Accelerometric Detection of Intentional Movements in the Presence of Dyskinesia

by

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A thesis submitted in conformity with the requirements for the degree of Master of Applied Science

Institute of Biomaterials and Biomedical Engineering
University of Toronto

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Abstract

This study investigated the potential to automatically decode unidirectional arm movements (up, down, left, and right), using an array of six muscle-situated tri-axial accelerometers in children with and without movement disorders. Fifteen typically developing children (aged 11±2 years) and four children with movement disorders (aged 9 ± 1.2 years) participated in the study. Participants repeatedly drew horizontal and vertical lines on the tablet using a digital stylus. In the typically developing group, the four movements could be discriminated with participant-independent classifiers (~80% accuracy) using either motion signals or their combination with low frequency MMG. For participants with movement disorders, neither motion nor its combination with low frequency MMG yielded high accuracy, possibly due to muscle atrophy and inconsistent muscle tone. In both groups, MMG alone provided the lowest accuracy. Low force contractions and developmental variations in the mechanical properties of muscles were likely contributing factors.
Dedication

To my parents who have always supported my dreams. To God for allowing me to be here.
Acknowledgements

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Finally I will like to thank all the participants of the study. Their energy and enthusiasm was a continuous reminder of why we do this work.

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## List of Abbreviations

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<tr>
<td>ANN</td>
<td>Artificial neural networks</td>
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<tr>
<td>AT</td>
<td>Access/assistive technologies</td>
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<td>CP</td>
<td>Cerebral palsy</td>
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<td>DCP</td>
<td>Dyskinetic cerebral palsy</td>
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<td>EMG</td>
<td>Electromyogram</td>
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<td>FS</td>
<td>Fisher scores</td>
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<td>HMM</td>
<td>Hidden Markov model</td>
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<td>ICA</td>
<td>Independent component analysis</td>
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<td>ID</td>
<td>Index of difficulty</td>
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<td>LDA</td>
<td>Linear discriminant analysis</td>
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<td>MK</td>
<td>Myokinetics</td>
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<td>MMG</td>
<td>Mechanomyogram/ Mechanomyography</td>
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<td>MVC</td>
<td>Maximum voluntary contraction</td>
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<td>TD</td>
<td>Typically developing children</td>
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<td>TMG</td>
<td>Tensiomyogram</td>
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<td>SVM</td>
<td>Support vector machines</td>
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<td>PCA</td>
<td>Principal component analysis</td>
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Chapter 1
Introduction

1.1 Motivation

Cerebral palsy (CP) is a permanent disorder that affects an individual’s development of movement and posture. Two out of a thousand births are affected by this disorder (Richards & Malouin, 2013). Individuals with CP may have motor disorders, characterized by spasticity, dystonia, dyskinesia or combinations thereof. Spasticity, dystonia, and dyskinesia are characterized by the presence of variable, involuntary movements that may limit an individual’s ability to communicate through writing, speaking, and sign language. However, access technologies may enable these individuals to communicate via alternative pathways (Tai, Blain, & Chau, 2008).

The contraction of individual motor units can be detected through the lateral movements of muscle fibers at different muscle sites in the body. For children and youth with physical disabilities, these sites can be used as access pathways to translate the individual’s functional intent into a functional activity. A promising method of monitoring muscle activity is the mechanomyogram (MMG). MMG has been used in the past for the study of muscle properties (Esposito, Orizio, & Veicsteinas, 1998; Gregori, Galié, & Accornero, 2003; Kim, Shimomura, Iwanaga, & Katsuura, 2008a), the development of access technologies (Alves & Chau, 2010b; Alves & Chau, 2011), and the control of powered upper-limb prostheses (Posatskiy & Chau, 2012b).

When using MMG with individuals who have hyperkinetic or dyskinetic movements, one of the most daunting challenges is finding a muscle site where intentional muscle contractions are
free from artifacts associated with involuntary activity. To enable the use of MMG as an access pathway, it is therefore necessary to detect motoric manifestation of intention in the presence of dyskinetic movements. This thesis investigates ways in which information from a group of muscles involved in a specific task may be combined to enhance the detection of functional intention amid dyskinetic movements.

1.2 Research Question

This research intended to answer the following question: Can different unidirectional upper extremity movements be decoded using muscle-situated accelerometers measuring a combination of limb motion and muscle vibrations? In particular, we were interested in whether such decoding could be achieved in the presence of dyskinetic movements.

To answer this question we set out to:

1. Model horizontal and vertical upper extremity movements for typically developing children and children with movement disorders using accelerometric signals.
2. Determine the discriminative value of the motion and muscle vibration components of the upper extremity acceleration signals for classifying different upper limb movements.

1.3 Thesis Roadmap

This thesis is divided into four main chapters. Chapter 2 provides background information on muscle physiology, movement disorders, and mechanomyography (MMG), as well as the contribution of MMG to the target population. Chapter 3 provides detail regarding the development and design of a Hidden Markov Model (HMM) for typically developing children using MMG. In this chapter, the description of the application and tailoring of HMMs to the
client population is also presented. Finally, Chapter 4 provides concluding remarks and directions for future work.
Chapter 2

Background

2.1 Skeletal Muscle Physiology

The muscular system can be described as the actuation machinery of the body. This description applies due to the main function of muscles to contract and create movement. The contraction of different groups of muscles in the body allows an individual to stand erect, walk, throw, grasp, and perform many other actions that are necessary for daily life. Skeletal muscle is one of the three types of muscles found in the body and its main function is to move the skeleton. Skeletal muscle consists of multinucleated cells that span the length of a muscle fiber and are considered the longest cells of the muscle fiber types (E. N. Marieb & Hoehn, 2007). These fibers are enclosed in a delicate connective tissue and when grouped with other fibers, form a bundle of fibers called a fascicle. Many fascicles are bound together to create a muscle that is attached by tendons to bones, cartilage, or connective tissue (refer to Figure 2.1) (E. Marieb & Hoehn, 2010). As skeletal muscle is subject to conscious control, it is denoted a voluntary muscle. However, it is often activated by reflexes that are not under the individuals ‘willful command.’
Skeletal muscle is also referred to as striated muscle due to its stripped appearance (E. N. Marieb & Hoehn, 2007). Alternating I-bands (light) and A-bands (dark) are aligned along the length of myofibrils and are responsible for the stripped appearance of muscle fibers. Myofibrils consist of chains of tiny contractile units called sarcomeres. Sarcomeres contain even smaller structures or cytoskeletal elements, called myofilaments, which control the actual contraction of a muscle. These structures consist of thick (myosin protein and ATPase enzymes) and thin (actin protein and regulatory proteins) filaments, which are responsible for the power of contraction and the control of the myosin head binding to actin, respectively. The stimulation and activation of the myofilaments is due to nerve impulses. The frequency and the number of myofilaments being stimulated determine the degree and power of the muscle contraction (Jones & Round, 1990).

### 2.2 Movement Disorders

Movement disorders in children may occur for several reasons and may affect one or more parts of the body. The central nervous system plays a major role in movement and any minor dysfunction in one or more of its components may compromise motor function. The basal ganglia and the frontal cortex are two components that are typically implicated in movement disorders.
disorders. However, coordinated movements are possible through a multilayered network of regions within the brain. This network includes basal ganglia, frontal cortex, thalamus, cerebellum, spinal cord, peripheral nerve, and muscle (Schlaggar & Mink, 2003). If any of these regions are affected movement disorders may occur. The classification of movement disorders can be based on the specific characteristics of the movements, age of onset, and parts or regions of the body that are affected. However, the classification of movement disorders can be challenging due to the similar presentation of some conditions, such as dystonia with spasticity or chorea with myoclonus. The main movement disorders presented in children are tics, chorea/ballismus, dystonia, myoclonus, tremor, and stereotypy (Sanger et al., 2010). Figure 2.2 depicts a general chart of the classes and sub-classes of movement disorders.

