study, I used these two concepts to describe how the muscle and kinematic synergies of the stroke-affected arm are altered compared to the kinematic and muscle synergies of the healthy population.
An altered synergy vector (i.e., non-similar to any of the healthy synergies) of the weak arm might be explained as multiple healthy synergies merging together. Following the work of Cheung et al. (Cheung et al. 2012), only a linear combination of healthy synergies in identifying merging of synergies is considered. To achieve this, I modelled merging for each affected-arm synergy vector as a linear combination of the healthy synergies (separately for kinematic and muscle synergies), as in Equation 5.1:

$$w_i^a = \sum_{k=1}^{N^a} m_i^k w_k^h, \quad (m_i^k \geq 0, i = 1 \ldots N^a)$$  \hspace{1cm} (Equation 5.1)

In this formulation, $w_i^a$ is the $i$th synergy of the weak arm, $w_k^h$ is the $k$th healthy synergy, $N^a$ is the number of weak arm synergies extracted, $N^h$ is the number of healthy synergies, and $m_i^k$ is the non-negative merging coefficient indicating the degree of contribution of the $k$th healthy synergy to the structure of the $i$th synergy of the weak arm. Note that each healthy synergy vector is allowed to contribute to the merging reconstruction of more than one weak arm synergy.

The non-negative merging coefficients were calculated and optimized using the non-negative least squares method. Contributions of healthy synergies with a merging coefficient below 0.2 were considered insignificant (Cheung et al. 2012). A merged reconstruction of each weak arm synergy was calculated and its similarity with the original weak arm synergy was quantified using dot product measure. If the dot product was greater than the similarity limit, that weak arm synergy was considered a merging of healthy synergies.

Stroke might fractionate a healthy synergy to create two or more of the weak arm synergies. Fractionation of healthy synergies was also modelled through a linear combination of the weak arm synergies, as in Equation 5.2:

$$w_k^h = \sum_{i=1}^{N^h} f_i^k w_i^a, \quad (f_i^k \geq 0, k = 1 \ldots N^h)$$  \hspace{1cm} (Equation 5.2)

In Equation 5.2, the non-negative fractionation coefficients $f_i^k$ indicate how the $k$th healthy synergy is fractionated into weak arm synergies. Just as with merging coefficients, fractionation coefficients were also identified using the non-negative least square method, and values under 0.2 were considered insignificant (Cheung et al. 2012). The least squares optimization was
constrained to ensure that each weak arm synergy was counted as fractionation of at most one healthy synergy.

5.2.8 Cluster Analysis of Weak Arm Synergies
I pooled together the weak arm synergies of all participants and grouped them into clusters using the k-means clustering method with Euclidian distance as the measure for in-cluster closeness. The cluster analysis was done in an eight- and ten-dimensional space for muscle and kinematic synergies, respectively (i.e., number of muscles and joints covered in the synergy vectors). The number of clusters was set as the minimum number that ensured each cluster had no more than one synergy from a participant and that all synergies in a cluster had a one-on-one dot product above the similarity measure. The cluster analysis helped identify which healthy synergies are more prone to merging and fractionation and which ones are preserved after stroke.

5.3 Results
The primary aim of the present study was to understand how the motor synergies underlying exploratory reaching motions change after stroke. I collected EMG and joint motion data as stroke-survivor participants completed 15 minutes of exploratory reaching by playing a motion-controlled video game. Participants set their own pace as long as they continuously moved their hands and played the game without any extended pauses. Using the collected data, I examined the similarity of the motor synergies of the strong arm of the stroke survivors with motor synergies of the healthy population. This was expanded to also study how stroke changes the structure of motor synergies in the weak arm.

5.3.1 Variation in the Data (Behaviour, Joint Kinematics, EMG) during the Task
Figure 5.1 shows the collected data from participant SS03 (male, left arm affected by stroke, 69 years old, UE-FMA 36, RPS 24) as an example. Figure 5.1.A shows the distribution of the wrist positions in the workspace (top two plots). The wrist positions were translated by the FEATHERS software into the motion of the cursor on the computer screen (Figure 5.1.A, bottom plot). Panels B and C of this figure show the recorded joint motion (degrees) and EMG (normalized to maximum observed in the channel) data for the participant. All the joints and muscles considered in this study were actively involved during the task. Note that this activity did not follow a specific pattern as the participant explored the workspace without inputs from the experimenters.
The contours in Figure 5.1.A show the minimum observed time spent at each point in the workspace in the frontal plane. The origin of the workspace in the top two plots was set to the lowest leftmost point that the participant’s left hand visited during game play. The participant has a similar side-to-side range of motion of both left and right arms. However, his vertical range of motion is about 10 cm greater on the strong side of his body (i.e., right arm).

Considering the joint motions (Figure 5.1.B), the left arm shows a lower activation in shoulder abduction/adduction. This can partially explain the participant’s smaller range of vertical motion on his left side. It is interesting to note the high spasticity in this participant; on the weaker side of the body (left side): 1) Shoulder is completely rotated inward and only rotates outward in spasm-like instances (see ShRot graph), 2) Elbow stayed more flexed compared to the strong arm (see ElFlEx graph), 3) Wrist stayed fully flexed for a major part of the motion (see WrFlEx graph). The difference between the activation of Biceps and Triceps (both long and lateral heads) between the two arms can also be associated with spasticity (Figure 5.1.C). The left Biceps muscle is continually active, whereas the Triceps has a low activation level combined with sudden peaks in activation. This regime of activation keeps the elbow at a flexed position.

Figure 5.1: Variation in the exploratory reaching data for participant SS03 (left limb affected by stroke). A) Contour plots show the time distribution of position of the wrists and the computer cursor during the task. The left (more-affected) side has a lower range of motion in both X and Y than the less-affected side. B) Joint motion data in degrees. Joint names are abbreviated. C) Normalized EMG data. Muscle names are abbreviated. All the joints and muscles considered in this study were actively involved during the task. However, no particular conclusion on how stroke changes the coordination of muscles and joints can be drawn from the data at this scale.
5.3.2 Number of Motor Synergies

To determine the number of synergy vectors, in the first step I factorized the muscle activation and joint motion data with the criteria mentioned in the Methods section (Figure 5.2). This resulted in two or three kinematic synergy and three or four muscle synergy vectors for the strong limb of the participants, with most of the participants requiring the greater number (~70% for kinematic and ~80% for muscle synergies). These strong-arm synergy vectors reconstructed more than 96% of the global VAF and at least 65% of the DOF VAF in both of the data sets. The number of synergy vectors on the strong arm of stroke survivors was comparable to those of the healthy population (see Chapter 4).

To facilitate similarity analysis between strong arm synergies of stroke survivors and the healthy synergy template, I chose the more frequent number of synergies for each data set as the number of required synergy vectors (three for kinematic and four for muscle synergies, similar to the number of synergies in the healthy templates) and re-extracted the motor synergies for each participant.

For all but one of the participants (SS11), 2 kinematic synergy vectors were enough to satisfy the factorization criteria for the weak arm. I did not re-extract kinematic synergies of SS11 with two
vectors as it would not pass the factorization criteria. Therefore, the weak arm kinematic synergies identified in this step were used in the next steps to understand how stroke changes kinematic synergies.

The number of weak arm muscle synergies varied between two and five for stroke-survivors. Given this wide range in the number of muscle synergies, I used the weak arm muscle synergies identified in this step in the next steps of analysis.

5.3.3 Muscle and Kinematic Synergies of the Less-affected Limb Are Preserved

Three metrics were used to quantify the similarity of each participant’s strong arm synergies with the healthy synergy template: dot product of synergy vectors, global VAF of reconstructed data, and mean DOF VAF of the reconstructed data. Here, reconstructed data refers to reconstructing the muscle or kinematic data based on the healthy synergy templates. Monte Carlo simulations were carried out to generate a sample distribution of possible values for the three similarity metrics. The 95th percentile of these distributions was used as a cut-off threshold for statistically significant similarity (see Section 5.2.6 for exact values). After identifying four muscle synergies and three kinematic synergies for the less-affected arm of all participants, I examined the similarity of the strong-arm synergies with the healthy template. This comparison was done separately for muscle and kinematic synergies.

Figure 5.3 details the distribution of dot product (left), global VAF (middle), and DOF VAF (right) measures of similarity between strong-arm muscle synergies and the healthy template. To generate the dot product similarity values, each participant’s strong arm muscle synergies were matched with the healthy template synergies to maximize the sum of dot products of the matched vectors. Considering all of the participants, the variability in the dot product values, moving from healthy template synergy #1 to #4, were: 0.932 ± 0.031, 0.916 ± 0.037, 0.948 ± 0.034, 0.926 ± 0.035. All of the 56 extracted strong arm synergy vectors (four pairs for each of the 14 participants) had a dot product value with one of the healthy template synergies that was above the similarity limit.

Figure 5.4 demonstrates the similarity in the structure of each individual’s strong arm muscle synergy set with the healthy template (leftmost column). Individual synergy sets were matched with the template to achieve the highest sum of dot products of the matched synergy vectors. In this figure, each column shows the synergy vectors of a single participant. The DP value reported
on top of each of the synergy vectors (i.e., bar graphs) is the dot product of that synergy vector with its matched healthy template synergy. Note that all exceed the minimum similarity level.

Figure 5.3: Distribution of muscle synergy similarity measures between less-affected arm of the participants and the healthy template. Left: dot product. Middle: global VAF. Right: average DOF VAF. All measures were above their respective minimum similarity limits, shown as a labelled horizontal line in the three graphs.

Figure 5.4: Strong arm muscle synergies of each of the participants matched with the healthy muscle synergy template (leftmost column). Muscle names are replaced with numbers: 1, 2, and 3 are anterior, medial, and posterior fibres of deltoid. 4 is biceps brachii. 5 and 6 are long and lateral heads of triceps. 7 is brachioradialis, and 8 is clavicular fibres of pectoralis major.

To generate the global VAF and DOF VAF distributions, both original strong arm (left boxplots on middle and right graphs of Figure 5.3) and healthy template (right boxplots on middle and right graphs of Figure 5.3) synergies were used to reconstruct the collected muscle activation
data for the strong arm of each participant. The distributions of global VAF and average DOF VAF were more compact when the original synergy set was used to reconstruct the data compared to when the healthy template synergies were used. However, all the values in these distributions were above the similarity limit. The original muscle synergies of the less-affected limb returned a global VAF of 95.7 ± 1.7 and reconstruction of the data using the healthy template returned a global VAF of 92.1 ± 2.7. The synergies of the strong arm accounted for 90.1 ± 2.4 of DOF VAF. This number was 84.6 ± 5.3 for the healthy template synergies.

The leftmost graph of Figure 5.5 shows the distribution of dot product similarity between strong arm kinematic synergies and the healthy template. For each participant, the kinematic synergies were matched to maximize the sum of the dot products. The variability in the dot product values, moving from healthy template synergy #1 to #3, were: 0.983 ± 0.017, 0.964 ± 0.016, 0.939 ± 0.016. All strong arm kinematic synergy vectors had a dot product value with the healthy template synergies that was above the similarity limit, as reported in Figure 5.6.

Figure 5.5: Distribution of kinematic synergy similarity measures between less-affected arm of the participants and the healthy template. Left: dot product. Middle: global VAF. Right: average DOF VAF. All measures were above their respective minimum similarity limits, shown as a labelled horizontal line in the three graphs.

Figure 5.5, middle and right graphs, shows global VAF and DOF VAF measures of similarity between the kinematic synergies of less-affected limb and the healthy template. Similar to Figure 5.3, the boxplots show the results of reconstructing the joint motion data of each individual with the original and the healthy template synergies. All the values of global VAF and DOF VAF were above the similarity limit. Similar to what was observed for muscle synergies, the distributions of global VAF and average DOF VAF for kinematic synergies were more compact when the original synergy set was used to reconstruct the kinematic data. The original kinematic synergies, on average, reconstructed a global VAF of 96.8 ± 0.6 and the healthy template synergies reconstructed a global VAF of 93.4 ± 1.5. The synergies of less-affected limb
accounted for 94.8 ± 1.0 of DOF VAF and the healthy template synergies reconstructed 91.9 ± 1.2 of DOF VAF.

Figure 5.6: Strong arm kinematic synergies of the participants matched with the healthy kinematic synergy template (leftmost column). Joint names are replaced with numbers: 1, 2, and 3 are Trunk Roll, Yaw, and Pitch. 4, 5, and 6 are shoulder flexion/extension, abduction/adduction, and rotation. 7 and 8 are elbow flexion/extension and pronation/supination. 9 and 10 are wrist ulnar deviation and flexion/extension.

5.3.4 Mechanisms of Disruption in Motor Synergies of the Affected Limb

After extracting muscle and kinematic synergies of the affected limb for each participant, the dot product metric was used to compare each of these synergy vectors with the healthy templates. The results showed that a number of each participant’s muscle and kinematic synergy vectors were similar to the synergies of healthy templates. This is referred to as preservation of a motor synergy after stroke. However, not all synergy vectors of the affected limb were preserved after stroke, which indicates that stroke can disrupt both muscle and kinematic synergy structures.

To reconstruct the collected data from the weak arm, only a small number of participants required the exact same number of synergy vectors as in the healthy templates (four for muscle synergy vectors and three for kinematic synergies). Only two participants had four muscle synergies, and only one had three kinematic synergies, accounting for 14% and 7% of the participants, respectively. The majority of the participants required a smaller number of synergy vectors. Other researchers (Cheung et al. 2012; Hashiguchi et al. 2016) have shown that this difference in dimensionality of the synergy structures could be attributed to a merging process that combines two or more healthy synergies. Such a merging process was present in the post-
stroke population recruited for this study and was used to reconstruct a number of affected arm synergies by linearly combining healthy synergies (see Section 5.2.7 for more details). Figure 5.7 shows how preservation and merging can be used to relate the affected arm muscle synergies of SS08 (left) and kinematic synergies of SS09 (right) to the healthy synergies. The dot product (DP) measure was used to assess the similarity of the original affected arm synergies with the original and merged healthy synergies.

Moreover, Cheung (Cheung et al. 2012) suggests that a number of healthy motor synergies might break into two or more synergies after a stroke, creating a sparser set of synergy structures. This is referred to as fractionation of healthy synergies. Using the computational procedure outlined in the Methods section, I confirmed that such a fractionation process can reconstruct a number of identified affected arm synergies with a dot product above the similarity limit. As an example, Figure 5.8 shows how preservation and fractionation can be used to reconstruct the weak arm muscle synergies of SS04. Note that healthy synergy #4 mostly involves activation of the deltoid.
muscles (top row, at right). The activation of the deltoid muscles was divided into three synergies in SS04, each controlling one of the deltoid muscles (bottom row, at right). This fractionation of a healthy synergy vector generated a sparser synergy structure and increased the dimensionality of the motion control strategy employed by the central nervous system.

![Preservation and Fractionation of Muscle Synergies (SS04)](image)

Figure 5.8: Preservation and fractionation can be used to relate the affected arm muscle synergies of SS04 to the healthy template synergies. H# identifies the healthy template synergies and A# identifies affected arm synergies. H#4 involves activation of deltoid muscles and it was fractionated into three different synergies, each controlling one of the deltoid muscles.

All 29 of the identified affected limb kinematic synergies could be categorized as preservation, merging, or fractionation of the healthy kinematic synergies. However, only 42 of the 45 identified affected limb muscle synergies could be categorized as preservation, merging, or fractionation of the healthy muscle synergies. The other three muscle synergy vectors could not be related to the healthy template synergies, and were categorized as new synergies.

5.3.5 Probability of Observing Different Mechanisms of Synergy Disruption and Their Relationship with Clinical Scores and Time Post-stroke

Certain healthy synergies were more likely to undergo the three mechanisms of synergy reorganization post-stroke (i.e., preservation, merging, and fractionation). Figure 5.9 shows an
overview of the probability of observing the three re-organization mechanisms. For each specific combination of mechanism and healthy synergy, the probability value was calculated based on how many participants demonstrated that specific combination of mechanism and healthy synergy. For example, the results showed that 5 of the 14 participants had a weak-side muscle synergy vector that was similar to synergy #1 of the healthy template (preservation). Therefore, the probability of observing preservation of synergy #1 of the healthy muscle synergy template was calculated as 5/14, or 36%. The error values reported are standard errors calculated based on these probabilities. The merging probability of a pair of healthy synergies includes both the instances where only those two synergies were merged, as well as any merging of those two synergies with a third synergy.

<table>
<thead>
<tr>
<th>Synergy</th>
<th>H#1</th>
<th>H#2</th>
<th>H#3</th>
<th>H#4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preservation</td>
<td>36 ± 12%</td>
<td>71 ± 12%</td>
<td>50 ± 13%</td>
<td>36 ± 12%</td>
</tr>
<tr>
<td>Fractionation</td>
<td>H#1</td>
<td>H#2</td>
<td>H#3</td>
<td>H#4</td>
</tr>
<tr>
<td></td>
<td>14 ± 9%</td>
<td>29 ± 12%</td>
<td>0 ± 0%</td>
<td>29 ± 12%</td>
</tr>
<tr>
<td>Merging</td>
<td>H#2</td>
<td>H#3</td>
<td>H#4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>21 ± 10%</td>
<td>14 ± 9%</td>
<td>29 ± 12%</td>
<td></td>
</tr>
</tbody>
</table>

**Figure 5.9:** An overview of the probability of observing the three post-stroke synergy re-organization mechanisms. H# identifies the healthy template synergies.

Healthy muscle synergies #2 and #3 had a higher chance of being preserved after a stroke. There was no observation of any fractionation of healthy muscle synergy #3. Healthy muscle synergies #2 and #4 were more likely to merge together. Interestingly, healthy kinematic synergy #1 was not preserved or fractionated. However, healthy kinematic synergy #2 was preserved in 12 of the participants. There were only two instances of kinematic synergy fractionation. All of the participants showed merging of kinematic synergies #1 and #3.
Post-stroke kinematic synergies of the weak arm had a distinct pattern of disruption that was independent of participants’ time post-stroke and function: healthy synergies #1 and #3 were merged for all participants, and healthy synergy #2 was preserved in all participants except for the two participants with the lowest function (i.e., the lowest Fugl-Meyer assessment and reaching performance scores).

Multiple linear regression was used to quantify the relationship between the presence of a mechanism of change in muscle synergies and time post-stroke or motor function. For each participant, a preservation index, a merging index, and a fractionation index were calculated. Each index was calculated as a percentage and indicates the ratio of the affected arm muscle synergies that could be reconstructed using the specific re-organization mechanism to the number of affected arm muscle synergies of a participant.

There was no linear relationship between fractionation index and either of post-stroke duration or motor function. The merging index showed a significant negative correlation with both Fugl-Meyer assessment and reaching performance scores (FMA: \( r = -1.8, p < 0.01 \), and RPS: \( r = -2.4, p < 0.001 \)). This suggests that as impairment becomes more severe, merging of muscle synergies in the more-affected side of the body becomes more likely. Furthermore, the preservation index and post-stroke duration (in logarithmic scale) also had a significant negative correlation (\( r = -44.3, p < 0.01 \)). This correlation indicates that as more time passes from the onset of stroke, the muscle synergies of the weaker arm are less likely to remain preserved. Figure 5.10 shows these significant linear relationships.

### 5.3.6 Between-Participants Similarity of Post-stroke Synergies: Cluster Analysis

To understand whether merging, fractionation, or generation of new synergies create post-stroke synergies that are similar between participants, a cluster analysis of all extracted weak arm synergies was performed. This was done separately for muscle and kinematic synergies.

The 45 extracted weak arm muscle synergies were grouped into seven clusters as shown in Figure 5.11. The number of synergy vectors in each cluster \( (n) \) and their mean dot product value \( (DP) \) is presented for each cluster. The mean vector of each cluster was compared to the healthy template synergies. Clusters #1 to #4 were similar to the four healthy template muscle synergies and represent preservation of the healthy synergies. Cluster #5 represents the merging of healthy synergies #2 and #4, whereas cluster #6 represents the merging of healthy synergies #1, #3, and
As mentioned previously, three weak arm muscle synergies could not be related to the healthy template synergies through either of the mechanisms of synergy re-organization and were named new synergies. Interestingly, these three new synergies were similar (measured by having DP values above the similarity limit) and were grouped together in cluster #7.

Figure 5.10: Muscle synergy merging index is correlated negatively with both Fugl-Meyer assessment and reaching performance scores (left and middle graphs). Muscle synergy preservation index is negatively correlated with post-stroke duration (in logarithmic scale, right graph).

Figure 5.11: Weak arm muscle synergies were grouped into 7 clusters. The number of synergy vectors in each cluster (n) and their mean dot product value (DP) are presented for each cluster.
The 29 extracted kinematic synergies from the affected limbs of the participants were grouped into two clusters, as shown in Figure 5.12. The previously identified distinct pattern of disruption in kinematic synergies of the individuals was also present when all participants were grouped together. In this case, cluster #1 represents preservation of healthy kinematic synergy #2, and cluster #2 represents merging of healthy kinematic synergies #1 and #3. The results of the cluster analysis suggest that despite the differences in functional ability and time since onset of stroke between participants, the motor synergies of the more-affected side of the body show a high degree of similarity between participants.

![Affected Arm Kinematic Synergy Clusters](image)

Figure 5.12: Weak-arm kinematic synergies were grouped into 2 clusters. Shown here are the averages of the synergy vectors in each cluster. The number of synergy vectors in each cluster (n) and their mean dot product value (DP) are presented for each cluster.

### 5.4 Discussion

The primary goal of this study was to use the concept of synergistic motor control to provide an understanding of motion coordination post-stroke. The study presented in the previous chapter showed that a unique group of muscle and kinematic synergies is shared between healthy participants (healthy synergy template). In the study presented in this chapter, these synergies were used as a baseline to investigate how stroke changes upper-body motion generation. To this end, the NNMF algorithm was used to extract muscle and kinematic synergies of 14 adults post-
stroke. Joint motion and EMG data collected as the participants completed a motor exploration task were used for this analysis. I found that a small number of muscle and kinematic synergies account for the majority of the variance in the muscle activation and joint motion data sets of the participants. This indicates that a modular organization of motion generation remains present after stroke. However, further analysis of these muscle and kinematic synergies, done separately for the strong and weak arms of the participants, showed how stroke alters the synergy structure.

### 5.4.1 Muscle and Kinematic Synergies of the Less-affected Limb Are Preserved

To ensure sufficient factorization and quality of synergy extraction, two or three kinematic synergy and three or four muscle synergy vectors for the strong limb of the participants were required (with most of the participants requiring the greater number). As there were three kinematic and four muscle synergy vectors in the healthy synergy templates and to facilitate easier comparison, three kinematic and four muscle synergies were extracted from the strong arm’s motion data of all stroke-survivor participants (Roh et al. 2013, 2015).

To show that the strong-arm synergies are similar to the healthy synergies, three metrics, each reflecting a different aspect of motion coordination similarity, were used. The first metric, Dot Product (DP) values between synergy vectors, can be used as a way to identify similarity in the synergy structure. The second metric, Variance Accounted For (VAF), is sensitive to how well a synergy set can reconstruct both overall shape and magnitude of a data set. The third metric, variance accounted for in each of the joint motions/muscle activations (VAF DOF), can be used to quantify how a synergy set can reconstruct the nuances in a data set on an element-by-element level. The results showed that for all participants, all of the extracted muscle and kinematic synergies from the less-affected limb passed the three similarity tests, suggesting preservation of the healthy synergistic motion generation in the strong arm of stroke-survivors.

Cheung et al., in a study with eight post-stroke participants with mild impairment (mean UE-FMA of 50), also showed that the muscle synergies of the strong arm were preserved after stroke (Cheung et al. 2009). The results presented in this chapter expands the work of Cheung et al. to include both muscle and kinematic synergies, as well as a more diverse range of post-stroke impairments.

A reconstructed data set captures more of the original variance in the data when the synergy vectors identified from the same data set (i.e., a participant’s own synergies) are used. The
captured variance decreases when the healthy template synergies were used in reconstructing the data. This was expected as a person’s synergies can capture more details of the person’s motion compared to a set of synergies that were produced by averaging the synergy sets of a group of people. Chapter 4 provides an in-depth explanation of this observation using the Uncontrolled Manifold hypothesis (Scholz and Schöner 1999; Tresch and Jarc 2009).

As the motor synergies of the strong arm are similar to the healthy synergy templates, the modular motion coordination in the less-affected limb can be discussed based the healthy template synergy vectors. For a detailed biomechanical explanation of these synergy vectors see 4.4.3 Biomechanical Interpretation of Healthy Motor Synergies.

5.4.2 Mechanisms of Change in Motor Synergies of the Affected Limb as Markers of Impairment and Recovery

By comparing the muscle and kinematic synergies of the affected limb with the healthy motor synergy templates, I showed how a stroke changes the motor synergy structure. This comparison showed three main patterns in motion coordination of the weak arm: preservation, merging, and fractionation of healthy synergies. All of the weak arm kinematic synergies and 94% of the muscle synergy vectors could be reconstructed with these synergy re-organizing mechanisms.

In (Cheung et al. 2012), Cheung et al. compared the post-stroke upper body muscle synergies of the weak and strong limbs and reported the existence of the aforementioned three synergy re-organizing mechanisms. However, that study relied on the assumption that the strong-arm synergies are not changed by stroke. This study addressed this shortcoming by demonstrating that the strong-arm synergies are indeed preserved after stroke, and directly comparing weak arm synergies with healthy synergy templates. Hashiguchi et al. (Hashiguchi et al. 2016) also demonstrated the existence of these mechanisms by comparing the lower-body muscle synergies of the affected side in sub-acute stroke survivors over a one-month interval. The study presented in this chapter expands our understanding of these mechanisms of change from muscle synergy analysis to also include kinematic synergies.

While previous studies have identified the three mechanisms of change in muscle synergies (Clark et al. 2010; Cheung et al. 2012; Hashiguchi et al. 2016), they did not show which synergies are more inclined to undergo these changes. Figure 5.9 shows an overview of such probabilities. While all healthy muscle synergies were preserved in one third to two thirds of the
participants, preservation of the kinematic synergies was more diverse. Specifically, healthy
kinematic synergy #1 was not preserved at all, whereas healthy kinematic synergy #2 was
preserved in almost all of the participants. It is hard to comment on whether preservation or lack
of preservation of a muscle synergy has an effect on preservation of a kinematic synergy, or vice
versa. This is due to the fact that the main difference between the three healthy kinematic
synergies is in the weights associated with the wrist DOFs and elbow supination-pronation and
that the muscles in charge of controlling these three joint motions are not present in muscle
synergies, as I did not collect their EMG data.

Fractionation of kinematic synergies was very rare and was only observed in 6% of the weak-
arm synergies. However, merging of kinematic synergies was very frequent as merging of
healthy kinematic synergies #1 and #3 was observed in all of the participants. This is an
interesting finding as it suggests that the change in the kinematic behaviour of stroke survivors is
more toward co-activation of joints (merging of synergies) rather than development of highly
specialized motions (fractionation of synergies into more sparse synergies).

Healthy muscle synergy #3 showed no fractionation as it is very sparse. In contrast, the densest
synergy (healthy muscle synergy #4) showed the highest probability of being fractionated.
However, sparsity was not the only reason for fractionation. Healthy muscle synergy #2, a highly
sparse synergy vector mainly involving two muscles, was fractionated in almost one third of the
participants, separating the control of anterior fibres of deltoid and the pectoralis major.
Moreover, the pairs of healthy muscle synergies #2 and #4, and #1 and #4, were more likely to
merge together to create dense synergies involving co-contraction of most of the muscles
included in the analysis.