![Figure 2.2 Movement disorders breakdown.](image)

**2.2.1 Dyskinetic Cerebral Palsy**

Cerebral palsy (CP) is a permanent disorder affecting individual’s development of movement and posture. Two out of a thousand births are affected by this disorder (Mervyn Fox, 2011; Richards & Malouin, 2013). These developmental limitations are caused by non-progressive disturbances occurring in the developing fetal or infant brain. CP is characterized as an upper
motor neuron syndrome that can cause spasticity, dyskinesia, and secondary musculoskeletal malformation (Himmelmann, Beckung, Hagberg, & Uvebrant, 2006; Richards & Malouin, 2013). Motor control in children with CP may be highly impaired. These impairments manifest as large stretch reflexes during passive movements, co-contraction of agonist and antagonist muscles, as well as reflex excitation at rest (Kukke & Sanger, 2011; van Doornik, Kukke, & Sanger, 2009; S. J. Young, van Doornik, & Sanger, 2011). Children with CP can also experience disturbances of cognition, communication, behaviour, perception, and sensation (Rethlefsen, Ryan, & Kay, 2010).

Dyskinetic CP (DCP), also called extra-pyramidal CP, is characterized by the presence of variable involuntary movements that may affect an individual’s ability to communicate and interact with their surroundings through writing, speaking, and sign language (Schneiberg, Mckinley, Gisel, Sveistrup, & Levin, 2010). Neuroimaging findings show that children with DCP may have bilateral lesions of the basal ganglia, especially in the putamen and thalamus (Hou, Zhao, Jian-hui, & Yu Rong, 2005). DCP is often divided into two subgroups: hyperkinetic and dystonic. Children in the hyperkinetic group present motor patterns characterized by involuntary movements and choreothetosis - jerky and rapid involuntary movements accompanied by writhing or contorting movements (Monbaliu et al., 2012). Children and youth with dystonic CP experience a disruption of the basal ganglia. This causes involuntary co-contraction of agonist and antagonist muscle groups when performing voluntary actions. These co-contractions may affect all limbs or only selected muscles when an individual attempts a voluntary motion (LeDoux, 2012). Dystonia has also been associated with involuntary activation of muscles at rest and overflow activity of uninvolved muscles during voluntary movements (Malfait & Sanger, 2007). Furthermore, the dystonic subgroup may have a tendency to retain abnormal postures and strong primitive reflexes (Kyllerman et
Abnormal motor patterns in DCP are usually increased during tension, emotional change, and fatigue. Rest and sleep have been shown to decrease the occurrence of abnormal movements (Hou et al., 2005).

2.3 Mechanomyography (MMG)

Muscle activity can reflect the condition of muscles as well as reveal an individual’s underlying intention. Researchers have used different measurement modalities to analyze muscle activity, such as electromyogram (EMG), myokinetics (MK), and tensiomyogram (TMG). While EMG is widely used in many fields, the mechanomyogram (MMG) is gaining popularity in biomedical engineering applications. MMG is a technique used to study the mechanical activity of muscles resulting from the lateral oscillation of muscle fibers during active voluntary contraction (Islam, Sundaraj, Ahmad, & Ahamed, 2013; Jaskólska, Madeleine, Jaskólski, Kisiel-Sajewicz, & Arendt-Nielsen, 2007; Kim, Shimomura, Iwanaga, & Katsuura, 2008b; Orizio, 1993; Posatskiy & Chau, 2012b; Uchiyama & Miyazaki, 2013). It has been suggested that the low frequency information captured by MMG is created by the spatial summation of active motor units (Orizio, Liberati, Locatelli, De Grandis, & Veicsteinas, 1996). The mechanical signal of muscles is influenced by the muscles’ properties, such as length, mass, tension, stiffness, and intramuscular pressure (Daoud & Ragai, 2012).

MMG has been described as a low frequency signal. However, there are some disparities in the literature on the actual MMG frequency range. Orizio (1993) suggested that for the MMG signal, the ideal frequency range is between 1Hz to 100Hz. The high frequency limit of 100Hz has been widely reported through the MMG literature (Alves & Chau, 2010a; Fara, Gavriel, Vikram, & Faisal, 2014; Islam et al., 2014; Stock, Beck, DeFreitas, & Dillon, 2010). Nonetheless, some studies described smaller frequency ranges such as 4Hz to 40Hz (Scheeren,
Krueger-Beck, Nogueira-Neto, Nohama, & Button, Vera Lúcia da Silveira Nantes, 2010) or 5Hz to 50Hz (Silva, Heim, & Chau, 2004). Other research has reported 2Hz as the lower spectral limit and 120Hz as the upper limit (Beck et al., 2008). Yet other studies have reported MMG frequencies up to 150Hz (Cescon, Gazzoni, Gobbo, Orizio, & Farina, 2004), 160Hz (Shima & Tsuji, 2009), and 250Hz (Uchiyama & Miyazaki, 2013). It is important to note that most of the research on MMG has focused on isometric contractions where limb movement is not present. When dynamic movements of the limbs are present, it has been suggested that a cutoff frequency of 5Hz suppresses the bulk movement of the limbs and associated motion artifacts (Kim et al., 2008a; Posatskiy & Chau, 2012b). However, given the findings in the literature cited above, there is a risk that a 5Hz cut-off could result in the suppression of genuine MMG signal components.

2.3.1 A Modality for Quantifying Muscle Activity

MMG is often compared to EMG given that both signals are captured from active muscle contractions. EMG measures the electrical activity of muscles and has been widely used for the control of access technologies as well as the study of muscle characteristics (Dideriksen, Enoka, & Farina, 2011; Fuglevand, Winter, Patla, & Stashuk, 1992; X. Zhang et al., 2013). Compared to EMG, MMG also provides a force-dependent signal but offers some instrumentation advantages. For instance, MMG is immune to changes in electrode-skin impedance due to perspiration (Hewson, Hogrel, Langeron, & Duchêne, 2003), and does not require skin preparation (Alves & Chau, 2010b). Further, EMG signal amplitude is often attenuated when the active muscle is more than 10 mm below the skin surface (Fuglevand et al., 1992; Islam et al., 2013). Additionally, MMG exhibits greater sensitivity to low power muscle contractions (Perry, Housh, Johnson, & Ebersole, 2001) and is an attractive alternative to EMG for quantifying contraction strength when muscle activity is electrically evoked.
MMG can be considered the mechanical counterpart of EMG; MMG reflects the physical movement of the muscle fibers subsequent to their electrical excitation (Esposito et al., 1998). Although there are advantages to either system depending of the application, EMG and MMG should not be seen as conflicting but rather as complementary measurements of muscle activity.

Researchers have been exploring MMG for a number of different health science applications, including for example, the study of muscle fatigue (Esposito et al., 1998; Gregori et al., 2003; Orizio et al., 1996), tremors (Kim et al., 2008a), muscle activity during exercise (Malek, Coburn, York, Ng, & Rana, 2010), and muscle force production (Cescon et al., 2004). MMG has also been utilized in a clinical setting for the control of powered upper-limb prosthetic devices (Alves & Chau, 2006; Silva, Heim, & Chau, 2005; Xia, Yang, Cao, & Cao, 2010) and novel access technologies for communication for individuals with severe disabilities (Alves & Chau, 2010b; Alves & Chau, 2011).

### 2.3.2 Instrumentation

Given that MMG represents a vibration on the surface of the skin, there are several recording options. The choice of MMG transducer hinges on considerations of portability, manufacturing, and robustness to motion artifact. Potential transducers include: piezoelectric contact sensors (Coburn, Malek, Housh, Johnson, & Beck, 2011; Esposito et al., 1998); laser distance sensors (Orizio, Baratta, Zhou, Solomonow, & Veicsteinas, 1999; Orizio et al., 2003); accelerometers (Cescon, Farina, Gobbo, Merletti, & Orizio, 2004; Cescon et al., 2004; Kim et al., 2008a; Orizio et al., 1996; Orizio et al., 1997; Posatskiy & Chau, 2012b; Stock et al., 2010); and microphones (Alves & Chau, 2011; Jaskólska et al., 2007; Kim et al., 2008a; Posatskiy & Chau, 2012a). Although, each of these sensors may capture a different signal (i.e. microphones capture pressure differences in the chamber and laser distance sensors capture...
gross motor dimensional changes in the muscle), the MMG signal is defined as the final vibration detected by each of the sensors (Islam et al., 2013). As well there has been customizations of different sensors to maximize signal-to-noise ratio. For instance, Silva and Chau (Silva & Chau, 2003) developed an MMG sensor that used both a microphone and an accelerometer to suppress noise due to gross limb movement. Although this sensor was demonstrated in upper extremity powered prostheses (Silva et al., 2004; Silva et al., 2005) and access technologies (Alves, Falk, & Chau, 2010; Alves & Chau, 2011), the sensor had some limitations associated with variability of the manufacturing of the chamber and accompanying silicone membrane (Posatskiy & Chau, 2012b).