Post-stroke kinematic synergies of the weak arm had a distinct pattern of disruption which was
independent of participants’ time post-stroke and function: merging of healthy synergies #1 and
#3 and preservation of healthy synergy #2. This was also reflected in the cluster analysis
presented in Figure 5.12. Merging of healthy kinematic synergies #1 and #3 can result in a
typical post-stroke postural change in which the elbow is supinated and the wrist is flexed.

Moreover, similar to the findings of both Cheung and Hashiguchi (Cheung et al. 2012;
Hashiguchi et al. 2016), the merging index for muscle synergies showed a significant negative
correlation with participants’ motor function (measured by both Fugl-Meyer assessment and
reaching performance scores). Thus, for more severe impairment post-stroke, it is more likely that weak-arm synergies represent merging of multiple healthy synergies. This is compatible with the typical co-contraction of muscles post-stroke as described in the literature (Beer et al. 1999; Neckel et al. 2006; Clark et al. 2010; Marciniak 2011). The stronger coupling of the shoulder and elbow muscles (Dewald et al. 1995; Ellis et al. 2005) is represented by the density of the merged synergies as captured by cluster synergies #5 and #6 in Figure 5.11 and can be the reason for spasticity post-stroke. In three of the participants a new synergy vector, as captured by cluster synergy #7 in Figure 5.11, emerged that activates posterior fibres of the deltoid and the lateral and long heads of the triceps. This synergy can extend and abduct the shoulder and extend the elbow. Therefore, this new synergy can be a response to the high co-activation of shoulder and elbow muscles that causes spasticity and curls the arm inward.

Furthermore, the preservation index and post-stroke duration (in logarithmic scale) had a significant negative correlation. This is an interesting finding that can suggest as time passes and stroke becomes chronic, stroke survivors reorganize their synergy structure to create compensatory solutions for their impairment. However, previous studies have not explored this relationship and at this point, it is hard to provide a definitive explanation for this result.

There was no linear relationship between fractionation index and either post-stroke duration or participant’s motor function. A previous study has reported a relationship between fractionation index and time post-stroke (Cheung et al. 2012). However, this study considered, on average, synergies between 13 muscles per participant, making the identified synergies denser and therefore more prone to fractionation. Fractionation of the muscle synergies might be a response to weakness, which is a common post-stroke impairment. Weakness post-stroke is believed to be due to agonist muscles not being activated properly as their neural drive through the corticospinal tract reduces (Steenbergen et al. 1996). Consequently, fractionation of muscle synergies can let the CNS focus its limited reserve of neural paths on activating one or two specific muscles.

As discussed in the previous chapters, the uncontrolled manifold (UCM) hypothesis suggests that the CNS divides the space into controlled and uncontrolled elemental variables. The variation of controlled variables ensures achieving the task goal and the variation in the uncontrolled manifold ensures flexibility and stability of the motion. UCM was used in Chapter 4 to explain the mechanisms behind the synergistic motor control in the healthy population. Although the
stroke population also shows evidence of synergistic control, UCM alone cannot be used to
describe the processes behind generation of these synergies. UCM was proposed to explain
healthy motor coordination and how the CNS manages an abundance of elemental variables to
generate motions by creating motor synergies. However, as shown by the results presented here,
post-stroke synergies might be the result of merging and fractionation of healthy synergies,
exceeding the limits of what UCM can provide as an explanatory framework. At this stage, it is
premature to support any hypothesis on the neural origin and physiological processes behind
preservation, merging, and fractionation of synergies. To provide any insight into this, future
studies should include data on the size and location of cortical lesion and explore the relationship
of such data with re-organization of synergies.

5.5 Conclusion

The primary aim of this study was to understand how the motor synergies underlying exploratory
reaching motions change after stroke. The results exhibited a similarity between the motor
synergies of the strong arm of the stroke survivors and motor synergies of the healthy population.
Moreover, this study showed that post-stroke motor synergies in the weak arm can be related to
healthy motor synergies through three distinct processes: preservation, merging, and
fractionation.

This study can be expanded to investigate how motor synergies change during the process of
physical therapy. Such studies will grow our understanding of the process of recovery: Is
recovery the process of generating new motor synergy structures or is it a process of fine-tuning
how existing damaged motor synergy structures are being activated?

Moreover, the results of this work can be used to build a method to better quantify motor
impairments in order to fulfil the need for objective and holistic clinical assessments (Lam et al.
2015; Tatla et al. 2015). A more in-depth and quantified measure of motor impairment, in turn,
can be used as a performance/improvement metric to create individualized and engaging care for
recovering stroke survivors.
6 Conclusions

6.1 Objectives and Contributions

The central nervous system must combine many degrees of freedom available in the human musculoskeletal system to generate coordinated motor behaviour. There is a growing body of work that supports the existence of a synergistic motor control mechanism utilized by the CNS to facilitate motor coordination. The theory of motor synergies suggests that the CNS controls groups of muscles and/or joints rather than controlling each muscle or joint separately, effectively reducing the high dimensionality of motor planning and execution. Furthermore, recent studies with stroke survivors suggest that motor impairment after stroke is due to the disruption caused by the cortical lesion in the recruitment and the combination of the motor synergies.

Several studies show how the concept of motor synergies can be used to explain a major fraction of variation in EMG or joint motion data of a range of goal-directed motor tasks. One of the critiques of these studies is that the synergies they report are task-specific and reflect the biomechanical constraints of the task rather than the underlying neural strategies of motor control. To address this critique of motor synergies, the studies covered in this dissertation focused on quantification of motor synergies demonstrated during exploratory motor tasks instead of goal-directed motor tasks with physical constraints. Exploratory motions have the potential to reveal individualized motion tendencies or motor deficits as the way a person explores a task space is a function of their own control strategies and biomechanical constraints.

The objectives of the work presented in this thesis were to investigate human upper body motor coordination and to demonstrate the viability of synergistic motor control theory in describing the natural upper body movements, as well as quantifying the effects of stroke on motion generation. As part of this work, I also investigated the robustness of several different dimensionality reduction methods for quantifying motor synergies. This work also included an
investigation of how much joint motion and muscle activation data would be minimally required to precisely quantify motor synergies.

The main contributions of this work are:

- Proposing a bimanual motor exploration task to study healthy and stroke-affected kinematic or muscle synergies
- Comparing robustness of analytical methods and metrics reported in literature in characterizing motor synergies
- Investigating how much exploratory motion data is needed to reliably extract motor synergies of healthy and stroke-survivor individuals
- Providing an understanding of the differences between motor synergies of the dominant and non-dominant hands of healthy adults (within-subject differences) and whether there is a set of “healthy” motor synergies shared within this population (between-subjects differences)
- Providing an understanding of the effects of stroke on motor control, specifically whether the strong side of the body utilizes a “healthy” synergy set and whether motor impairment after stroke is due to disruption in the structure of synergies
- Proposing motor synergies as a clinical score to quantify the motor recovery process after stroke and answering fundamental questions about the nature of this process.

6.2 Comparison of Matrix Factorization Methods for Motor Synergies Analysis

Several recent studies have demonstrated that a range of functional tasks can be explained by motor synergies. These studies have shown that between 75-90% of the variance in the measured EMG can be explained by combinations of muscle synergies. Similarly, studies have shown that a low-dimensional space accounts for a large portion of the kinematic variance in a range of tasks.

Although these studies support the motor synergies hypothesis, they have used several different computational methods to provide this support by identifying underlying synergies in human motor behaviour. A range of factorization methods has been used in these studies to reconstruct the experimental data by linearly combining a small set of basis vectors or motor synergies. Chapter 2 presented a systematic comparison of the performance of the most reported
factorization methods in literature to determine their robustness in identifying motor synergies. The three considered factorization methods were: Non-Negative Matrix Factorization (NNMF), Principal Component Analysis (PCA), and Independent Component Analysis (ICA).

A k-fold cross validation \((k = 20)\) was implemented to compare the performance of the factorization algorithms. Once the synergy structure of a fold of training data was extracted, six metrics were used to quantify the performance of the factorization methods: number of identified synergies, average reconstruction error of both training and validation data sets, average correlation coefficient between the original data and the reconstructed data for both training and validation data sets, and dimension of the common subspace between the training and validation data sets (number of synergy vectors of the two data sets that have a strong correlation \(r > 0.9\)).

These six goodness-of-fit metrics can be divided into three categories: category 1) two metrics to study the structure of the data (synergy vectors), category 2) two metrics to quantify how well identified synergies can be used to reconstruct the data (reconstruction error) and category 3) two metrics to observe correlation of the original and reconstructed data sets. Considering the six goodness-of-fit metrics, PCA and NNMF had a comparable performance on both EMG and joint motion data, both outperforming ICA.

Moreover, NNMF identifies vectors that describe a subspace within which all data points will lie. The non-negativity constraint dictates that only the points between the identified vectors can be reconstructed. In this way, NNMF basis vectors identify the edges of the data set. The first PCA basis vector aligns with the “centre” of the data and explains most of the variance in the data. The rest of the PCA vectors are orthogonal to the first one and to each other and explain a much lower variance in the data. PCA basis vectors capture the mean and (residual) variance from the mean. This means some data points might have a negative activation along any of the second to the last basis vectors, making interpretation of activation matrix of synergies difficult (e.g., a muscle can be negatively activated). Therefore, NNMF’s non-negativity condition for activation of synergies helps in identifying physiologically meaningful synergies, making it a more appealing synergy extraction method. ICA synergy vectors shift from describing the edge of the data to the major direction of the data depending on the data set and can cause confusion in interpreting the results of the decomposition if the nature of the data is unknown.
6.3 Exploratory Motion Data Sample Size Needed for Motor Synergies Analysis

The first logical step to consider exploratory motions in a study of motor synergies is to determine how much data is required to reliably and fully profile the motion patterns of an individual. Chapter 3 presented a study on how the quality of a motor synergies analysis depends on the amount of exploratory motion data included in the analysis. In this study, 10 healthy and 10 post-stroke participants were recruited and electromyography and joint motion data of their arms as they completed a motor exploration task were collected. The effects of clinical status and limb strength/dominance on the amount of data required to identify synergies were investigated.

Increasing the amount of data included in motor synergy analysis gradually increased the quality of synergy characterization. Clinical status had a significant effect on the required amount of data for both datasets. Limb strength had a significant effect only for kinematic data. Based on the samples analysed in this study, 95% confidence intervals (CI) of time-to-synergy characterization were built. The upper bound of these CIs can be treated as the minimum amount of data required to reliably quantify motor synergies. The upper bound of the time-to-characterization CIs for the stroke survivors was higher than for the healthy participants for both muscle synergies (264 sec vs. 231 sec) and kinematic synergies (265 sec vs. 238 sec).

6.4 Upper-body Kinematic and Muscle Synergies in Healthy Adults

Chapter 4 covered the results of a study on the use of non-negative matrix factorization to identify muscle and kinematic synergies in healthy upper-limb exploratory motions. I recruited 15 healthy participants and collected electromyography and joint motion data of both their arms as they completed an upper-body exploratory motion task. Four muscle synergies and three kinematic synergies were sufficient to reliably reconstruct the motion data of each participant. The number of synergy vectors was determined as the minimum number of synergies that achieves a global Variance Accounted For (VAF) > 90%, with less than a 5% increase in global VAF upon addition of another synergy vector. As a local criterion, the VAF for each muscle or joint (DOF VAF) was required to exceed 65%. The low number of identified synergies suggests that the healthy CNS uses a modular motion coordination scheme for arm motion control.
The similarity of synergies was established with three metrics: dot product of synergy vectors, global VAF of reconstructed data, and DOF VAF of reconstructed data. The dot product of synergy vectors can be used as a way to quantify the similarity in the synergy structure by identifying the shared (i.e., parallel) vectors of the two data sets. VAF is sensitive to both shape and magnitude of the original measured data and reconstructed (factorized) data. Therefore, VAF and DOF VAF can be used as a measure to quantify how well synergy vectors of one data set can be used in reconstructing (i.e., explaining the variation in) another data set, both at a holistic and an element-by-element level.

The identified synergies were similar between the dominant and non-dominant limbs of all healthy participants. Moreover, the results showed that healthy participants share the same muscle and kinematic synergies. Using the identified synergies, I introduced healthy templates for muscle/kinematic synergies and explained the biomechanical meaning of each of the synergy vectors in these templates.

6.5 Upper-body Kinematic and Muscle Synergies in Chronic Stroke

In general, research concerning motor synergies has been focused on developing methods to characterize synergies using behavioural data from the healthy population. Chapter 5 covered a study that explores upper-body motion coordination post-stroke from a motor synergies perspective. The templates for healthy motor synergies reported in Chapter 4 were used as a benchmark for healthy motion coordination to study how stroke alters motion coordination patterns and causes impairment.

The results showed that the motor synergies of the less-affected side of the body are preserved after stroke. Although a number of the more-affected arm synergies were similar to those of the healthy population, a considerable portion of them were altered. The majority of these altered synergies could be related to the synergies of the healthy population through merging and fractionation of healthy synergies. The alteration in the synergies of the weak arm was linearly related to each participant’s motor function and time post-stroke, indicating motor synergies can be used as an objective way of quantifying impairment post-stroke.
6.6 Methodological Considerations and Future Studies

The small sample size and the limited number of muscles considered for synergy analysis are the main limitations of the current work. Future studies should include more participants with a more diverse range of impairments in order to be able draw more generalizable conclusions. As an example, the small sample size of the study presented in Chapter 5 led to only including two participants with severe impairment (commonly used upper-extremity FMA cut-off scores define three categories of impairment: 0 to 20 = severe, 21 to 50 = moderate, and 51 to 66 = mild (Kwakkel et al. 2004)). These two participants were the only ones who did not show preservation of kinematic healthy synergy #2. Expanding the sample size to include more participants with severe impairment will clarify whether lack of preservation of kinematic healthy synergy #2 observed in the current sample is a trend or an outlier.

The healthy muscle and kinematic synergy templates were derived based on data collected from young healthy participants with an average age of ~25 years. In the study presented in Chapter 5, these templates were used to understand how stroke changes the motor synergies in a considerably older population with an average age of ~60 years. This was done based on the assumption that motor synergies are not altered as healthy individuals age. Although the literature does not provide any evidence contradicting this assumption, future studies must include a comparison of motor synergies between young and older healthy adults.

The 16-channel Delsys EMG system used for collecting muscle activation data limited the experiments to only include eight muscles on each side of the body. Including more muscles for synergy analysis would provide a more holistic view of how the CNS generates motions and could provide a better understanding of the merging and fractionation processes in the stroke-survivor population. However, as more muscles are included, the possibility of crosstalk between EMG channels placed over muscles that are anatomically close to each other increases.

For the studies presented in this dissertation, surface electromyography was used to collect muscle activation data. Although the signal collected by an EMG electrode placed over the location of a muscle is dominated by that muscle’s activity, the signal also includes traces of activation of nearby muscles. This is known as crosstalk between EMG channels. Matrix factorization methods (Non-Negative Matrix Factorization here) are based on the assumption that the incoming signals are independent. Crosstalk of EMG signals violates this assumption and can skew the results toward identifying synergistic relationships between muscles that are
anatomically close to each other. This effect was reduced in this study by using differential EMG electrodes and collecting EMG data of large muscles, which is supported by the unique pattern of activation observed for each muscle as shown in Figure 4.1 and Figure 5.1. It is recommended to study if inclusion or exclusion of muscles known to be affected by crosstalk in synergy analysis leads to different sets of synergies.

The goal of this work was to study motor synergies exhibited during an unconstrained task to get a more general view of how the CNS controls motions. The task used for the studies presented here did not incorporate any physical constraints. The healthy synergies found in Chapter 4 matched those reported in other studies of motor synergies in unconstrained tasks. This suggests that the task used in the present study successfully removed task constraints. However, the bimanual nature of the task and playing a video game can still be considered a constraint. To address this, future studies should collect data from different tasks involving the arm muscles and joints (reaching to predefined targets, throwing, catching, etc.) and show that the healthy synergies discussed in Chapter 4 can explain the variance in the collected muscle activation and joint motion data.

At this time, it is premature to support any hypothesis on the neural origin and physiological processes behind preservation, merging, and fractionation of synergies after stroke. To provide any insight into this, future studies should include data on the size and location of the cortical lesion and explore the relationship of such data with re-organization of synergies. Long-term studies involving quantification of the change in the brain’s connectivity post-stroke can answer whether the origin of merging and fractionation in synergies is under cortical control or is organized in the brainstem and spinal cord. Moreover, quantifying and comparing motor synergies of stroke survivors over time and as they undergo therapy can expand our understanding of the process of recovery post-stroke. Specifically, such studies can answer one main question: Is recovery the process of generating new motor synergy structures or is it a process to fine-tune how existing damaged motor synergy structures are being activated?

The results of this work provide a means to quantify motor impairments and can be used to satisfy the need for objective and holistic clinical assessments (Lam et al. 2015; Tatla et al. 2015). This in-depth quantitative measure of motor impairment, in turn, can be used as a metric of performance or improvement during a physical therapy regimen. Moreover, my previous work
(Shirzad and Van der Loos 2012, 2013, 2016) can be expanded to generate individualized and engaging exercise programs for recovering stroke survivors based on their own motor synergies.
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**References for Appendix A**


Appendix A – FEATHERS, A Bimanual Upper Limb Rehabilitation Platform: A Case Study of User-centred Approach in Rehabilitation Device Design

The healthcare sector is increasingly becoming dependent on medical devices and technologies. This is facilitated, in part, by the emphasis that is being put on the robustness of the design of medical and rehabilitation devices. The robustness of the design, and thus the adoption of a new medical device, relies heavily on its ability to fit into the multifaceted medical environment and satisfy a wide range of user needs. In order to achieve this, users and stakeholders must be involved early and frequently in the design process. This appendix outlines a user-centred approach to design of physical therapy devices using a case study on developing an upper-body motor rehabilitation platform.

A.1 Introduction

Stroke is the most common source of long-term disability among adults in North America and one of the leading causes of disability in children diagnosed with cerebral palsy. Hemiparesis, especially weakness and loss of control of the upper and lower limb on one side of the body, is the main impairment after stroke (Van Peppen et al., 2004). In children with cerebral palsy (CP), hemiparesis and impaired function of the upper extremity has a prevalence of one in three cases (Gordon et al., 2006). Hemiparesis can lead to non-use of the affected side of the body and a near-exclusive reliance on the unaffected upper extremity, which in turn leads to loss of independence in activities of daily living.

Individuals post-stroke need to complete a rehabilitation therapy program in order to recover from the hemiparesis caused by stroke. The main clinical goal of such rehabilitation programs is to speed up the recovery process as much as possible. To guide this process, physical and occupational therapists work alongside each other to deliver a rehabilitation program that is
tailored to the needs and conditions of each individual. However, this important goal of individualization is usually overlooked when biomedical engineers embark on designing new therapy tools. The end goal of “speed up the recovery process for the therapy clients as individuals” is often assumed to be “use technology to speed up the process of motor function recovery”. Without involving the users and stakeholders in the design process, such false assumptions become accepted and unquestioned which leads to development of devices that will not be accepted by the users.

Traditionally, development of physical therapy devices has been based on motor learning principles and relies on the strengthening effect of physical exercise (Lohse et al., 2014a). Motor learning principles are largely driven by the findings of Neuroscience: in order to acquire new motor skills or to recover lost motor function, intensive, high-dose, repetitive physical exercises are required to induce brain plasticity and initiate long-term changes in the structure of the brain (Schaechter, 2004). A large variety of motor rehabilitation programs have emerged in the past two decades by applying these motor learning principles (Langhome et al., 2009), such as: constraint induced movement therapy, splinting, repetitive physical fitness training, and functional electrical stimulation. The same principles have been used in developing therapy tools that incorporate physiological biofeedback (Novak et al., 2011; Guerrero et al., 2013; Shirzad and Van der Loos, 2013 and 2014a), robotics (Patton et al., 2004; Brewer et al., 2007; Shirzad and Van der Loos, 2012), and virtual reality (Lohse et al., 2014b; Saposnik and Levin, 2011).

Physical therapy needs to be repetitive and task oriented (Sucar et al., 2014). However, the motivation of the therapy clients during exercise regimens also plays an important role in the success of the therapy they receive. Motivation to continue therapy exercises is key to therapy compliance and reduces the chance of early abandonment of therapy (Colombo et al., 2007; Harris and Reid, 2005). Using virtual reality (Saposnik and Levin, 2011), game design principles (Lohse et al., 2013), variations in task challenge (Shirzad and Van der Loos, 2015), and adding social connectedness through social medias (Alankus et al., 2010) are suggested to address this issue.

Despite the clinical research results that have shown the robustness of new rehabilitation tools developed in the recent years, most of these new technologies are not adopted by users in long-term. This is due to the fact that development of physical therapy devices is mainly driven by what “can” be achieved by technology and not by what “needs” to be achieved by technology.
(i.e., technology driven and not user-driven). The clinical environment of physical therapy is a multifaceted setting that delivers a program based on the needs of the therapy clients. In conventional therapy, the client is always involved in forming the therapy regimen. In order to bridge the gap between what users need and what biomedical engineers can produce, the design philosophy has to shift from traditional goal-oriented view of the past couple of decades to a user-centred approach.

The user-in-the-loop approach in design of medical technologies has gained momentum in the past decade to study, and ultimately to fix, the link between device design, human error, ergonomics, bad usability and patient safety. The traditional design strategies usually exclude the user from the development process and only involve them at the end of the design process to evaluate efficiency of the device in achieving the functional goals. This indicates that acceptance by the users and device adoption is “assumed” to be only a matter of the functional effectiveness of the device. Unfortunately, ample evidence exists to show that the adoption of medical devices actually depends heavily on their ability to fit into their complex medical setting and satisfy the users’ needs (Zenios et al., 2009; Martin et al., 2012; Shirzad et al., 2014b). The user-centred design approach that will be demonstrated in this appendix demonstrates the critical role of users in the iterative process of design as early as possible and as often as possible.

**A.2 User-centred Approach in Design of Rehabilitation Tools**

The outcomes of the research in the field of Ergonomics have led to industry regulations that make the user-centred design approach a necessity in design of medical devices (FDA, 2000). However, the increase in industry regulatory requirements and awareness about efficacy and benefits of user-centred design has not led to an increase in publication of practical guidelines on implementation of this design approach. The goal here is to address this issue by presenting a case study on implementation of the user-centred approach to design a bimanual upper-body rehabilitation system called “FEATHERS” (Functional Engagement in Assisted Therapy through Exercise Robotics).

The user-centred design (UCD) process involves three core steps: assessment of user and functional needs, development of prototypes with users in the loop to ensure the user needs are met, assessment of the solutions that are derived from the prototypes to ensure the functional needs are met (Figure A.1). UCD is a top-heavy and iterative process. The main emphasis is on: 1) understanding the contextual needs (i.e., the first step) making UCD a top-heavy process, and
2) meeting the contextual needs (i.e., the second step) by iterating different prototypes through user testing and user feedback.

![Figure A.1: User-centred design approach.](image)

### A.3 Step 1: Assessment of Contextual and Functional Needs

As the UCD process starts with needs finding, the main focus of the first step is on identifying a technology gap. This, from an industry or research perspective, is usually done by a thorough literature review in the field of interest. Specifically to the medical sector, consultation with medical professionals, clinical research, and clinical immersion must be considered. Often innovators become experts in a particular medical or clinical domain as they spend their time designing and developing new concepts and tools in that field. These innovators, who have now become experts in a particular field, can easily spot technology gaps and initiate the design process to address such gaps. This was the case for the FEATHERS project. By experience, the team knew that even though most of the developed devices for upper-body therapy are functionally efficient, the therapy clients and therapists do not use them in therapy regimens.

Once a technology gap is discovered, the design team needs to gain an unbiased understanding of the functional needs in the context of the relevant medical setting. As illustrated in Figure A.1, this involves reviewing the literature to understand the functional needs, observing the clinical culture of utilizing the traditional solutions, and developing an in-depth understanding of the user needs through mechanisms such as focus group studies.

The stroke therapy literature shows high-dose therapeutic regimens result in substantial improvements in function. A high-dose regimen involves tens of thousands of repetitions; however, currently in a regular clinical setting only up to 30 repetitions are practiced per therapy
session (Lang et al., 2009). Through clinical observations, we learned that the limited practice opportunity and the necessary repetitive nature of current therapy compromise the motivation of individuals with hemiplegia to persist. Patients frequently report that traditional rehabilitation exercises are uninteresting, making it difficult to maintain motivation for sustained treatment. The design team’s understanding of the problem up to this point was that a new physical therapy tool or regimen needs to be repetitive in order to be clinically effective, but at the same time the repetition of the exercises needs to be engaging.

In order to get a deeper understanding of the issue and to find out what type of solutions might be appealing to the users (therapy clients and therapists), four focus group studies were conducted, two with physical therapists, and two with therapy clients and their families or caregivers (Tatla et al., 2015; Lam et al., 2015). Despite reporting several challenges in integrating gaming and social media technology in therapy, therapists identified opportunities in this integration and showed interest in partaking in the development of an upper-body training system that could make therapy more “fun” for therapy clients with hemiplegia. Both user groups agreed that by considering the needs of therapists and clients, the developed technologies will have a higher chance of being used routinely. From the focus group studies, we learned that an exercise system that utilizes upper-arm movement to play games and connects users via social media platforms has the potential to address both functional and contextual needs. Specifically, users would play their favourite video games on a social media platform (i.e., Facebook©) and would receive positive social and therapeutic feedback from their social network. The games are controlled through a modified commercial motion capture system that maps the user’s arm motions to computer cursor motion.

A.4 Step 2: Development of Solutions with the User in the Loop

Based on what was learned in the need-finding step, the design team started developing different concepts and prototypes to address different aspects of the identified needs. The key point in this second step is to involve the users in the ideation-evaluation iterations to produce concepts around the contextual needs. This ensures that the design is driven by the context and what the technology needs to do rather than a technology-driven design that might not be able to address user needs. The concepts are then further developed to verify they are capable of producing the desired therapeutic effects (i.e., functional needs). Based on this, the second design step, development of solutions with the user in the loop, was divided into two sub-steps: 1) interaction
engineering to meet the contextual user needs and 2) rehabilitation engineering to meet the functional needs.

A.4.1 Interaction Engineering to Meet User Needs

In this section, we describe the design process of the FEATHERS System based on the identified user needs in the first step. A motion tracking application, adapted controllers, and a social media interface were developed and tested. Specifically, the motion tracking application allows the users to control computer cursor using bimanual upper-arm motions while holding the adapted controllers.

FEATHERS Motion Controllers: The controller design involved transforming the original PlayStation® Move hardware (Figure A.2, left) into a device more suitable for the targeted population. The design process began with research in the form of verbal interviews with physiotherapists, user observations, empathy studies, gesture explorations, and a literature review on the emotional and therapeutic needs of potential users. The analysis of the aforementioned data indicated that ease of use and ergonomics were some of the most important factors contributing to the users’ sense of control when interacting with a computer, which in turn would enable them to improve performance and have fun playing games.

Based on these criteria, a number of prototypes were developed and tested with users, and the design was refined based on the received feedback. The body of the final prototype consists of two parts: an ABS plastic upper body and a bottom wooden tip (Figure A.2, right). The smooth wooden pointed tip aids in the insertion of the controller into the grasp of a hand with high muscle tone, which is the case for a large proportion of the target population. The wooden parts also mirror each other in the left and right controllers, thus enabling the user to identify which controller goes into which hand prior to starting the game.