Another innovative MMG sensor was developed by Posatskiy and Chau (Posatskiy & Chau, 2012a). Their conical chamber design was motivated by the susceptibility of previous sensors to excessive limb and body movement. They found that the recommended optimal conical dimensions for increasing signal gain were 7mm in diameter and 5mm in height (Posatskiy & Chau, 2012a). With these dimensions, they demonstrated in vivo that the sensor could be more robust to motion artifact when measuring forearm MMG amid unidirectional gross limb movement (Posatskiy & Chau, 2012b). However, the manufacturing of this sensor required specialized machinery and consistency between sensors remained a challenge. Due to the lack of consistency of mechanical response among microphone sensors manufactured specifically for this project, we decided to use tri-axial accelerometers for this study.
Figure 2.3 Schematic of coupled accelerometer and microphone MMG transducer designed by Silva and Chau (2003).

Figure 2.4 Microphone-based MMG sensor designed by Posatskiy and Chau (2012a).
2.3.3 Limitations of MMG

Although MMG has been used in a variety of applications there remains a few outstanding challenges that preclude routine MMG use. MMG transducers are highly susceptible to gross motor movement due to the overlapping frequencies of muscle contraction and motion artifact (Alves et al., 2010; Alves & Chau, 2010a; Posatskiy & Chau, 2012b; Silva & Chau, 2003). One of the most difficult challenges when using MMG as an access pathway is the decoding of intention in the presence of involuntary muscle contractions and excessive gross limb movements (Posatskiy & Chau, 2012a). Although there have been sensors created to optimize performance in these circumstances (Posatskiy & Chau, 2012a; Silva & Chau, 2003), these sensors have only been tested in controlled laboratory settings. One untested notion is to simultaneously consider the signals that occur due to muscle vibrations and those that occur due to gross limb motion for movement recognition. In any case, in situ measurements with clinical populations are necessary to further advance MMG acquisition and processing.

2.4 MMG and Movement Disorders

Individuals with profound physical disabilities rely on access technologies to interact with the world. Access technologies are typically user-specific, depending in part on the user’s functional goals, motor function, sensory capabilities, and cognitive development. For instance, some individuals may be able to use standard input devices on a computer while others may only be able to activate one or more switches via arm movements.

MMG has been used as an access pathway for individuals with disabilities (Alves & Chau, 2009; Alves et al., 2010; Alves & Chau, 2011). Children with movement disorders may retain sufficient control of specific muscles to use them as MMG access sites. However, these children may encounter difficulties when trying to use MMG as a control signal. Due to the
variable motor system of DCP, an MMG-based access technology has difficulty distinguishing between the voluntary and involuntary contractions of muscles (Alves & Chau, 2011; Posatskiy & Chau, 2012b). Alves and Chau (Alves & Chau, 2011) performed a case study using an MMG switch as an alternative access pathway. The MMG switch was used by seven individuals who controlled the switch by contracting muscles either in their forehead, forearm, or shoulder. This study demonstrated that the MMG switch could be viable for individuals who have extant control of one of these access sites. However, the MMG switch was problematic when muscle activity was confounded by motion artifact accompanying involuntary spastic contractions and dystonic movements. Figure 2.5 shows an example of a filtered MMG signal measured from a forearm muscle. Both voluntary (note red asterisks) and involuntary (note blue diamonds) contractions are depicted. Clearly, their differentiation is challenging.

![Graph of MMG signal from a forearm muscle affected by spasticity and involuntary twitches. Red asterisks mark voluntary contractions and blue diamonds marks involuntary contractions (Alves & Chau, 2011).](image)

It is commonly believed that unintentional dystonic movements and hyperkinetic movements are caused by co-contraction of agonist and antagonist muscles (Kukke & Sanger, 2011). In contrast, there have been several studies that suggest that these movements are not only caused by co-contraction, but rather reflex activity and overflow of non-task muscles (Kukke & Sanger, 2011; Malfait & Sanger, 2007; van Doornik et al., 2009; S. J. Young et al., 2011; S. J. MMG signal amplitude vs. Time (s))
Young, Van Doornik, & Sanger, 2011). Due to the highly variable effects of dystonic movements, MMG-based control systems can be easily compromised. To the best of our knowledge, MMG studies of dyskinetic movements have only involved one or two muscles sites to activate assistive technologies (AT) directly (Alves & Chau, 2006; Alves & Chau, 2010b; Alves & Chau, 2010c; Alves & Chau, 2011; Fara, Vikram, Gavriel, & Faisal, 2013; Posatskiy & Chau, 2012b). However, more information could be gained by exploring muscle activity from multiple sites.

2.5 Generative Modeling of Movement Time Series

In certain classes of problems, discriminative techniques for classification are known to be superior over generative techniques for recognition (Jaakkola & Haussler, 1999). For movement classification, the most popular discriminative approaches include support vector machines (SVM) (Alkan & Günay, 2012), artificial neural networks (ANN) (Fara et al., 2014), and linear discriminant analysis (LDA) (Hargrove, Scheme, Englehart, & Hudgins, 2010). However, discriminative techniques cannot naturally accommodate time series data of variable length as they represent movements with discrete features, many of which may be influenced by the length of the signal. In contrast, generative techniques directly capture the temporal characteristics of movement time series, independent of signal length. Knowing that dyskinetic movements present variable length contractions and movements, we opted for a generative approach to create prototypical movement models (Samadani, Gorbet, & Kulic, 2014). Specifically, we propose the development of a generative technique for the prediction and modeling of upper limb movements. Specifically, the proposed approach explores Hidden Markov Models (HMMs) for the recognition of arm movements in typically developing children as well as children with dyskinetic and hyperkinetic movements.
HMMs consist of a probabilistic model based on Markov chains which has an observable layer and a hidden state sequence. Markov chains are defined as a stochastic process sequence of events where the probability of the subsequent event is based exclusively on the current state.

An HMM has 5 main elements, $N$, $M$, $A$, $B$, and $\pi$, which generate an observation vector $O = O_1 O_2 \ldots O_T$. $N$ is the number of hidden states, $S = \{S_1, S_2, \ldots, S_N\}$. Let $q_t$ denote the state at time $t$. $M$ is the number of distinct observation symbols, $V = \{v_1, v_2, \ldots, v_M\}$ per state. $A$ is the state transition probability matrix where $A = \{a_{ij}\}$ and

$$a_{ij} = P[q_{t+1} = S_j | q_t = S_i], \ 1 \leq i, j \leq N$$

(1)

With

$$\sum_{j=1}^{N} a_{ij} = 1 \quad \text{and} \quad a_{ij} > 0$$

(2)

The observation symbol probability distribution in state $j$ is defined as $B = \{b_j(k)\}$, the set of probabilities corresponding to observing symbol $v_k$ at time $t$, given that the current state is $S_j$.

The initial state distribution is defined as $\pi = \{\pi_i\}$ where

$$\pi_i = P[q_1 = S_i], \ 1 \leq i \leq N$$

(3)

Given the observation vector $O_t$, the HMM then computes the probability of the observation sequence, given the specified model (Rabiner, 1989).

The underlying signal model is determined by several design decisions, namely: the topology of the model, the number of states in the model, and the number of Gaussian mixtures. The standard topology of an HMM consists of a stochastic approach where all states are fully connected and can be reached from any state of the model. However, a left-to-right topology is
particularly fitting when the expected sequence of signal events progresses strictly in one direction such that the state index would either move to the subsequent state or remain in the current state (refer to Figure 2.6). This topology is advantageous for signals whose properties change serially over time (e.g., with distinguishable start and end points). The second design decision, the number of states, is a hidden parameter that relates to the inherent nature of the signal under study. For instance, in speech recognition, three distinct states are typically used, representing the beginning, middle and end of the produced sound (Caballero-Morales, 2013; Gales & Young, 2008). Lastly, the model order of the Gaussian mixtures is the number of components used to represent the probability distributions of the state probabilities (Caballero-Morales, 2013).