The control buttons are programmable, allowing the therapists to prescribe fine motor exercises of the affected hand as the user progresses, preventing the unaffected hand from doing all the work. An adjustable strap is also designed to allow the user to easily fasten the controller to a flaccid hand (Figure A.3), which is the case for users who have impaired grasp ability.

The new position of the tracker was strategically placed in the front of the controller, to enable the therapist to prescribe a wide range of hand movements while the user maintains a sense of
control over the cursor on the screen, as the users feel that they are pointing towards the screen, rather than having the tracker on the top as in the original PlayStation controller (Figure A.4).

Figure A.2: Original PlayStation® Move controller (left) and FEATHERS controllers (right).

Figure A.3: Adjustable strap for the affected hand.

Figure A.4: New tracker position allows for a more natural user interaction.

Social Media Application (FEATHERS Play): In order to increase user engagement in rehabilitation and based on the outcomes of the focus group studies, a social media application on Facebook for the two different user groups (therapy clients and therapists) was developed. Two similar interfaces were designed for each user group with slightly different functionality. For therapy clients, this application serves as an online community that promotes interactions between them and their therapists, or other clients, as well as a platform to access a large variety of games and the client’s game scores. For therapists, in addition to communicating with their patients, they can monitor their patients’ progress and recommend specific games depending on
their clients’ rehabilitation goals. The initial design of the application interface (Figure A.5, left) was tested in a usability study with rehabilitation professionals. Four Likert-type questions regarding the application’s interface and function were administered in a “cognitive walkthrough” setting:

Q1. It was simple to review my game scores using the Facebook patient/therapist application.

Q2. There was enough information provided in the Facebook patient/therapist application to help me complete all the required tasks.

Q3. The steps for starting and registering in the Facebook patient/therapist application were easy to follow.

Q4. It was simple to link to a therapist using the Facebook patient/therapist application.

The initial design of the interface received 73% or more positive responses from rehabilitation professionals (Figure A.6, left) on each of the questions. Qualitative comments were also recorded throughout the test session for specific design improvements (Valdés et al., 2014). Based on this feedback, the second iteration of the application was developed (Figure A.5, right) and tested with 5 teenagers with CP and 5 stroke participants. Only Q1 and Q2 were administered due to the design changes. The modified interface design did not receive any negative feedback from teenagers with CP and stroke participants (Figure A.6, right).

Figure A.5: Initial FEATHERS Play interface (left), finalized FEATHERS Play interface (right).
**Design of Feedback to Keep Therapy Clients Engaged:** From the focus group study with therapists, one of the key features needed in a virtual rehabilitation system was identified as the ability to provide adequate feedback to the users when their gaming session is over. By doing so, users are able to track their progress and get information about their functional ability and level of achievement. This feedback takes the form of three key measurements: *time played*, *distance travelled* by the user’s hands and *game scores*. The metric *time played* indicates how much time the user has spent using the rehabilitation system, and it can be observed in different time frames, e.g., days, weeks, or months. *Distance travelled* by the user’s hands measures the total three-dimensional movement during a single gaming session, and the information is given for both the paretic and non-paretic hands of the users, encouraging the user to move more symmetrically. Finally, the *game scores* are taken directly from the Facebook games and are charted to allow users to see if they are getting higher scores over time. This is a popular method in the game industry to increase the replay value of games, which in this case will lead to an increase in the replay value of the FEATHERS system and thus an increase in dose of therapy.

**A.4.2 Rehabilitation Engineering to Meet Functional Needs**

A bimanual therapy computer application (*FEATHERS Motion*) was built around the interfaces described in the previous section. The goal of this application is to provide a means of interacting with a personal computer by controlling the computer cursor using bimanual hand movements. The technologies that were selected as input interfaces were the *FEATHERS Controllers* and the Microsoft Kinect. These technologies provide sufficient motion capture accuracy, have a low cost and are commercially available, all of which make them a suitable match to the design specifications.
The initial applications were stand-alone programs that worked independently for each of the motion control systems. After the completion of the usability testing with the rehabilitation professionals, it was decided that combining the two applications into one would improve their ease of use and reduce the cognitive load on users and therapists. This led to the second iteration of *FEATHERS Motion*.

Based on the therapists’ comments from the focus group studies, two motion modes were implemented. These were the Mirror Mode (Visual Symmetry) and the Wheel Mode (Point Mirror Symmetry), both are shown in Figure A.7. The Mirror Mode requires participants to move both hands independently in a symmetrical manner (both at the same time, and in the same direction) in the frontal plane: both vertical and horizontal movements are mapped into the cursor’s motions. This condition was implemented to promote the use of the affected side and to prevent users from compensating with their unaffected arm. For the Wheel Mode, users are required to move their hands around an imaginary circle, and turn them in opposite directions to turn left and right, similar to when turning a steering wheel of a vehicle. In addition, the vertical motion remains the same as in the Mirror Mode: moving both hands up and down. Both modes were selected because therapists wanted their clients to practice symmetrical tasks using both hands, similar to activities that users would encounter in everyday activities, e.g., lifting objects, pushing carts or doors, and reaching for objects in front of them. At the same time, therapists wanted users to cross their bodies’ midline with the Wheel Mode as a means of practicing reaching across their body and lifting their hands against gravity.

Apart from the two available motion modes, the applications can be adapted depending on the users’ motor abilities. Using a “Settings” menu, therapists are capable of adjusting the cursor sensitivity, which allows them to adjust the FEATHERS system to the therapy client’s range of motion. Also, therapists can choose which hand the users will be using for clicking, depending on whether the user is capable of grasping with the weak hand.
A.5 Step 3: Assessment of the Solution in the Clinical Setting

While the second step in the UCD process ensures the developed concepts and solutions meet the contextual needs of the new medical device, the third step is necessary to ensure the functional efficiency of the design. This step is similar to the evaluation step of the traditional design method and involves clinical testing of the device. Usability testing and user testing that are carried out in the second step of UCD are mainly done in the controlled environment of design studios and usually do not expose the prototypes to real-world conditions. However, the goal of clinical testing in the third step is to study the functional robustness of the design under real working conditions and in clinical settings.

The literature on the design of clinical studies is very rich and the methods of experimental design are well established. In general, such studies involve stress testing of the device to show that the device embodies the minimum required specifications. Moreover, in the field of physical therapy, it is required to show that the device is capable to initiate and sustain therapeutic effects in the user. This involves long-term comparative studies in which a group of control participants receive a conventional, best-practices method of therapy and a second group of participants (the experimental group) receives therapy exercises that utilize the new intervention, and in this case a new device. The effectiveness of the new device and its therapeutic effects as well as its effects on the clients’ psychosocial health is then compared with the baseline effects that are expected from conventional methods of therapy.

A.6 Conclusion

This appendix outlined the user-centred design process as adapted to the biodesign sector, and specifically applied to the design of rehabilitation devices. The FEATHERS project as a case in point has maintained a central tenet grounded in the theory that neural plasticity will lead to functional upper-limb improvements through highly repetitive movements, and that bimanual exercising has the potential to speed recovery of function when used in conjunction with unimanual exercise [Lum et al., 2006].

However, the design process does not end at Step 3. First, the goal of this research and development is to create demonstrably effective therapies and devices that improve healthcare delivery. Follow-on multi-site trials, and trials with a more varied clinical population than initially targeted, are essential to establish the safety and usefulness of the system. Second,
devices can only be made available to clients if successfully converted to products, so the business case must be developed in parallel with the clinical case. [For FEATHERS, commercialization efforts are being pursued.] Third, usability is only one component of user acceptance and interest in the devices as a consumer. With the increasing empowerment of the consumer in health care decision-making, and the increase in available income among older persons (i.e., those most at risk for stroke), choice of products, such as the WiiFit and other health-focused client-bought technologies, is obviously driven by product attractiveness and effectiveness.

FEATHERS has a long road of R&D and commercialization ahead. The adoption of the design process described above from the beginning has provided the team with substantial user-centred grounding to instil the confidence to proceed to future implementation and deployment steps.

**Acknowledgements:** The following rehabilitation clinics were involved in the usability/user testing: Sunny Hill Health Centre for Children (Vancouver, Canada), BC Centre for Ability (Vancouver, Canada), and Abilities Neurological Rehabilitation, Inc. (Surrey, Canada). Reality Controls (Vancouver, Canada) was involved in the design of FEATHERS software.
Appendix B – Data Collection Protocols

B.1 Protocol for Healthy Adult Participants

Before participant arrives:

1. Prepare a gift card for the participant.

2. Print the consent form (last page needs to be printed twice).

3. Take Navid’s lab PC (plus monitor, keyboard, and mouse) to the data collection room.

4. Take the EMG Suite out of its box and connect all the cables except for the electrodes.

5. Clean the electrodes with rubbing alcohol.

6. Connect a new ground electrode to the EMG system and write participant’s ID on the ground electrode.

7. Connect Toblerone’s (i.e., the laptop that will run the Kinect application) power cord and turn it on.

8. Connect Toblerone to the monitor.

9. Connect Kinect to Toblerone and run FEATHERS’ desktop application “FEATHERS Motion”. Make sure Kinect’s setting in the software is set to 75% for cursor sensitivity and 50% for centreing sensitivity.

10. Close the “FEATHERS Motion” application and check the uploaded file on the FTP server.

11. Open “Lucky Pirate” game in Google Chrome on Toblerone.

   - Facebook account: rcfethers@hotmail.com (Usability7)
• Open the game in a new window (after it is loaded) to make it full screen without any ads on the right side.

**Participant preparation and introducing the setup:**

1. Greet participant.

2. Explain to the participant the goal of the research and the tasks that he/she will be doing.

   • Briefly talk about motor synergies and how kinematic and muscle activation data can help us understand motor synergies better.

   • The participant has to play a simple game called “Lucky Pirate”. Do not explain how one can play the game at this point.

   • EMG sensors will be attached on the upper body (multiple on arms and elbows, a couple on the shoulder area) to measure muscle activation data.

   • A Kinect camera will be used to track the motion of different joints and also to control the mouse cursor to control the game.

   • There will be a training session to make sure the participant is comfortable with all aspects of the setup.

   • The data collection itself runs for a maximum of 6 minutes, but EMG sensor placement will take ~25 minutes.

   • Participants can ask questions whenever they want.

   • Participants can withdraw from the study at any time.

   • Travel reimbursement and gift card.

3. Ask participant how old he/she is and note it on the consent form.

4. Ask the participant to read the consent form and sign it. Encourage the participant to ask questions if he/she is uncertain about any part of the consent form or the research.

   • Explain any disabilities that will exclude the participant from the experiment.
• Explain the possibility of following risks: May cause physical and mental fatigue. There will be scheduled breaks after each trial. However, the participant can request pauses anytime during the experiment to rest.

• The participant may refuse to participate any further anytime during the experiment.

• Information obtained from this study may be presented in reports and/or scientific publications.

• All personal information will be kept confidential. Physical documents will be stored in a locked cabinet in the main investigator’s laboratory. Digital data will be stored on a password-protected computer. Only investigators of this study have access to the above documents and data.

• When referring to individual data, the only identification used will be the participant number. All identification features will be blurred in published video and photographs.

• All data will be destroyed within 5 years after the dissemination of results to ensure anonymity.

• Signing the consent form will NOT limit the participant’s legal rights against the sponsors, investigators, or anyone else.

5. Use the “EMG Sensor Placement” document to setup the EMG sensors (attach an adhesive interface to each of the electrodes).

6. Explain how “Lucky Pirate” game is played. Let the participant try it.

7. Explain how the Kinect camera and FEATHERS software can be used to control the game. Use both hands to click!

8. Seat participant in front of the white blinds on the stool and ask him/her to play a round of Lucky Pirate using the Kinect camera (familiarization).

9. As the participant plays the game (more than a minute), collect EMG data to make sure all the sensors are properly attached (use the test template). Resolve all issues.
Data Collection:

1. Stop FEATHERS Motion to close the kinematic data collection file.

2. Navigate to the saved EMG data collection template (called motor synergies) in the EMGWorks Acquisition software.

3. Answer participant’s questions, if any.

4. When ready, start FEATHERS Motion and EMG data collection at the same time (one is on the laptop and the other is on the PC).

5. Quickly navigate to the lucky pirate window and let the participant play the game for at least 5 minutes (EMG data collection template is designed to stop data collection after 5 minutes).

Post-experiment:

1. Stop the FEATHERS Motion application to stop kinematic data collection. Data is automatically saved.

   - Save the EMG data. For healthy subjects use “Normal_Subj##” as template: Normal_Subj01 will be participant #1 in the healthy group.

2. Thank the participant and help them remove the EMG sensors. When removing the EMG sensors, do it in one quick move to minimize the pain.

3. Reimbursement and gift card. Use the proper forms and make sure the participant signs for it.

4. Answer the participant’s questions, if any.

5. After the participant has left, transfer the Kinematic data from Toblerone to Navid’s PC.

6. Remove the adhesive interface from the EMG sensors and store the EMG suite.

7. Store the ground sensor.

8. Take Navid’s PC to the CARIS Lab.

9. Download the Kinect data and back-up EMG and Kinect data.
B.2 Protocol for Adult Post-stroke Participants

Before participant arrives:

1. Prepare a gift card for the participant.

2. Print the consent form (last page needs to be printed twice).

3. Take Navid’s lab PC (plus monitor, keyboard, and mouse) to the data collection room.

4. Take the EMG Suite out of its box and connect all the cables except for the electrodes.

5. Connect a new ground electrode to the EMG system and write participant’s ID on the ground electrode.

6. Connect Toblerone’s (i.e., the laptop that will run the Kinect application) power cord and turn it on.

7. Connect Toblerone to the monitor.

8. Connect Kinect to Toblerone and run FEATHERS’ desktop application “FEATHERS Motion”. Make sure Kinect’s setting in the software is set to 75% for cursor sensitivity and 50% for centring sensitivity.

9. Close the “FEATHERS Motion” application and check the uploaded file on the FTP server.

10. Open “Lucky Pirate” game in Google Chrome on Toblerone.

   - Facebook account: rcfeathers@hotmail.com (Usability7)
   - Open the game in a new window (after it is loaded) to make it full screen without any ads on the right side.

11. Turn Navid’s PC on and connect the EMG serial cable to it.

12. Open EMGWorks Acquisition and open the test template.

Participant preparation and introducing the setup:

1. Meet the participant and walk them to the data collection room.

2. Explain the goal of the research to the participant and the tasks that he/she will be doing.
• Briefly talk about motor synergies and how kinematic and muscle activation data can help us understand motor synergies better.

• The participant has to play a simple game called “Lucky Pirate”. Do not explain how one can play the game at this point.

• EMG sensors will be attached on the upper body (multiple on arms and elbows, a couple on the shoulder area) to measure muscle activation data.

• A Kinect camera will be used to track the motion of different joints and also to control the mouse cursor to control the game.

• There will be a training session to make sure the participant is comfortable with all aspects of the setup.

• The data collection itself runs for a maximum of 15 minutes, but EMG sensor placement will take ~25 minutes.

• Participants can ask questions whenever they want.

• Participants can withdraw from the study at any time.

3. Ask participant how old he/she is and note it on the consent form.

4. Ask the participant to read the consent form and sign it. Encourage the participant to ask questions if he/she is uncertain about any part of the consent form or the research.

• Explain any disabilities that will exclude the participant from the experiment.

• Explain the possibility of following risks: May cause physical and mental fatigue. There will be scheduled breaks after each trial. However, the participant can request pauses anytime during the experiment to rest.

• The participant may refuse to participate any further anytime during the experiment.

• Information obtained from this study may be presented in reports and/or scientific publications.
• All personal information will be kept confidential. Physical documents will be stored in a locked cabinet in the main investigator’s laboratory. Digital data will be stored on a password-protected computer. Only investigators of this study have access to the above documents and data.

• When referring to individual data, the only identification used will be the participant number. All identification features will be blurred in published video and photographs.

• All data will be destroyed within 5 years after the dissemination of results to ensure anonymity.

• Signing the consent form will NOT limit the participant’s legal rights against the sponsors, investigators, or anyone else.

5. Use the “EMG Sensor Placement” document to setup the EMG sensors.

6. Explain how “Lucky Pirate” game is played. Let the participant try it.

7. Explain how the Kinect camera and FEATHERS software can be used to control the game. Use both hands to click!

8. Seat participant in front of the white blinds on the stool and ask him/her to play a round of Lucky Pirate using the Kinect camera (familiarization).

9. As the participant plays the game (more than a minute), collect EMG data to make sure all the sensors are properly attached (use the test template). Resolve all issues.

Data Collection:

1. Stop FEATHERS Motion to close the kinematic data collection file.

2. Navigate to the saved EMG data collection template (called stroke motor synergies) in the EMGWorks Acquisition software.

3. Answer participant’s questions, if any.

4. When ready, start FEATHERS Motion and EMG data collection at the same time (one is on the laptop and the other is on the PC).
5. Quickly navigate to the lucky pirate window and let the participant play the game for 3 minutes (EMG data collection template is designed to stop data collection after 3 minutes).

6. Repeat steps 1-6 at least 5 times (15 minutes of data). In between each of the sessions give the participant some time to rest. Offer them water/snack/juice.

7. Stop the FEATHERS Motion application to stop kinematic data collection. Data is automatically saved.

8. Save the EMG data. Use “Stroke_Subj##_Part#” as template (example: Stroke_Subj04_Part1).

9. Thank the participant and help them take the EMG sensors off (do it in one quick move to minimize the pain).

10. When data collection is over, deal with travel reimbursement and gift card. Use the proper forms and make sure the participant signs for it.

11. Answer the participant’s questions, if any.

12. Walk the participant to their car if needed / call a taxi.

**Post-experiment:**

1. After the participant has left, transfer the Kinematic data from Toblerone to Navid’s PC.

2. Remove the adhesive interface from the EMG sensors and store the EMG suite.

3. Clean the electrodes with rubbing alcohol.

4. Attach an adhesive interface to each of the electrodes

5. Store the ground sensor.

6. Take Navid’s PC to the CARIS Lab.

7. Download the Kinect data and back-up EMG and Kinect data.
Appendix C - Advertisements, Consent forms, and Clinical Assessments

This appendix presents the details of the study advertisements used to recruit participants, consent forms, and the questionnaires used in the human-subject studies of this thesis.

C.1 Study Advertisements

Figure C.1 presents the “call for volunteers” that was posted around the campus of the University of British Columbia to recruit participants.

C.2 Information Booklet and Consent Form

The information booklet and consent form presented to the healthy participants is presented in Figures C.2 to C.8. The information booklet and consent form presented to the stroke-survivor participants is presented by Figures C.9 to C.15.

C.3 Clinical Assessments

Fugl-Meyer assessment procedure is presented in Figures C.16 to C.18. Reaching Performance Scale assessment procedure is presented in Figure C.19.
Like Video Games?
Want to help people with stroke?
Join our study!

About: This project uses video games as a way to understand how we coordinate the motion of our upper limbs.

Who: Healthy young adults (19+) and adults post-stroke with hemiparesis

What: Play a Facebook game using the Microsoft Kinect system.

Sign up/more information

✉️ contact@ubc.ca
📞 604-500-0000

Figure C.1: Contents of the “call for volunteers” that was posted around the campus of the University of British Columbia to recruit participants for the studies presented in this thesis.
Informed Consent Form:

Upper-body Motion Coordination after Stroke:
Insights from Kinematic and Muscle Synergies
Phase 1: Healthy Motor Synergies

Principal Investigator
Name: Hendrik F. Machiel (Mike) Van der Loos
Position title: Associate Professor
Organization: UBC Department of Mechanical Engineering
Mailing address: 6250 Applied Science Lane
Phone: 
Email: 

Co-Investigators
Name: Navid Shirzad
Position title: PhD Candidate, Research Assistant
Organization: UBC, Biomedical Engineering Graduate Program
Mailing Address: 6250 Applied Science Lane
Phone: 
Email: 

Name: Lara Boyd
Position title: Associate Professor
Organization: UBC, Faculty of Medicine, Department of Physical Therapy
Mailing Address: Brain Research Centre, 212-2177 Wesbrook Mall, Vancouver
Phone: 
Email: 

Contact Person:
Please contact Hendrik F. Machiel (Mike) Van der Loos (office 604), cell 604 or mech.ubc.ca in the event of any unusual occurrences or difficulties related to this research.

Description: Consent form, phase 1
Version: January 11th, 2016, version 3

Page 1 of 7

Figure C.2: Information booklet and consent form presented to the healthy participants (page 1 of 7).
Introduction

We invite you to take part in a research study being conducted by Mike Van der Loos, who is a professor at the University of British Columbia, and his colleagues. As part of this study, you will help provide data on how healthy adults use their upper body joints and muscles to generate bimanual motions. The data collected from this study may help develop a metric for measuring upper-limb rehabilitation progress.

Your participation in this study is voluntary and you may withdraw from the study at any time. The study is described below. This description tells you about the risks, inconvenience, or discomfort which you might experience. Participating in the study will likely not benefit you directly, but we may learn things that will benefit others. You should discuss any questions you have about this study with Dr. Van der Loos or the other investigators on the project.

Purpose of the Study

This study aims to gain more insight into the motion of healthy adults when they move their hands in synchrony. More specifically we are interested in understanding how the healthy human brain combines the motion of different upper body joints and activation of different upper body muscles to generate reaching motions that involve both arms.

Study Design

In this study, participants will be asked to play a simple video game on a computer screen for 10 minutes. The game is controlled by the synchronous motion of the two hands. A Microsoft Kinect uses a special camera to capture the upper body motion of the participant. A suite of EMG sensors will collect activation of participants’ upper body muscles. EMG or electromyography is a technique for evaluating and recording the electrical activity produced by muscles.

We will collect basic demographic data (age, gender) at the beginning of the study session.

Who Can Participate in This Study?

We are looking for healthy adults who are:

i. 19 years of age and over
ii. Able to speak and understand English
iii. Able to communicate verbally
iv. Ability to maintain a standing position for 30-45 minutes
How Many Participants Will Take Part in this Study?

We are aiming to recruit a maximum of 15 adults to participate in this study.

Who is conducting the research?

The study is being conducted by Dr. Van der Loos and colleagues listed on the title page of this form.

What Will This Study Cost Me?

This study will be at no cost to you.

What Will You Be Asked to Do?

You will be asked to read and sign this consent form. If you choose to consent, you will be considered a participant in the study. A note taker will document important events as they occur, and data from the motion tracking system and EMG sensors will be recorded. For more details about the confidentiality and anonymity and use of the collected data, please refer to the Confidentiality and Anonymity section of this consent form.

We will help you put on 16 adhesive EMG sensors on your arms and will ask you to play a computer game in front of a Microsoft Kinect camera for 10 minutes. We may shave and use alcohol to clean where the electrodes are placed on the skin.

Will There Be any Negative Consequences for You by Participating in This Study?

Physical or mental fatigue could occur after using the system. If at any time you do not want to continue, you are under no obligation to do so. One or more of the researchers will also be available to answer your questions after the session.

What Are the Benefits to Your Participation in This Study?

There are no direct benefits to your participation. However, you may benefit from the knowledge that a new upper extremity therapy is being developed that could potentially be used by people with hemiparesis (one-sided weakness).

After the Study is Finished

If you are interested in the results of the study, you can contact the researchers, and they will provide you with information about the results from this study.
Confidentiality

Only research assistants to Dr. Van der Loos will be present in the room.

According to the UBC Policy on Scholarly Integrity, the notes, and motion tracking/EMG data from the sessions will be used for the purposes of analysis and then destroyed after 5 years from the publication of this study. All collected data will be kept in a secure, locked room at UBC for five years after the publication of this study. After the study has been completed, all data will be stored on CD/DVD disks and kept in a locked cabinet in room X015 in the ICICS building at the University of British Columbia and accessible only by the PI and Co-Investigators. Data will be mechanically destroyed when no longer needed to be stored. The CD/DVD disks will not be used to transfer data out of ICICS X015. If data needs to be transferred out of X015, we will use encrypted, password protected drives.

We will use the collected data only in relation to this particular study. Also, manuscripts based on the findings will be submitted to scientific journals for publication. In the event that quotes from a discussion are used, there will be no information included that could identify the speaker or the client, and you will not be identifiable in any report.

Your confidentiality will be respected. However, research records and health or other source records identifying you may be inspected in the presence of the Investigator or his or her designate by representatives of the UBC Clinical Research Ethics Board for the purpose of monitoring the research. No information or records that disclose your identity will be published without your consent, nor will any information or records that disclose your identity be removed or released without your consent unless required by law.

You will be assigned a unique study number as a subject in this study. Only this number will be used on any research-related information collected about you during the course of this study, so that your identity [i.e. your name or any other information that could identify you] as a subject in this study will be kept confidential. Information that contains your identity will remain only with the Principal Investigator and/or designate. The list that matches your name to the unique study number that is used on your research-related information will not be removed or released without your consent unless required by law.

Your rights to privacy are legally protected by federal and provincial laws that require safeguards to insure that your privacy is respected and also give you the right of access to the information about you that has been provided to the sponsor and, if need be, an opportunity to correct any errors in this information. Further details about these laws are available on request to your study doctor.

Figure C.5: Information booklet and consent form presented to the healthy participants (page 4 of 7).
What if You Still Have Some Questions?

If you have any questions or desire further information about this study before or during participation, you can contact the principal investigator of the study, Machiel (Mike) Van der Loos at.

What Happens if Something Goes Wrong?

Signing this consent form in no way limits your legal rights against the sponsor, investigators, or anyone else, and you do not release the study doctors or participating institutions from their legal and professional responsibilities.

Do You Have to Participate?

Your participation is completely on a volunteer basis. There are no penalties if you do not wish to participate. If you do volunteer, you have the right to withdraw at any time, for any reason, without penalty. Similarly, the researchers have the right to terminate this research project at any time.

If you do not wish to participate, you do not have to provide any reason for the decision nor will you lose the benefit of any medical care to which you are entitled or presently receiving.

We will give you two options at the time of recruitment for reimbursement of costs:

Option 1: reimbursement without receipts (all modes of transportation and parking)
At the time of recruitment we will ask you to indicate their mode of travel and distance traveled to UBC. Based on this information and UBC travel reimbursement guidelines, we will calculate the round-trip cost and inform you of this amount. We will have this reimbursement ready to give you when you come for the study and will ask you to sign for this reimbursement.

Option 2: reimbursement with receipts (for taxi or transit)
You can submit travel receipts (taxi receipts or transit fare stubs) and we will reimburse them for the amount spent to travel from your residence to UBC. However, in this case, we will not be able to reimburse you on the spot and will have to mail the reimbursement to you afterwards.

In addition, you will be given a $10 coffee shop gift card for their time. Participants will receive their compensation at the conclusion of the experiment.

What Happens if I Decide to Withdraw?

You may withdraw from this study at any time without giving reasons. If you choose to enter the study and then decide to withdraw at a later time, you have the right to...
request the withdrawal of your information collected during the study. This request will be respected to the extent possible. Please note however that there may be exceptions where the data will not be able to be withdrawn for example where the data is no longer identifiable (meaning it cannot be linked in any way back to your identity) or where the data has been merged with other data. If you would like to request the withdrawal of your data, please let your study doctor know. Otherwise, if you do not request withdrawal, your data may or may not be used in later analysis depending on the quality, quantity, and relevancy of the data to the rest of the study.