![Figure 2.6 Example of a three state stochastic model (a) and a three state left-to-right model (b). States are numbers from one to three, π represents the initial state probability, a represents the transition probability, and b represents the observation probability.](image)

HMMs have been widely studied for speech recognition (Caballero-Morales, 2013; Rabiner, 1989), physiological signal modeling (Chan & Englehart, 2005; Chiang, Wang, & McKeown, 2008; Rossi, Benatti, Farella, & Benini, 2015) as well as movement representation (Chan &
Englehart, 2005; Chiang et al., 2008; Samadani et al., 2014). In the automatic recognition of gestures made by individuals with motor-impairments, HMMs have performed comparably to discriminative techniques (Cole, Roy, De Luca, & Nawab, 2014) and in some cases offer lower error rates (Morrison & McKenna, 2002).
Chapter 3
Predicting Movement Intention in Children with and without Dyskinesia using Accelerometry

3.1 Abstract

Children with movement disorders often communicate or interact with their environment via targeted upper extremity gestures (e.g., contacting one or more switches on a wheelchair tray or swiping across the screen of a wheelchair-mounted tablet). However, due to involuntary athetoid or dystonic movements, these gestural intentions can become ambiguous. In this study, we investigated the potential of detecting movement intention using six tri-axial accelerometers positioned over the biceps brachii long head, triceps brachii long head, flexor carpi radialis, extensor carpi radialis longus, anterior deltoïd, and pectoralis major muscles. In these positions, the accelerometers would capture both limb motion and mechanomyographic (MMG) activity. Fifteen typically developing children and three children with dyskinetic cerebral palsy (CP) completed a tablet drawing protocol, consisting of self-paced, linear motions in the cardinal directions. Using participant-independent Hidden Markov models, the four movements were discriminated with cross-validated accuracies of 80% for the typically developing group, when considering motion and combined motion and low frequency MMG. However, MMG alone was not discriminative. For the children with dyskinetic CP, neither motion, nor MMG, nor the combination of the two proved discriminative. The prevalence of low force, isometric contractions and developmental variation in the mechanical properties of maturing muscles were likely contributing factors to low classification accuracies with MMG.
In addition, for the children with dyskinetic CP, muscle fiber atrophy and inconsistent tone, may have further compromised the quality of the recorded MMG signals. Our findings demonstrate limited independent and complementary value of MMG in decoding upper extremity movement intentions for simple, low force targeted movements. Further research with muscle-situated accelerometers, with a wider range of movements and participants with dyskinetic CP are required to confirm our findings.

3.2 Introduction

3.2.1 The Access Challenge

Cerebral palsy (CP) is a permanent disorder that affects an individual’s development of movement and posture. Two out of a thousand births are affected by this disorder (Richards & Malouin, 2013). Individuals with CP may have motor disorders, characterized by spasticity, dystonia, dyskinesia or combinations thereof. Spasticity, dystonia, and dyskinesia are characterized by the presence of variable and involuntary movements, typically associated with lesions in the frontal cortex (Sanger et al., 2010) and basal ganglia (Hou et al., 2005). Across affected individuals, the severity of impairment and the involvement of the extremities may vary (Schlaggar & Mink, 2003). Children with movement disorders may experience weakness in their legs and arms, and difficulty with speech and fine motor movement (Casellato et al., 2014; Himmelmann et al., 2006; Kyllerman et al., 1982). Consequently, these children may not be able to communicate via speech, sign language, or writing. In these situations, individuals may depend on access technologies (AT) to translate functional intentions into corresponding functional activities (Alves & Chau, 2010b; Davies, Chau, Fehlings, Ameratunga, & Stott, 2010). Access technology may be used to respond to “yes” and “no” questions as well as to navigate and make selections on an augmentative and alternative
communication device. Figure 3.1 depicts two typical alternative access arrangements for a child using a tablet in one instance and two physical buttons in the other.

![Image](image_url)

**Figure 3.1 Typical alternative access arrangements for children with movement disorders:** (a) two virtual switches on a wheelchair mounted tablet; (b) two physical switches secured to a wheelchair tray.

The typical multi-switch access depicted in Figure 3.1 entails targeted arm movements. For an individual without movement disorders, one would expect that these movements, if they are executed on the right side, to potentially involve the shoulder, elbow and wrist joints. See summary in Table 1.

<table>
<thead>
<tr>
<th>Joint</th>
<th>Direction of Arm Movement</th>
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<tr>
<td></td>
<td>Right-to-left</td>
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<tr>
<td>Shoulder</td>
<td>Horizontal adduction; medial rotation</td>
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<tr>
<td></td>
<td>Horizontal abduction; lateral rotation</td>
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<tr>
<td></td>
<td>Flexion</td>
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<tr>
<td></td>
<td>Extension</td>
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<tr>
<td>Elbow</td>
<td>Fixed at ~45°; possibly slight flexion</td>
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<tr>
<td></td>
<td>Fixed at ~45°; possibly slight extension</td>
</tr>
<tr>
<td></td>
<td>Extension</td>
</tr>
<tr>
<td></td>
<td>Flexion</td>
</tr>
<tr>
<td>Wrist</td>
<td>Ulnar deviated position; possibly slight flexion</td>
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<td></td>
<td>Ulnar deviated; possibly slight flexion</td>
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<td></td>
<td>Ulnar deviated position; possibly slight flexion</td>
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Table 1 Involvement of the joints for targeted right-arm movements
Access technologies have the potential to enhance the function and well-being of children with conditions such as DCP (Alves et al., 2010; Alves & Chau, 2011). However, accurate interpretation of user intention by way of access technology remains a major challenge in the presence of movement disorders, which may encumber the targeting and post-activation release of switches, preclude the generation of appropriate activation force and heighten the tendency for multiple successive activations (Chau et al., 2012). Specifically, dyskinetic movements, or involuntary, tick-like movements, tend to occur when the affected individual intends to perform an action (e.g., when reaching for a communication button on one’s wheelchair tray) (Lebiedowska, Gaebler-Spira, Burns, & Fisk, 2004; Malfait & Sanger, 2007). As a result, intentional movements can manifest as highly variable and poorly targeted, leading to false activations of the access technology. Unsurprisingly, when access technology becomes ‘response inefficient’ due to the aforementioned complications, technology abandonment likely ensues (Mumford, Lam, Wright, & Chau, 2014).

### 3.2.2 Intention within Dyskinetic Movements

It has been suggested that hyperkinetic movements may at times encode the underlying intention of the individual. Lesperance, Blain, and Chau (2011) studied upper extremity hyperkinetic movements in children with cerebral palsy in an effort to identify potential communicative intent. Children were asked to indicate their preference (like vs. dislike) via a deictic gesture when presented with images of familiar objects or characters. This study combined both clinician and caregiver’s observations along with signals from multiple accelerometers to decipher the hyperkinetic movements and gestural expressions of the child. In the two pediatric participants, the authors found discernible, but subtle movement idiosyncrasies associated with positive versus negative preference. An earlier study also reported the identification of meaningful gestures of a child with cerebral palsy through
biomechanical analyses of arm positions and movements within a drama and mime context (Roy & Panayi, 1994). Despite these promising findings, we observe that the prediction of movement intention in the face of dyskinetic movements remains an elusive goal; these movements are highly variable and may change in terms of timing, intensity, and range of motion (Sanger, 2006). Further, these stochastic differences appear between individual as well as within-individuals.

### 3.2.3 Mechanomyography

Mechanomyography (MMG) is the measurement of the lateral oscillation of muscle fibers during active voluntary contraction (Orizio, 1993). MMG has been widely used for the study of muscle activity during exercise (Malek et al., 2010), the study of fatigue (Esposito et al., 1998; Gregori et al., 2003), as well as the study of tremor and spasticity (Kim et al., 2008a). MMG has also been exploited as an access pathway for individuals with severe disabilities, including those with DCP (Alves & Chau, 2010b), particularly through intentional contraction of muscles of the forehead, forearm, and shoulder (Alves et al., 2010; Alves & Chau, 2011). As in the case of physical switches, however, the variable motor system of DCP can complicate MMG-based detection of voluntary muscle contractions; signals from co-contracting non-task muscles and the associated unwanted limb and body motions can obscure the MMG of the targeted muscle (Alves & Chau, 2011; Posatskiy & Chau, 2012b). Previous studies of MMG as an access pathway have only focused on one target muscle (i.e., agonist muscle) (Alves et al., 2010; Alves & Chau, 2011; Posatskiy & Chau, 2012b). However, more discriminatory information could be derived by considering the contractions of the surrounding muscles. Further, past research has only considered MMG as the primary access pathway and has not contemplated the role of MMG as a complementary access signal when the primary pathway (e.g., physical or virtual switches) requires limb movement (e.g., as
seen in Figure 3.1). In these instances, MMG may help to mitigate inadvertent activations or improve sensitivity to intentional movements.

3.2.4 Quantification of Disordered Upper Extremity Movements

Disordered movements have been quantified through computer-vision (Morrison & McKenna, 2002), optical tracking (Jaspers et al., 2011), accelerometry (Cole et al., 2014), and EMG (Chiang et al., 2008). In particular, given their small size and low cost, accelerometry has been widely used for the detection of upper extremity motions (Godfrey, Conway, Meagher, & ÓLaighin, 2008), such as those associated with feeding (S. Zhang, Ang, Xiao, & Tham, 2009), hand flapping in children with autism (Goodwin, Intille, Albinali, & Velicer, 2011), locomotion (A. J. Young, Simon, & Hargrove, 2013) and activities of daily living (Uswatte et al., 2000). The modeling and prediction of disordered movement has been explored through discriminative (Cole et al., 2014; Lesperance et al., 2011; X. Zhang et al., 2013) as well as generative (Cole et al., 2014; Morrison & McKenna, 2002) techniques. Discriminative techniques such as linear discriminant analysis or support vector machines cannot be directly applied to variable-length time-series observations. In contrast, generative alternatives such as Hidden Markov models (HMM) can encode the dynamics of time-series observations and are robust to the phase and signal length variability commonly present in time-series observations recorded under naturalistic settings. Given the variable length of naturally occurring muscle contractions, HMMs offer a means of encoding muscle activities related to specific movements. Indeed, other accelerometry-based movement studies have deployed HMMs to determine the severity of Parkinsonian tremors (Rigas et al., 2012) and the occurrence of specific gait events (Guenterberg, Ghasemzadeh, & Jafari, 2009). With this backdrop, the combination of accelerometry and Hidden Markov Models appear to be a potent sensing-modeling approach for dyskinetic movements.
In light of the above findings, this study investigates the potential of recognizing four different upper extremity movements from children with and without movement disorders, using Hidden Markov modelling of multiple accelerometry signals, specifically representing MMG from multiple muscles along with gross limb motion.

### 3.3 Methods

#### 3.3.1 Participants

A convenience sample of 15 typically developing children (TD) (five males), aged $11 \pm 2$ years with no previous musculoskeletal conditions were recruited. A client group of four children (three males), aged $9 \pm 1.2$, diagnosed with cerebral palsy (CP) were recruited from Holland Bloorview Kids Rehabilitation Hospital and nearby schools. The data of one of the client participants were excluded from this analysis since his arms were highly compromised and he was unable to complete the study. The remaining three participants were diagnosed with spastic cerebral palsy and presented with dystonic movements as well as upper extremity weakness. Two participants (client 1 and 2) were wheelchair users and client 3 used a walker. Clients 1 and 2 were able to communicate verbally and client 3 communicated through sign language. Client 1 had difficulty maintaining a static hand position. Client 2 exhibited a high level of hyperkinetic movements when performing the experimental task and also struggled to maintain a static hand position for any length of time. Client 3 was the least compromised, but also found static hand positions to be very challenging, due to involuntary movements.

This research was approved by the ethics board of Holland Bloorview Kids Rehabilitation Hospital, the Toronto District School Board, and University of Toronto. All participants provided written consent prior to the experimental session.
3.3.2 Instrumentation

To acquire MMG, tri-axial accelerometers (MMA7361L Freescale Semiconductor) were positioned over the muscle belly of six different muscles along the upper limb, namely, the biceps brachii long head, triceps brachii long head, flexor carpi radialis, extensor carpi radialis longus, anterior deltoid, and pectoralis major muscles, as shown in Figure 3.2. The accelerometers were adhered to the skin via medical tape (3M™ Micropore surgical tape 1530-1) and oriented such that the z-axis was perpendicular to the skin surface. The accelerometers were wired to a custom terminal box, which interfaced to a custom LabView program (National Instruments, 2010). The tri-axial MMG signals where sampled through an analog signal conditioning input module at a rate of 1KHz. The digitized signals were stored on a desktop computer. Data were then transferred to a secure network after each session for off-line analysis.

Two video cameras were used to record the performance of each participant. One camera was situated above the participant and a second was located in front of the participant, providing transverse and frontal perspectives, respectively. Participants were comfortably seated on a chair in front of a desk. The stimuli were presented on a 26cm x 16cm tablet (Wacom LCD tablet) situated on the desk in front of the participant as shown in figure 3.3. The data acquired from the tablet included time, position of the digital stylus (x and y axis), the force on the tip of the stylus, and the azimuth and elevation angles of the stylus. These data were acquired at a sampling rate of 140 Hz with a 1050x768 pixels resolution, but not were considered in the present analysis.
Figure 3.2 Location of MMG sensors on each participant’s arm.
3.3.3 Experimental Protocol

Prior to data collection, each participant completed a proprioceptive examination. The experimenter positioned the participant’s arm with palm facing upwards and the elbow flexed at a 90° angle. Subsequently, the experimenter would move the participant’s arm to a 45° angle and back, pausing at each position. The participant closed his or her eyes and responded to the movement by either saying “up” (flexion) or “down” (extension). This test was performed in order to ensure intact perception of the arm in space (Johnson & Soucacos, 2010).

Participants were asked to perform a discrete targeting task as naturally as possible. A discrete task is one that has a well-defined beginning and an clear end point, determined by the task itself, rather than by the participant (Schmidt & Lee, 2005). A discrete task was chosen for this
experiment due to the fact that the variable motor system may unduly affect the performance of a continuous task. As noted in Holmes (1939), the effects of cerebellar lesions are more evident when participants are asked to change the direction of the movement (as in a continuous task). Previous studies of muscle activity in children with dystonia have also used discrete tasks (Kukke & Sanger, 2011; Malfait & Sanger, 2007; van Doornik et al., 2009; S. J. Young et al., 2011).

Using a digital stylus, participants performed horizontal and vertical targeting movements in a pseudo-randomized order on a tablet. Figure 4 depicts the stimuli, where the star and circle represented the start and end points, respectively. The four movements that the participants completed were: (a) bottom-to-top (b) top-to-bottom, (c) left-to-right and (d) right-to-left. A computer program instructed the participants when to start and stop each trial. An experimental session consisted of five blocks of 32 trials, for a total of 160 trials. For each trial, participants started at a position on the tablet indicated by a green star. The typically developing group was asked to hold the pen for two seconds in the start position before a target circle appeared on the opposite side of the screen and the participant was cued to draw a line to the target. Upon reaching the target, participants also waited for 2 seconds before the target disappeared. For the client group, the 2 seconds at the beginning and end of the task were removed because those participants had difficulty maintaining a static hand position. For the client group, the start and target cues appeared on the screen at the same time and were removed once the pen entered the target circle. Participants had 5 seconds to return to the start position after each trial and were given a 30 second rest between each block of trials. For the typically developing group, the length of the session was no longer than one hour. For the client participants, one child was able to complete the study in one hour session. The other two participants required two separate sessions to complete data collection.
Figure 3.4 Start (star) and target (circle) stimuli shown for each movement direction. (a) bottom-to-top (b) top-to-bottom (c) left-to-right (d) right-to-left.

For the vertical movements, the distance between the starting and end points was 11.5 cm long. For the horizontal movements, this distance was 19 cm. The diameters of the circular target were 5.7 cm and 9.5 cm for vertical and horizontal movements, respectively. The amplitude and diameter of the targets were selected according to Fitts' Law, which quantifies the tradeoff between speed and accuracy through an Index of difficulty (ID). As the level of difficulty increases, the time to accomplish the movement also increases (Grosjean, Shiffrar, & Knoblich, 2007; MacKenzie, 1992; Wong, Manson, Tremblay, & Welsh, 2013). A low index of difficulty (ID=2) was selected to ensure successful performance and avoid frustration for both participant groups, namely:

\[
ID = \log_2 \left( \frac{2A}{W} \right)
\]

(4)

where A is the amplitude of the movement (length of line segments) and W is the width of the target (diameter of the target circles).
3.3.4 Signal Preprocessing

All data analysis was performed offline using MATLAB (MathWorks, Inc., MA, 2013). To extract MMG, the acceleration signals were denoised via 8-level wavelet decomposition with a Daubechies 10 mother wavelet (Alves & Chau, 2010a), and reconstructed with soft-thresholding (Donoho, 1995). Specifically, the low frequency coefficients (approximation and detail wavelet coefficients at level 8 responsible for 0Hz to 4Hz frequency content) of the decomposed signal were set to 0 to suppress gross motor movement. High frequency coefficients (the detail wavelet coefficients at levels 1 to 3) were similarly attenuated, leaving an estimated frequency range between 3.9Hz and 62.5Hz. Upon reconstruction, signals were normalized to [-1,1].

To extract motion-exclusive signals, the same procedure as above was applied, except that coefficients from levels 1 to 7 were suppressed, leaving behind frequencies in the 0Hz to 4Hz range. To derive a combined MMG and motion signal, we applied a root-mean-square filter with a moving window size of 50 samples and 90% overlap. The effective 3-dB cutoff of this low-pass filter was 6Hz.

3.3.5 Motion Modeling and Prediction

Accelerometric signals associated with each targeted, directional movement were encoded by a separate HMM. The axial accelerometric signals from each accelerometer were concatenated. For MMG, only z-axis signal (perpendicular to the skin surface) was considered given that the vibration along the transverse axis of the muscle is stronger than the lateral and longitudinal vibrations (Islam et al., 2014; Orizio, 1993; Scheeren et al., 2010).

The axial accelerometer signals from the six accelerometers for the $i^{th}$ observation $O_i$ of length $T_i$ were concatenated as $[x_1^i, y_1^i, z_1^i, x_2^i, y_2^i, z_2^i, \ldots, x_6^i, y_6^i, z_6^i] \in \mathbb{R}^{18 \times T_i}$, where $x_j^i, y_j^i, z_j^i$ are univariate
time-series accelerations in $O_I$ measured along $x$, $y$, and $z$ axes of $j^{th}$ accelerometer. In other words, for each instance of time, we would have an 18-dimensional observation vector (6 accelerometers x 3 axes each). Note that the off-diagonal entries of the covariance matrices of the Gaussian mixtures capture the interactions among signals and hence the order of concatenation is not important.

The resulting class-specific HMMs were then used to predict the direction of movement using maximum likelihood classification. The HMMs were implemented in MATLAB (MathWorks, Inc., MA, 2013) using the HMM Toolbox (Murphy, 1998). As the targeted movements were unidirectional, we selected a left-to-right HMM topology, as illustrated by Figure 3.5. This means that the possible paths from the current state are either to transition to the subsequent state or remain in the current state. Transition to a previous state was ruled out given that the task did not require a change in movement direction. Since all the targeted, directional movements were composed of a start, middle (movement), and stop, we decided to invoke three states. For the estimation of HMM state probability distributions, we considered Gaussian mixtures with two to five components.
Figure 3.5 Example of a three-state left-to-right HMM topology for modelling the accelerometry signals associated with arm movements. $\pi_1$ is the initial state probability, which in our left-to-right models is 1 for the first state and 0, otherwise. $a_{ij}$ is the transition probability from state $i$ to state $j$. $b_i(o)$ is the distribution of observations at $i^{th}$ state, which is modeled as a mixture of Gaussians in the present study.

3.4 Results

Figure 3.6 exemplifies a raw accelerometer signal and its various filtered versions. We note that the motion signal reflects the lowest frequency aspect, i.e., non-stationary mean, of the recording, whereas the MMG signal is 0 mean but exhibits many oscillations, as expected. Finally, the combined signal captures the nonstationary feature of the motion and the lowest frequency undulations of MMG.
Figure 3.6 Raw z-axis MMG accelerometer signal of the triceps biceps brachii muscle of a typically developing participant during a left-to-right movement; (b) filtered for motion only (0Hz to 3.9 Hz); (c) filtered for MMG only (3.9Hz to 62.5 Hz); and (d) filtered for motion and selected MMG (0Hz to 6 Hz)

For the typically developing group, average inter-personal four-movement classification accuracies of 81.2±2.5 and 76.3±3.0 were achieved using the motion signal alone and combined motion-selected MMG signal, respectively. Figure 3.7 summarizes the 4-class accuracies for the typically developing group and the three participants with movement disorders. A one-way repeated measures ANOVA confirmed that the accuracies were different (p << 0.05) among the three scenarios (i.e., motion, MMG and combined motion and the selected MMG) for the typically developing group. Post-hoc pairwise comparisons, confirmed that accuracies with the motion signal alone were higher than accuracies obtained with either
MMG or the combined signal ($p \leq 0.0043$; paired $t$-test with Bonferroni-adjusted significance level). No differences in accuracies were found among the three filtering methods (motion, MMG, combined motion and MMG) for each of the participants with movement disorders ($p > 0.078$). The four-movement accuracies for participants with movement disorders were generally below 60%.

Figure 3.8 summarizes the binary classification accuracies, considering each pairing of the targeted, directional movements. For the typically developing group, the differentiation
between left-to-right and right-to-left movements using the motion signal alone exceeded that achieved with the combined signal ($p < 0.014$; paired $t$-test with Bonferroni-corrected significance level). For the remaining binary problems for the typically developing group, classification based on motion alone was statistically equivalent to that based on the combined signal ($p > 0.088$). For all binary problems for the typically developing group, classification by MMG alone yielded the lowest accuracies. For the participants with

<table>
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<th>MMG</th>
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Figure 3.8 Hinton diagrams showing accuracies for the various binary classification problems for (a) the typically developing group, and (b)-(d) the participants with movement disorders. The pairs of arrows on the left of each row denote the movements under consideration (↑ up, ↓ down, ← left, → right). The x-axis labels indicate the data being considered, namely, motion only, MMG only or a combination of motion and selected MMG. The larger the square in the Hinton diagram, the higher the accuracy.
movement disorders. There were some binary problems for which the combined signal seemed to be preferred over the motion signal alone (e.g., P1 for the ←↓ problem and P2 for the ↓↑ and →↑ problems).

Figures 3.9 and 3.10 exemplify the mean trajectories (dark lines) produced on the tablet for vertical (bottom-to-top) and horizontal (right-to-left) movements by the typically developing group and the participants with movement disorders. The grey shading depicts the variation within and across participants. Evidently, participants with movement disorders produced a much wider variety of trajectories and were less consistent in terms of starting and ending positions, despite the provision of visual anchors (star and circle).
To better appreciate the challenges with automatic classification of movements based on
MMG in the typically developing group, Figure 3.11 depicts the trial-averaged MMG response
across participants in the typically developing group, for each muscle and each movement.
There are no obvious distinguishing trends that suggest potential for multi-class
discrimination. To illustrate the classification challenges in the face of dyskinetic movements, we exemplify MMG (Figure 3.12) and motion (Figure 3.13) signals for participant 2 with movement disorders. From Figure 3.12, it appears that the MMG signals exhibit little movement-specific patterns. At first glance, the motion signals in Figure 3.13 seem to reveal some movement-related trends. However, upon deeper examination, it appears that these trends would only facilitate binary classification at best, as they are not unique to one motion. For example, the motion signals for up and down movements look somewhat distinguishable. However, right-to-left motion signals also resemble those of downward motions.

Figure 3.11 Across-participant average MMG responses for each muscle (rows) and for each movement (columns) for the typically developing group. The shaded band depicts standard error around the mean. Signals have been amplitude and time-normalized for visualization purposes.
Figure 3.12 Average MMG responses for each muscle (rows) and for each movement (columns) for participant 2 with movement disorders. The shaded band depicts standard error around the mean. Signals have been amplitude and time-normalized for visualization purposes.

Figure 3.13 Average motion signals detected at each muscle site (rows) and for each movement (columns). The shaded band depicts standard error around the mean. Signals have been amplitude and time-normalized for visualization purposes.
3.5 Discussion

We investigated the potential of recognizing four different upper extremity movements in children with and without movement disorders, using HMM modeling of multiple upper extremity accelerometry signals. Participants repeated a series of targeted movements in four different directions while donning six tri-axial accelerometer sensors positioned over selected muscles of the upper extremity. For the typically developing children, left-to-right HMM models predicted movement directions with close to 80% accuracy when considering motion signals exclusively and when combining motion with MMG components. MMG signals alone, however, were not discriminatory. For the participants with movement disorders, discrimination among movement disorders was poor regardless of the type of signal considered.

3.5.1 Inter-participant versus Participant-specific Movement Models

Although classification accuracies were significantly different among the three signal types (i.e. motion, MMG, and combined) for the typically developing children, all accuracies exceeded chance levels for a four-class problem (28.3% for 160 samples) (Mueller-Putz, Scherer, Brunner, Leeb, & Pfurtscheller, 2008). It is important to note the HMM models for the typically developing children were participant-independent. In other words, for each signal type, one model predicted movements for all participants, suggesting that there is consistency in the movements across participants. Figure 3.9 (a) and 3.10 (a) provide further evidence of this inter-participant consistency in the typically developing group.

For the participants with movement disorders, we estimated participant-specific models due to the unique presentation of dyskinesia in each case. Nonetheless, HMM classification yielded
uniformly unimpressive accuracies whether motion, MMG, or the combined signals were considered. A number of factors may have contributed to the poor discrimination based on motion signals alone, which, given the promising results with the typically developing group, we expected to yield accuracies in excess of chance levels. Participant 2 with movement disorders for example, exhibited qualitatively similar, excessive arm motions regardless of the movement direction. These sustained movements likely overlapped with the directional accelerations, both in time and frequency, thereby precluding meaningful separation. Participant 1 had very slow movements in every direction, with inconspicuous initial accelerations and terminal decelerations, and hence accelerations were generally very low in magnitude. Participant 3 occasionally produced movements with directional changes midway, potentially obfuscating the accelerometric clarity between movements in opposite directions. Indeed from visual inspection of the acceleration signals for participant 2 (Figure 3.13), we note a lack of discernible patterns in acceleration magnitude among movements.

3.5.2 Mechanomyographic Ambiguity

Classification accuracies using the MMG signals were the lowest among the signal types for the typically developing children. MMG has been used to accurately operate a robotic manipulator (Shima & Tsuji, 2009), control upper limb prosthesis (Silva et al., 2004), and classify forearm muscle patterns (Alves & Chau, 2010d; Shima & Tsuji, 2009; Silva et al., 2004). Although our MMG classification results are lower than those reported in these studies, some key experimental differences are noteworthy; all of these studies focused on hand and wrist movements that specifically invoked the forearm flexors and extensors while the forearm was stationary. In Alves & Chau (2010f), the forearm was immobilized such that the MMG was not contaminated with motion artefact. Likewise using forearm MMG, Silva, Heim, and Chau (2004) studied effortful contractions in amputees and Shima and Tsuji (2009) classified
hand opening/closing and wrist flexion/extension, both in the absence of limb motion. In contrast, the present study recorded MMG from multiple locations of the upper extremity specifically during full limb motion, with the hand in a static posture. Further, the generated forces were likely very low, leading to minimal myogenic acceleration of the skin surface. Although MMG has been touted as being informative even for contractions below 20% maximum voluntary contraction (Madeleine & Arendt-Nielsen, 2005), isometric contractions (in hand muscles) below 50% MVC are associated with much smaller amplitude MMG than concentric and eccentric contractions at the same percentage MVC (Madeleine, Bajaj, Søgaard, & Arendt-Nielsen, 2001). In our protocol, we would expect low intensity isometric contractions of the forearm flexors and extensors for all movements, given the steady pencil grasp posture. As well, for left-to-right movements, the biceps and triceps would exhibit minimal lengthening/shortening. Hence, MMG amplitude may have been indistinguishably small within certain muscles for a subset of movements, and hence would have offered little discriminatory value.

The mechanomyographic ambiguity in the MMG of participants with movement disorders may in part be attributed to various neuromuscular differences. Akataki et al. (1996) observed deterioration in bicep contractile properties (reduced ratios of MMG amplitude to muscle cross-sectional area across different force levels) in youth with cerebral palsy, which they speculated to be due to muscle fiber atrophy. Incidentally, participants 2 and 3, with movement disorders, had very modest upper extremity muscle mass. There is also speculation that increases or decreases in muscle stiffness, as one might expect in dystonia, leads, respectively, to reduced or increased propensity for muscle fiber oscillations (Evetovich et al., 1997) and hence inconsistent MMG amplitudes over time. While these effects may account in part for the dismal classification accuracies using MMG alone in participants with movement disorders, the Hinton diagrams
(Figure 3.8) suggest that for some movements, the addition of MMG may potentially offer incremental discriminatory value for some individuals.

### 3.5.3 Developmental Factors

Differences in physical development may have also contributed to the lack of discrimination using MMG signals alone. Neu et al. (2002) documented developmental increases in grip force and muscle cross-sectional area, while Grosset et al. (2005) reported age-related changes, in pre-pubescent children, in the contractile kinetics and musculo-tendinous stiffness, albeit for a lower limb muscle (triceps surae). Muscle maturation is generally expected between 1 to 18 years of age (Baldwin, 1984), which overlaps with the age range of our study sample. Collectively, these age-dependent effects may have heightened inter-participant variation in the measured MMG signals and thus may have compromised the discrimination among different contractions.

### 3.5.4 The Impact of Dyskinesia

Participants with movement disorders generally experienced some level of difficulty in completing the movements. Participant 1 had trouble grasping the stylus and in fact used a highly atypical grasp. The stylus was lodged between the index and middle fingers, and supported by the opposing thumb against the most proximal interphalangeal joint of the index finger. He completed the movements with the palmar side of the hand facing the tablet. The participant also struggled to keep his palm off the tablet and would often drag his index finger along the writing surface during a movement. Initiation of movement was a challenge for this participant and movements were generally very slow and effortful.

Participant 2 held the stylus in what appeared to be a tripod grasp, but contacting the thumb close to its interphalangeal joint rather than tip. At times, only the thumb and index seemed to
be supporting the utensil. His movements were highly variable and included directional changes, exaggerated loops throughout the trajectory, and occasional mid-trajectory pauses. His upper extremity, shoulders and trunk were in constant motion throughout the sessions, likely contributing extensive motion artefact. Further, participants 1 and 2 were unable to complete the data collection in one session due to fatigue and frustration with the challenge of holding the stylus. Both had to stop frequently between trials to re-establish a functional grasp of the writing implement.

Participant 3 held the stylus in a fist grasp. Among the participants, her movements were the most stable and appeared to be the most repeatable. Nonetheless, she seldom produced a straight trajectory, tending to follow a curvilinear path, which likely complicated the acceleration patterns.

The heightened variability of dyskinetic arm movements observed here and by others (Sanger, 2006; van Doornik et al., 2009) encumbered the prediction of movement intention with either motion or MMG signals. It is particularly important to note that unlike the typically developing group, even the motion signal was not predictive of movement intention for the three participants with movement disorders. This finding suggests that perhaps a different sensing or signal treatment strategy is required for the meaningful quantification of upper limb movements of children with dyskinetic cerebral palsy.

3.5.5 Differentiation from other Accelerometry Studies

Although many other studies have reported accurate movement discrimination using accelerometry, it is important to note a fundamental methodological difference with the work reported herein. Typically, accelerometry signals are collected with sensors positioned over bony prominences (e.g., wrist and ankles) or on rigid segments (e.g., shank) of the body.
minimally impacted by soft tissue deformation (Guenterberg et al., 2009; Rigas et al., 2012). The intention in these studies is to minimize accelerations unrelated to the limb or body motion of interest, through careful sensor placement, orientation and signal filtering (Godfrey et al., 2008). Indeed, typical low frequency cutoffs for deriving limb motions are very low, e.g., 0Hz to 3Hz in Rigas et al. (Rigas et al., 2012). In contrast to traditional accelerometry studies, here we have placed accelerometers specifically over soft tissue, namely the bulk of six different muscles. Hence, discrimination based on the motion signal itself would be more challenging, as artifacts due to the elastic effects of soft tissue and subsequent shifts in sensor orientation with respect to the skin surface would inherently be embedded within the frequency range of motion.

3.5.6 Limitations and Future Work

We only recorded activity from six muscles. Other studies of forearm reaching movements have uncovered time-varying synergies involving muscles such as the trapezius, pronator teres and brachioradialis (d’Avella, Portone, Fernandez, & Lacquaniti, 2006), which we did not monitor. We were only able to recruit three participants with movement disorders and each had a unique physical presentation of dyskinetic cerebral palsy. Thus the reported differences from the typically developing sample must be considered only as case descriptions. Further, participants with movement disorders struggled with grasping the stylus due to their poor fine motor control. This difficulty may have affected the performance of the task and thus the signals obtained from the participants. Finally, the movements studied were unidirectional, presented low force and were brief in duration. MMG collected under these circumstances appears to have limited discriminative value. Future studies with more muscle sites, a more homogeneous sample of participants, a task that does not involve a fine motor activity (i.e.
grasping stylus), and a broader variety of movements are necessary to more fully ascertain the potential value of MMG in decoding movement intent in children with dyskinesia.

3.6 Conclusion

We investigated the potential of discriminating four unidirectional arm movements using Hidden Markov modelling of accelerometer signals collected over six upper extremity muscles in both typically developing children and a small sample of children with dyskinetic movements. In the typically developing group, signals associated with limb motion alone or in combination with low frequency mechanomyography were useful in predicting the direction of movement, with a participant-independent model. Mechanomyography alone was not discriminatory. In the participants with movement disorders, no signals could predict movement. Due to exaggerated movement variability, alternative sensing or signal treatment schemes may be necessary for the automatic decoding of movements in the presence of dyskinesia.
Chapter 4
Conclusions

4.1 Contributions

This thesis documents the exploitation of multichannel upper extremity accelerometry for the prediction of arm movements in a group of typically developing children as well as three participants with dykinetic cerebral palsy. The contributions of this research to rehabilitation science are as follows:

1. Development of an inter-participant HMM for typically developing children using tri-axial accelerometers on six different upper extremity muscles.

2. Determination that MMG signals alone are less discriminative than motion signals alone in typically developing children when performing short, unidirectional targeting tasks of low force.

3. Generated participant-specific HMMs using accelerometer sensors for three clients with movement disorders. Our findings showed that with the selected muscles, a left-to-right HMM topology does not provide compelling discrimination among simple targeted movements in the presence of dyskinetic movements.

4.2 Future work

4.2.2 Future Work

This research could be extended in the following ways:
1. It has been suggested that the combination of generative and discriminative classifiers may result in an increase of recognition rates (Jaakkola & Haussler, 1999; Samadani et al., 2014). Future research could use the HMMs to compute Fisher Scores (FS) – the model’s likelihood with respect to the parameters - and use this information to perform discriminative movement prediction.

2. A further study of movement recognition for the purpose of access technologies may consider the combination of both motion frequency components (0Hz to 5Hz) and a broader range of MMG frequency components (5Hz to 100Hz).

Further research in this area is necessary to determine the potential value of MMG in decoding movement intent in children with dyskinesia.
Appendix A

Ethics Approval

Dear Dr. Chau,

The Holland Bloorview Research Ethics Board (REB) has reviewed the above named study. This was a delegated review. The board is granting ethics approval for a period of one year. The approval of this study includes the following documents:

- Protocol (version date April 30, 2014)
- TAHSN form received August 27, 2014
- Information Letter and Consent Form – Dyskinetic Cerebral Palsy (DCP) (version dated 09/09/2014)
- Information Letter and Consent Form – Typically Developing Control (TDC) (version dated 09/09/2014)
- Assent Guide (version dated 09/09/2014)
- Determination of Capacity to Consent (version dated 2014/09/15)
- Participant Recruitment Notice – DCP Email (version dated 09/09/2014)
- Participant Recruitment Notice – TDC Email (version dated 09/10/2014)
- Recruitment Flyer DCP (version dated 09/10/2014)
- Recruitment Flyer TDC (version dated 09/09/2014)
- Telephone Screening Script DCP (version dated 08/15/2014)
- Telephone Screening Script TDC (version dated 08/15/2014)
- Demographic Form DCP (version dated 08/15/2014)
- Demographic Form TDC (version dated 08/15/2014)
- Reimbursement Receipt Form (version dated 08/15/2014)

This study must be conducted in accordance with the description in the application and any supplementary documents for which ethics approval has been granted. The REB needs to be notified of any unanticipated or unintentional divergence or departures from the protocol through a “Protocol Deviation Form.” Any intentional changes to the protocol need be submitted through an “Amendment...”
Form* to the REB for approval before the changes are implemented, except where necessary to eliminate immediate hazards to the participants.

Any adverse events that occur as a result of your study must be reported to the REB by submitting an "Adverse Event/Unanticipated Problem Form".

If the study is expected to continue beyond the new expiry date, you must request another renewal, at least thirty days prior to the expiry date, by submitting an "Annual Renewal Form". When the study is completed or terminated, you need to submit a "Study Closure Form" to the REB.

Best wishes for the successful completion of your project.

Sincerely,

[Signature]

Stephen Ryan, PhD, PEng
Chair, Research Ethics Board
P: 416 425 6220 x3526
sryan@hollandbloordview.ca
February 10, 2015

Dear Marcela Correa Villada & Tom Chau,

Re: Mechanomyogram detection of intentional muscle activity in the presence of dyskinetic movements

On behalf of the External Research Review Committee (ERRC), I reviewed and accepted your recent responses related to the study of muscle activity in DCP students for final ERRC approval. Thank you for clarifying our questions/issues about recruiting the DCP students sample, the site locations for testing, and for making the recommended revisions to the consent letters and procedures which we now have on file.

While ERRC approval does not oblige schools to participate, we are aware that the Principal at Sunny View PS is willing to assist in distributing recruitment flyers to students on your behalf.

Upon completion, ERRC will also look forward to receiving an electronic and hard copy of your study findings and which you expect to be available by September 2015.

Sincerely,

Sally Erling, Chair
External Research Review Committee, TDSB
E-mail: ERRC@tdsb.on.ca
c.c. Principal, Sunny View J&SPS

2014-2015-39
PROTOCOL REFERENCE # 30616

October 1, 2014

Dr. Tom Chau
APSC.INST OF BIOMATERIALS & BIOMEDICAL ENG
FAC OF APPLIED SCI & ENG

Ms. Marcela Correa Villada
APSC.INST OF BIOMATERIALS & BIOMEDICAL ENG
FAC OF APPLIED SCI & ENG

Dear Dr. Chau and Ms. Marcela Correa Villada,

Re: Administrative Approval of your research protocol entitled, "Mechanomyogram detection of intentional muscle activity in the presence of dyskinetic movements"

We are writing to advise you that the Office of Research Ethics (ORE) has granted administrative approval to the above-named research protocol. The level of approval is based on the following role(s) of the University of Toronto (University), as you have identified with your submission and administered under the terms and conditions of the affiliation agreement between the University and the associated TAHSHN hospital:

- Graduate Student research - hospital-based only
- Storage or analysis of De-identified Personal Information (data)

This approval does not substitute for ethics approval, which has been obtained from your hospital Research Ethics Board (REB). Please note that you do not need to submit Annual Renewals, Study Completion Reports or Amendments to the ORE unless the involvement of the University changes so that ethics review is required. Please contact the CRE to determine whether a particular change to the University’s involvement requires ethics review.

Best wishes for the successful completion of your research.

Yours sincerely,

Dino Kuzmanovic
REB Manager
References


Richards, C. L., & Malouin, F. (2013). *Cerebral palsy: Definition, assessment and rehabilitation*