**Problems or Concerns**

If you have any concerns about your rights as a research subject or your experience while participating in this study, contact the Research Participant Complaint Line in the University of British Columbia Office of Research Ethics at the following email: RSIL@ors.ubc.ca, telephone: 604-822-8598 or toll free telephone number: 1-877-822-8598.
Participant Consent
My signature on this consent form means:

- I have read and understood the information in this consent form.
- I have had enough time to think about the information provided.
- I have been able to ask for advice if needed.
- I have been able to ask questions and have had satisfactory responses to my questions.
- I understand that all of the information collected will be kept confidential and that the results will only be used for scientific purposes.
- I understand that my participation in this study is voluntary.
- I understand that I am completely free at any time to refuse to participate or to withdraw from this study at any time, and that this will not change the quality of care that I receive.
- I understand that I am not waiving any of my legal rights as a result of signing this consent form.
- I understand that there is no guarantee that this study will provide any benefits to me.

I will receive a signed copy of this consent form for my own records.

I consent to participate in this study.

<table>
<thead>
<tr>
<th>Participant’s Signature</th>
<th>Printed name</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signature of Person Obtaining Consent</td>
<td>Printed name</td>
<td>Study Role</td>
</tr>
<tr>
<td>Investigator Signature</td>
<td>Printed name</td>
<td>Date</td>
</tr>
</tbody>
</table>

My signature above signifies that the study has been reviewed with the study participant by me and/or by my delegated staff. My signature may have been added at a later date, as I may not have been present at the time the participant’s signature was obtained.

[ ] Yes, I can be contacted for future studies
Phone: 
email:
[ ] No, I do not want to be contacted for future studies.

Description: Consent form, phase 1
Version: January 11th, 2016, version 3
Informed Consent Form:

Upper-body Motion Coordination after Stroke: Insights from Kinematic and Muscle Synergies
Phase 2: Motor Synergies post-stroke

Principal Investigator
Name: Hendrik F. Machiel (Mike) Van der Loos
Position title: Associate Professor
Organization: UBC Department of Mechanical Engineering
Mailing address: 6250 Applied Science Lane
Phone: 
Email: 

Co-Investigators
Name: Navid Shirzad
Position title: PhD Candidate, Research Assistant
Organization: UBC Biomedical Engineering Graduate Program
Mailing Address: 6250 Applied Science Lane
Phone: 
Email: 

Name: Lara Boyd
Position title: Associate Professor
Organization: UBC, Faculty of Medicine, Department of Physical Therapy
Mailing Address: Brain Research Centre, 212-2177 Wesbrook Mall, Vancouver
Phone: 
Email: 

Contact Person:
Please contact Hendrik F. Machiel (Mike) Van der Loos (office 604 cell 604-822-2403 @mech.ubc.ca) in the event of any unusual occurrences or difficulties related to this research.
Introduction

We invite you to take part in a research study being conducted by Mike Van der Loos, who is a professor at the University of British Columbia, and his colleagues. As part of this study, you will help provide data on how adults post-stroke use their upper body joints and muscles to generate bimanual motions. The data collected from this study may help develop a metric for measuring upper-limb rehabilitation progress.

Your participation in this study is voluntary and you may withdraw from the study at any time. The study is described below. This description tells you about the risks, inconvenience, or discomfort which you might experience. Participating in the study will likely not benefit you directly, but we may learn things that will benefit others. You should discuss any questions you have about this study with Dr. Van der Loos or the other investigators on the project.

Purpose of the Study

This study aims to gain more insight into the motion of adults post-stroke when they move their hands in synchrony. More specifically we are interested in understanding how stroke affects the way the brain combines the motion of different upper body joints and activation of different upper body muscles to generate reaching motions that involve both arms.

Study Design

In this study, participants will be asked to play a simple video game on a computer screen for 10 minutes. The game is controlled by the synchronous motion of the two hands. A Microsoft Kinect uses a special camera to capture the upper body motion of the participant. A suite of EMG sensors will collect activation of participants’ upper body muscles. EMG or electromyography is a technique for evaluating and recording the electrical activity produced by muscles. We ask you to put on a tank top or a sleeveless shirt during this session to make EMG sensor placement easier.

We will collect basic demographic data (age, gender) at the beginning of the study session. A physical therapist will perform a clinical assessment to see how well you move your arms. These are simple hand and arm tasks such as moving blocks from one box to another, or picking up a soda can or stacking checkers.

Who Can Participate in This Study?

We are looking for adults who are:

- At least 19 years old
- Have hemiparesis (one-sided weakness) as a result of a single non-traumatic cerebral stroke (ischaemic or hemorrhagic)
- Stroke occurred at least 6 months prior to study
Who Should Not Participate in This Study?

We are excluding persons who are/have the following:
1) Shoulder dislocation or significant shoulder pain
2) Orthopaedic, botox injection, or other condition that limits the use of arm
3) Mini-mental status exam score less than 24
4) Legally blind
5) Under current rehabilitation care
6) An upper-limb amputation
7) Uncorrected poor vision
8) Cannot maintain a standing position for 30-45 minutes without help
9) Cannot personally give informed consent
10) Trunk pain

How Many Participants Will Take Part in this Study?

We are aiming to recruit a maximum of 15 adults to participate in this study.

Who is conducting the research?

The study is being conducted by Dr. Van der Loos and colleagues listed on the title page of this form.

What Will This Study Cost Me?

This study will be at no cost to you.

What Will You Be Asked to Do?

You will be asked to read and sign this consent form. If you choose to consent, you will be considered a participant in the study. A note taker may document important events as they occur, and data from the motion tracking system and EMG sensors will be recorded. For more details about the confidentiality and anonymity and use of the collected data, please refer to the Confidentiality and Anonymity section of this consent form.
THE UNIVERSITY OF BRITISH COLUMBIA

We will help you put on 16 adhesive EMG sensors on your arms and upper body and will ask you to play a computer game in front of a Microsoft Kinect camera for 10 minutes. We may shave and use alcohol to clean where the electrodes are placed on the skin.

Will There Be any Negative Consequences for You by Participating in This Study?

Physical or mental fatigue could occur after using the system. If at any time you do not want to continue, you are under no obligation to do so. One or more of the researchers will also be available to answer your questions after the session.

What Are the Benefits to Your Participation in This Study?

There are no direct benefits to your participation. However, you may benefit from the knowledge that a new upper extremity therapy is being developed that could potentially be used by people with hemiparesis (one-sided weakness).

After the Study is Finished

If you are interested in the results of the study, you can contact the researchers, and they will provide you with information about the results from this study.

Confidentiality

Only research assistants to Dr. Van der Loos will be present in the room.

According to the UBC Policy on Scholarly Integrity, the notes, and motion tracking/EMG data from the sessions will be used for the purposes of analysis and then destroyed after 5 years from the publication of this study. All collected data will be kept in a secure, locked room at UBC for five years after the publication of this study. After the study has been completed, all data will be stored on CD/DVD disks and kept in a locked cabinet in room X015 in the ICICS building at the University of British Columbia and accessible only by the PI and Co-Investigators. Data will be mechanically destroyed when no longer needed to be stored. The CD/DVD disks will not be used to transfer data out of ICICS X015. If Data needs to be transferred out of X015, we will use encrypted, password protected drives.

We will use the collected data only in relation to this particular study. Also, manuscripts based on the findings will be submitted to scientific journals for publication. In the event that quotes from a discussion are used, there will be no information included that could identify the speaker or the client, and you will not be identifiable in any report.

Your confidentiality will be respected. However, research records and health or other source records identifying you may be inspected in the presence of the Investigator or his or her designate by representatives of the UBC Clinical Research

Consent Form, phase 2, v4       September 7th, 2016       Page 4 of 7

Figure C.12: Information booklet and consent form presented to the stroke-survivor participants (page 4 of 7).
Ethics Board for the purpose of monitoring the research. No information or records that disclose your identity will be published without your consent, nor will any information or records that disclose your identity be removed or released without your consent unless required by law.

You will be assigned a unique study number as a subject in this study. Only this number will be used on any research-related information collected about you during the course of this study, so that your identity [i.e. your name or any other information that could identify you] as a subject in this study will be kept confidential. Information that contains your identity will remain only with the Principal Investigator and/or designate. The list that matches your name to the unique study number that is used on your research-related information will not be removed or released without your consent unless required by law.

Your rights to privacy are legally protected by federal and provincial laws that require safeguards to insure that your privacy is respected and also give you the right of access to the information about you that has been provided to the sponsor and, if need be, an opportunity to correct any errors in this information. Further details about these laws are available on request to your study doctor.

**What if You Still Have Some Questions?**

If you have any questions or desire further information about this study before or during participation, you can contact the principal investigator of the study, Machiel (Mike) Van der Loos at.

**What Happens if Something Goes Wrong?**

Signing this consent form in no way limits your legal rights against the sponsor, investigators, or anyone else, and you do not release the study doctors or participating institutions from their legal and professional responsibilities.

**Do You Have to Participate?**

Your participation is completely on a volunteer basis. There are no penalties if you do not wish to participate. If you do volunteer, you have the right to withdraw at any time, for any reason, without penalty. Similarly, the researchers have the right to terminate this research project at any time.

If you do not wish to participate, you do not have to provide any reason for the decision nor will you lose the benefit of any medical care to which you are entitled or presently receiving.

We will give you two options at the time of recruitment for reimbursement of costs: Option 1: reimbursement without receipts (all modes of transportation and parking)

Figure C.13: Information booklet and consent form presented to the stroke-survivor participants (page 5 of 7).
At the time of recruitment we will ask you to indicate their mode of travel and distance traveled to UBC. Based on this information and UBC travel reimbursement guidelines, we will calculate the round-trip cost and inform you of this amount. We will have this reimbursement ready to give you when you come for the study and will ask you to sign for this reimbursement.

Option 2: reimbursement with receipts (for taxi or transit)
You can submit travel receipts (taxi receipts or transit fare stubs) and we will reimburse them for the amount spent to travel from your residence to UBC. However, in this case, we will not be able to reimburse you on the spot and will have to mail the reimbursement to you afterwards.

In addition, you will be given a $10 coffee shop gift card for their time. Participants will receive their compensation at the conclusion of the experiment.

What Happens if I Decide to Withdraw?

You may withdraw from this study at any time without giving reasons. If you choose to enter the study and then decide to withdraw at a later time, you have the right to request the withdrawal of your information collected during the study. This request will be respected to the extent possible. Please note however that there may be exceptions where the data will not be able to be withdrawn for example where the data is no longer identifiable (meaning it cannot be linked in any way back to your identity) or where the data has been merged with other data. If you would like to request the withdrawal of your data, please let your study doctor know. Otherwise, if you do not request withdrawal, your data may or may not be used in later analysis depending on the quality, quantity, and relevancy of the data to the rest of the study.

Problems or Concerns

If you have any concerns about your rights as a research subject or your experience while participating in this study, contact the Research Participant Complaint Line in the University of British Columbia Office of Research Ethics at the following email: RSIL@ors.ubc.ca, telephone: 604-822-8598 or toll free telephone number: 1-877-822-8598.
Informed Consent Form:
Upper-body Motion Coordination after Stroke:
Insights from Kinematic and Muscle Synergies (phase 2)

Participant Consent

My signature on this consent form means:

- I have read and understood the information in this consent form.
- I have had enough time to think about the information provided.
- I have been able to ask for advice if needed.
- I have been able to ask questions and have had satisfactory responses to my questions.
- I understand that all of the information collected will be kept confidential and that the results will only be used for scientific purposes.
- I understand that my participation in this study is voluntary.
- I understand that I am completely free at any time to refuse to participate or to withdraw from this study at any time, and that this will not change the quality of care that I receive.
- I understand that I am not waiving any of my legal rights as a result of signing this consent form.
- I understand that there is no guarantee that this study will provide any benefits to me.

I will receive a signed copy of this consent form for my own records.

I consent to participate in this study.

<table>
<thead>
<tr>
<th>Participant’s Signature</th>
<th>Printed name</th>
<th>Date</th>
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<tr>
<th>Signature of Person Obtaining Consent</th>
<th>Printed name</th>
<th>Study Role</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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</table>

<table>
<thead>
<tr>
<th>Investigator Signature</th>
<th>Printed name</th>
<th>Date</th>
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</tbody>
</table>

My signature above signifies that the study has been reviewed with the study participant by me and/or by my delegated staff. My signature may have been added at a later date, as I may not have been present at the time the participant’s signature was obtained.

[ ] Yes, I can be contacted for future studies
   Phone:  
   email:

[ ] No, I do not want to be contacted for future studies

Consent Form, phase 2, v4  September 7th, 2016  Page 7 of 7

Figure C.15: Information booklet and consent form presented to the stroke-survivor participants (page 7 of 7).
## FUGL-MEYER ASSESSMENT
### UPPER EXTREMITY (FMA-UE)

Assessment of sensorimotor function

---

### A. UPPER EXTREMITY, sitting position

#### I. Reflex activity

<table>
<thead>
<tr>
<th>Flexors: biceps and finger flexors</th>
<th>0</th>
<th>can be elicited</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extensors: triceps</td>
<td>0</td>
<td>can be elicited</td>
<td>2</td>
</tr>
</tbody>
</table>

**Subtotal I (max 4)**

#### II. Volitional movement within synergies, without gravitational help

| Flexor synergy: Hand from contralateral knee to ipsilateral ear | Shoulder retraction | 0 | 1 | 2 |
|                                                               | elevation          | 0 | 1 | 2 |
| From extensor synergy (shoulder adduction/ internal rotation, elbow extension, forearm pronation) to flexor synergy (shoulder abduction/ external rotation, elbow flexion, forearm supination). | Elbow flexion      | 0 | 1 | 2 |
|                                                               | Forearm supination  | 0 | 1 | 2 |
|                                                               | Shoulder adduction/internal rotation | 0 | 1 | 2 |
|                                                               | Elbow extension     | 0 | 1 | 2 |
|                                                               | Forearm pronation   | 0 | 1 | 2 |

**Subtotal II (max 16)**

#### III. Volitional movement mixing synergies, without compensation

| Hand to lumbar spine | cannot be performed; hand in front of SIAS hand behind of S1AS (without compensation) | 0 | 1 | 2 |
|                      | hand to lumbar spine (without compensation)                                         |   |   |   |
| Shoulder flexion 0°-90° | immediate abduction or elbow flexion abduction or elbow flexion during movement complete flexion 90° maintains 0° in elbow | 0 | 1 | 2 |
| elbow at 0° pronation-supination 0° | no pronation/supination, starting position impossible limited pronation/supination, maintains position complete pronation/supination, maintains position | 0 | 1 | 2 |

**Subtotal III (max 8)**

#### IV. Volitional movement with little or no synergy

| Shoulder abduction 0°-90° | immediate supination or elbow flexion supination or elbow flexion during movement abduction 90°, maintains extension and pronation | 0 | 1 | 2 |
| forearm pronated          | immediate abduction or elbow flexion abduction or elbow flexion during movement complete flexion, maintains 0° in elbow |   |   |   |
| 0° pronation-supination 0° | no pronation/supination, starting position impossible limited pronation/supination, maintains extension full pronation/supination, maintains elbow extension | 0 | 1 | 2 |

**Subtotal IV (max 6)**

#### V. Normal reflex activity evaluated only if full score of 6 points achieved on part IV

| biceps, triceps, finger flexors | 0 points on part IV or 2 of 3 reflexes markedly hyperactive 1 reflex markedly hyperactive or at least 2 reflexes lively maximum of 1 reflex lively, none hyperactive | 0 | 1 | 2 |

**Subtotal V (max 2)**

**Total A (max 36)**

---

Approved by Fugl-Meyer AR 2010

---

Figure 0C.16: Fugl-Meyer Assessment for upper extremity (page 1 of 3).
## B. WRIST

<table>
<thead>
<tr>
<th>Support at wrist</th>
<th>None</th>
<th>Partial</th>
<th>Full</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stability at 15° dorsiflexion</strong></td>
<td>less than 15° active dorsiflexion</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Elbow at 90°, forearm pronated</td>
<td>maintains position against resistance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shoulder at 0°</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Repeated dorsiflexion / volar flexion</strong></td>
<td>cannot perform voluntarily</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Elbow at 90°, forearm pronated</td>
<td>limited active range of motion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shoulder at 0°, slight finger flexion</td>
<td>full active range of motion, smoothly</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Stability at 15° dorsiflexion</strong></td>
<td>less than 15° active dorsiflexion</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Elbow at 0°, forearm pronated</td>
<td>maintains position against resistance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slight shoulder flexion/abduction</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Repeated dorsiflexion / volar flexion</strong></td>
<td>cannot perform voluntarily</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Elbow at 0°, forearm pronated</td>
<td>limited active range of motion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slight shoulder flexion/abduction</td>
<td>full active range of motion, smoothly</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Circumduction</strong></td>
<td>cannot perform voluntarily</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Jerky movement or incomplete</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complete and smooth circumduction</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Total B (max 10)**

## C. HAND

<table>
<thead>
<tr>
<th>Support at elbow to keep 90° flexion, no support at the wrist, compared with unaffected hand, the objects are interposed, active grasp</th>
<th>None</th>
<th>Partial</th>
<th>Full</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mass flexion</strong></td>
<td>from full active or passive extension</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Mass extension</strong></td>
<td>from full active or passive flexion</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>GRASP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A - flexion in PIP and DIP (digits II-V)</td>
<td>cannot be performed</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Extension in MCP II-V</td>
<td>can hold position but weak</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maintains position against resistance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B - thumb abduction</td>
<td>cannot be performed</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1-st CMC, MCP, IP at 0°, scrap of paper between thumb and 2-nd MCP joint</td>
<td>can hold paper but not against tug</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Can hold paper against a tug</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C - opposition pulp of the thumb</td>
<td>cannot be performed</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Against the pulp of 2-nd finger, pencil, tug upward</td>
<td>can hold pencil but not against tug</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Can hold pencil against a tug</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D - cylinder grip</td>
<td>cannot be performed</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Cylinder shaped object (small can) tug upward, opposition in digits I and II</td>
<td>can hold cylinder but not against tug</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Can hold cylinder against a tug</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E - spherical grip</td>
<td>cannot be performed</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Fingers in abduction/abduction, thumb opposed, tennis ball</td>
<td>can hold ball but not against tug</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Can hold ball against a tug</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Total C (max 14)**

## D. COORDINATION/SPEED

<table>
<thead>
<tr>
<th>After one trial with both arms, blind-folded, tip of the index finger from knee to nose, 5 times as fast as possible</th>
<th>Marked</th>
<th>Slight</th>
<th>None</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tremor</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Dysmetria</td>
<td>pronounced or unsystematic slight and systematic no dysmetria</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time</td>
<td>more than 5 seconds slower than unaffected side</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2-5 seconds slower than unaffected side</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum difference of 1 second between sides</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Total D (max 6)**

**TOTAL A-D (max 66)**

---

Figure 0C.17: Fugl-Meyer Assessment for upper extremity (page 2 of 3).
### H. SENSATION, upper extremity

<table>
<thead>
<tr>
<th></th>
<th>anesthesia</th>
<th>hyposthesia</th>
<th>dysesthesia</th>
<th>normal</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Light touch</strong></td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>upper arm, forearm, palmar surface of the hand</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>absence less than 3/4</td>
<td>-</td>
<td>-</td>
<td>3/4 correct</td>
<td>1 1 1 2</td>
</tr>
<tr>
<td>Position</td>
<td>-</td>
<td>-</td>
<td>correct 100%</td>
<td>1 1 1 2</td>
</tr>
<tr>
<td>small alterations in the position</td>
<td>-</td>
<td>-</td>
<td>little or no difference</td>
<td>1 1 1 2</td>
</tr>
<tr>
<td>shoulder</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>elbow</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>wrist</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>thumb (IP-joint)</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

**Total H** (max 12)

### J. PASSIVE JOINT MOTION, upper extremity

<table>
<thead>
<tr>
<th>Sitting position, compare with unaffected side</th>
<th>Shoulder</th>
<th>Elbow</th>
<th>Forearm</th>
<th>Wrist</th>
<th>Fingers</th>
<th>Total (max 24)</th>
</tr>
</thead>
<tbody>
<tr>
<td>only few degrees (less than 10° in shoulder)</td>
<td>Flexion</td>
<td>Flexion</td>
<td>Pronation</td>
<td>Flexion</td>
<td>Flexion</td>
<td>/36</td>
</tr>
<tr>
<td>decreased</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>/10</td>
</tr>
<tr>
<td>normal</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>/14</td>
</tr>
<tr>
<td>pronounced constant pain during or at the end of movement</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>/6</td>
</tr>
<tr>
<td>some pain</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>/66</td>
</tr>
<tr>
<td>no pain</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>/12</td>
</tr>
</tbody>
</table>

### J. JOINT PAIN during passive motion, upper extremity

<table>
<thead>
<tr>
<th>Sitting position, compare with unaffected side</th>
<th>Shoulder</th>
<th>Elbow</th>
<th>Forearm</th>
<th>Wrist</th>
<th>Fingers</th>
<th>Total (max 24)</th>
</tr>
</thead>
<tbody>
<tr>
<td>only few degrees (less than 10° in shoulder)</td>
<td>Flexion</td>
<td>Flexion</td>
<td>Pronation</td>
<td>Flexion</td>
<td>Flexion</td>
<td>/36</td>
</tr>
<tr>
<td>decreased</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>/10</td>
</tr>
<tr>
<td>normal</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>/14</td>
</tr>
<tr>
<td>pronounced constant pain during or at the end of movement</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>/6</td>
</tr>
<tr>
<td>some pain</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>/66</td>
</tr>
<tr>
<td>no pain</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>/12</td>
</tr>
</tbody>
</table>

**A. UPPER EXTREMIT Y** /36

**B. WRIST** /10

**C. HAND** /14

**D. COORDINATION / SPEED** /6

**TOTAL A-D (motor function)** /66

**H. SENSATION** /12

**J. PASSIVE JOINT MOTION** /24

**J. JOINT PAIN** /24

Figure 0C.17: Fugl-Meyer Assessment for upper extremity (page 3 of 3).
### Figure 0C.19: The Reaching Performance Scale (page 1 of 1)

<table>
<thead>
<tr>
<th>□ 1. Trunk Displacement</th>
<th>Far Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Close Target</strong></td>
<td><strong>Far Target</strong></td>
</tr>
<tr>
<td>3. No or almost no forward trunk displacement</td>
<td>3. Appropriate forward trunk displacement related to the amount of trunk movement</td>
</tr>
<tr>
<td>2. Small displacement of the trunk flexion, rotation, or flexion accompanied by rotation</td>
<td>2. Excessive trunk displacement related to a limitation of the active movement of the elbow or shoulder</td>
</tr>
<tr>
<td>1. More than half the movement is made by the trunk</td>
<td>1. Excessive trunk displacement: about half of the displacement of the hand toward the target is accomplished by the trunk, but the hand arrives at the target</td>
</tr>
<tr>
<td>0. Task is accomplished only by forward trunk displacement</td>
<td>0. Excessive trunk displacement: more than three fourths of the displacement of the hand to the target is accomplished by the trunk, and the hand does not arrive at the target</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>□ 2. Movement Smoothness*</th>
<th>Far Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Close Target</strong></td>
<td><strong>Far Target</strong></td>
</tr>
<tr>
<td>3. The combination of movement of the arm and trunk is fluid and smooth</td>
<td>3. The combination of movement of the arm and trunk is fluid and smooth</td>
</tr>
<tr>
<td>2. More than one movement of the arm is made to perform the task, or the movement is segmented (not smooth)</td>
<td>2. More than one movement of the arm is made to perform the task, or the movement is segmented (not smooth)</td>
</tr>
<tr>
<td>1. Several small movements of the arm and trunk in a sequential manner</td>
<td>1. Several small movements of the arm and trunk in a sequential manner</td>
</tr>
<tr>
<td>0. Complete segmentation of arm and trunk movement</td>
<td>0. Complete segmentation of arm and trunk movement</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>□ 3. Shoulder Movements</th>
<th>Far Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Close Target</strong></td>
<td><strong>Far Target</strong></td>
</tr>
<tr>
<td>3. Adequate shoulder flexion and horizontal abduction with scapular elevation to perform the task</td>
<td>3. Adequate shoulder flexion and horizontal abduction with scapular elevation to perform the task</td>
</tr>
<tr>
<td>2. Shoulder flexion and horizontal abduction occurs with excessive scapular elevation</td>
<td>2. Shoulder flexion and horizontal abduction occurs with excessive scapular elevation</td>
</tr>
<tr>
<td>1. Shoulder flexion occurs only in combination with excessive scapular elevation. Shoulder horizontal abduction is decreased.</td>
<td>1. Shoulder flexion is combined with scapular elevation. Shoulder horizontal abduction is decreased.</td>
</tr>
<tr>
<td>0. No or almost no shoulder flexion or horizontal abduction is possible (all the movement is made by the scapula)</td>
<td>0. No or almost no shoulder flexion or horizontal abduction is possible (all the movement is made by the scapula)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>□ 4. Elbow Movements</th>
<th>Far Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Close Target</strong></td>
<td><strong>Far Target</strong></td>
</tr>
<tr>
<td>3. Extending the hand to the target is principally attributed to elbow extension</td>
<td>3. Elbow extension is almost full</td>
</tr>
<tr>
<td>2. More than half of the reaching movement is attributed to elbow extension</td>
<td>2. More than half of the reaching movement is attributed to elbow extension</td>
</tr>
<tr>
<td>1. Less than half of the reaching movement is attributed to elbow extension</td>
<td>1. Less than half of the reaching movement is attributed to elbow extension</td>
</tr>
<tr>
<td>0. No elbow extension occurs</td>
<td>0. No elbow extension occurs</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>□ 5. Preflection</th>
<th>Far Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Close Target</strong></td>
<td><strong>Far Target</strong></td>
</tr>
<tr>
<td>3. Adequate hand opening and closure to perform the task</td>
<td>3. Adequate hand opening and closure to perform the task</td>
</tr>
<tr>
<td>2. Opening or relaxing the hand is difficult</td>
<td>2. Opening or relaxing the hand is difficult</td>
</tr>
<tr>
<td>1. Use of compensatory grasping strategies (e.g., winding fingers around a cone, downward grasping)</td>
<td>1. Use of compensatory grasping strategies (e.g., winding fingers around a cone, downward grasping)</td>
</tr>
<tr>
<td>0. Preflection is not possible</td>
<td>0. Preflection is not possible</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>□ 6. Global Score</th>
<th>Far Target</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Close Target</strong></td>
<td><strong>Far Target</strong></td>
</tr>
<tr>
<td>3. The task can be done easily, with or without mild tremor or dystonia, following a smooth and direct trajectory</td>
<td>3. The task can be done easily, with or without mild tremor or dystonia, following a smooth and direct trajectory</td>
</tr>
<tr>
<td>2. The task is done in the presence of tremor; dystonia; small, jerky movements; arc-shaped trajectory; or segmentation. Preflection is possible but may be modified or difficult</td>
<td>2. The task is done in the presence of tremor; dystonia; small, jerky movements; arc-shaped trajectory; or segmentation. Preflection is possible but may be modified or difficult</td>
</tr>
<tr>
<td>1. The task is done partially (more than 50%) or with modification (such as stabilization of the cone, sliding the cone on the table, modification of table height, shorter distance to the cone). Preflection may be absent.</td>
<td>1. The task is done partially (more than 50%) or with modification (such as stabilization of the cone, sliding the cone on the table, modification of table height, shorter distance to the cone). Preflection may be absent.</td>
</tr>
<tr>
<td>0. Less than half the task is accomplished despite modifications</td>
<td>0. Less than half the task is accomplished despite modifications</td>
</tr>
</tbody>
</table>

*Excludes assessment of tremor (rhythmic movements of constant frequency) or dystonia (inaccuracies in aiming).*
Appendix D – Publications on Development of the FEATHERS System

The author of this thesis was directly involved in the design and development of the experiment setup and equipment used in the studies presented in this thesis. The different stages of the R&D process leading to the final design used in this thesis have been published in several journal and conference papers:


