Development of Brain-Machine Interfaces

by

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A brain-machine interface (BMI) uses signals from the brain to control electronic devices. One application of this technology is the control of assistive devices to facilitate movement after paralysis. Ideally, the BMI would identify an intended movement and control an assistive device to produce the desired movement. To implement such a system, it is necessary to identify different movements involving a single limb and users must be able to issue commands at any instant instead of only during specific time windows determined by the BMI itself.

A novel processing technique to identify voluntary movements using only four electrodes is presented. Histograms containing the spectral components of intracranial neural signals displaying power changes correlated with movement were unique for each of three movements performed with one limb. Off-line classification of the histograms allowed the identification of the performed movement with an accuracy of 89%.

This movement identification system was interfaced with a neuroprosthesis for grasping, fitted to a tetraplegic individual. The user pressed a button triggering the random selection and classification of a brain signal previously recorded intracranially from a different person while performing specific arm movements. Correct identification of the movement triggered grasping functions. Movement identification accuracy was 94% allowing successful operation of the neuroprosthesis.

Finally, two BMIs for the real-time asynchronous control of two-dimensional move-
ments were created using a single electrode. One EEG-based system was tested by a healthy participant. A second system was implemented and tested using recordings from an individual undergoing clinical intracranial electrode implantation. The users modulated their 7 Hz-13 Hz oscillatory rhythm through motor imagery. A power decrease below a threshold activated a “brain-switch”. This switch was coupled with a novel asynchronous control strategy to control a miniature remotely-controlled vehicle as well as a computer cursor. Successful operation of the EEG system required 6 hrs of training. ECoG control was achieved after only 15 minutes. The operation of the BMI was simple enough to allow users to focus on the task at hand rather than on the actual operation of the BMI.
Dedication

To my wife Marlene, love of my life and unwavering accomplice, who provided unconditional encouragement and support throughout the pursuit of this dream.

To my son Liam, may you always do what you love.
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Nomenclature

ALS  Amyotrophic lateral sclerosis
AR   Autoregressive
BCI  Brain-computer interface
BMI  Brain-machine interface
CH   Closing of the hand
CNS  Central nervous system
DA   Differential adjacent
DBI  Direct brain stimulation
DMD  Duchenne muscular dystrophy
DN   Differential nonadjacent
ECoG Electrocorticograph
EEG  Electroencephalograph
EF   Elbow flexion
EP   Evoked potential
EPSP Excitatory postsynaptic potential
ERP  Event-related potential
ET   Essential tremor
FES  Functional electrical stimulation
IPSP Inhibitory postsynaptic potential
LFP  Local field potential
MI   Primary motor cortex
MP   Monopolar
NNC  Nearest neighbour classifier
PNS  Peripheral nervous system
RTL  Reaching to the left
RTR  Reaching to the right
SCI  Spinal cord injury
SCP  Slow cortical potentials
SMA II Spinal Muscular Atrophy type II
WF   Wrist flexion
Chapter 1

Introduction

1.1 Motivation

A brain-machine interface (BMI) uses signals from the brain to generate control commands for electronic devices. It offers an artificial efferent pathway that the brain can use for communication and control. The operation of a BMI does not require its user to move (e.g., to press a switch or issue a verbal command). Consequently, this technology has enormous potential to assist individuals with limited or no ability to perform voluntary movements.

A BMI has three fundamental components: an input (i.e., a signal or group of signals recorded from the brain), an output (e.g., a control command), and an intermediate stage that translates the input into the output [3]. Accordingly, current areas of research focus on determining which brain signal is best suited for BMI implementation, what are the strategies to elicit changes in these signals conveying the users’ intentions, what are the processing methods applied to these brain signals to maximize reliability and efficiency, and what are the appropriate applications of this technology.

In its most general implementation, a BMI requires users to adopt a particular brain-state to elicit predefined changes in brain activities. Upon detection of these changes
a command is generated, effectively creating the interface between the brain and an external device.

One approach to voluntarily elicit changes in the brain activity is the use of motor imagery [4–6]. Imagination of voluntary movements elicits changes in the activity of the brain which are similar to those observed while performing the actual movements [7–9]. These changes can be observed by recording the brain activity using standard electroencephalographic (EEG) techniques. They are also present in local field potentials (LFP), which reflect the collective activity of a small group of neighbouring neurons and are recorded intracranially using subdural electrodes or intracortical micro electrodes. The same micro electrodes can be used to record the activity from individual neurons also reflecting changes associated with execution or imagination of voluntary movement.

BMI development using the activity elicited through motor imagery or performance has taken several directions. One area that has received attention is the identification of specific movements in which each identified movement can be used as an independent command available to the user [9–15]. A second approach has consisted in extracting kinematic parameters of real or imagined movements from the activity of neuronal ensembles which are then used to control computer cursors [16,17] and robotic devices [18–20].

The use of imagined voluntary movement as an activation strategy for BMI operation provides an interesting opportunity to control prosthetic devices for movement restoration with a high degree of transparency. Examples of assistive technology for the restoration of movement include prosthetic limbs, which replace a non-existing body part, and motor neuroprostheses implemented with functional electrical stimulation (FES), which use electrical stimulation to facilitate functional movements of paretic limbs. With this approach a user would simply attempt to perform a specific movement and the BMI would issue the commands to a prosthetic limb or a neuroprosthetic device that would in turn perform the intended action. It is likely that the fusion of the BMI and motor prosthetics fields represents the natural next step in the evolution of these two technologies [21].
BMI systems have been used to control neuroprosthetic [22, 23] and prosthetic [16] limbs successfully. These implementations have made it possible to identify some of the limitations that must be addressed to create a practical integration of BMI with assistive devices for motor restoration. For example, the voluntary movements identified using BMI technology are often performed with different body parts [10–12, 14, 24, 25]. This makes the implementation of transparent interaction modalities between the user and the assistive device difficult as prosthetic limbs or neuroprostheses are primarily designed to assist with the function of a single body part.

It is likely that successful integration of BMI and a motor prosthetic device will also require a large number of commands available to the user; using current FES technology, it is possible to generate seven different grasping styles which can be combined resulting in dozens of hand movements that can be facilitated. There is no practical user interface that allows the control of all of these functions. The complexity of prosthetic devices is also increasing. A BMI capable of identifying multiple movements would have the potential to command devices with multiple degrees of freedom (e.g., FES systems facilitating multiple grasps or multi-joint upper limb prostheses).

The benefit of integrating a BMI with assistive devices would be enhanced even further if users were able to generate control commands at any desired instant. With a few exceptions, most of the work conducted on BMI development has focused on synchronous control modalities in which a user can issue commands only during small time windows determined entirely by the BMI itself. In contrast, an asynchronous BMI would allow the users to issue a command whenever needed. The asynchronous BMI would likely increase the transparency of interaction between the user and BMI technology as well.

The implementation of an asynchronous BMI requires constant monitoring of the brain activities [26]. Today, asynchronous control remains one of the biggest challenges that the development of BMI technology faces.
1.2 Objective

The objectives of the work presented in this document were:

1) To explore the feasibility of using electrocorticographic recordings from subdural electrodes placed over the motor cortex to identify the upper limb motion performed by a human subject.

2) To test the feasibility of using electrocorticographic (ECoG) signals as a control strategy for a neuroprosthesis for grasping.

3) To explore the use of BMI technology for asynchronous control in the context of two-dimensional control.

1.3 Approach

1.3.1 Research Path

To reach our objectives, we first created a novel system for the identification of performed movements using the same limb through the analysis of electrocorticographic signals. This work was published in the peer reviewed scientific publication Journal of Neural Engineering and constitutes Chapter 3 of this document.

Once it was possible to identify voluntary movements performed with the same limb, we developed a neuroprosthesis for grasping controlled using electrocorticographic signals. This work, which is described in detail in Chapter 4, materialized our ideas on the integration of BMI technology and neuroprosthetic devices. Chapter 4 was published in the peer reviewed publication Spinal Cord.

Our attention was then focused on the development of asynchronous BMI systems. We created two systems for two-dimensional motion control by integrating BMI technology and a novel control strategy. First, we developed a system to control the movement of a miniaturized remote control vehicle using a single EEG signal. This material was
Chapter 1. Introduction

published in the journal Topics in Spinal Cord Rehabilitation and constitutes Chapter 5. Later, we created a second system for the control of a computer cursor using one subdural electrode. This material constitutes Chapter 6 and has been submitted for publication to the peer reviewed journal Medical Engineering & Physics. Given the similarities between both systems for two-dimensional motion control that we developed, there is a degree of repetition of the material covered in Chapter 5 and Chapter 6.

1.4 Organization of the Document

Chapter 2 presents a review of the literature relevant to the work presented in this document. Chapters 3 and 4 describe the development of an arm movement identification system and its application for the control of a neuroprosthesis for grasping respectively. The document then describes the implementation of asynchronous BMI systems for the control of two-dimensional motion. In Chapter 5 a system for the control a miniature remotely-controlled car using a single EEG electrode is presented. In the following Chapter 6, the use of a single electrocorticographic (ECoG) electrode for the real-time asynchronous control of the two-dimensional movement of a cursor is described. The document ends with a discussion presented in Chapter 7.
Chapter 2

Literature Review

2.1 Introduction

A BMI uses signals reflecting brain activity to control electronic devices. Operation of this technology does not require the user to move, making it a potential assistive device for individuals with limited or no ability to move voluntarily. At present, some of the populations that have benefited from BMI technology include individuals with amyotrophic lateral sclerosis (ALS) [27–31], high levels of spinal cord injury (SCI) [23,32–34], severe cerebral palsy [35], Duchenne Muscular Dystrophy (DMD) [36], Spinal Muscular Atrophy type II (SMA II) [36], and stroke [27,37,38].

BMI systems have an input (i.e., a brain signal), an output (i.e., a control command), and a translation stage that converts the input into the output. The nature of the brain signals used for the development of BMI technology is as diverse as the methods that exist to measure brain activity. It is possible to find BMI systems that use magnetic [39–46], metabolic [47–49], and electrical recordings from the brain. For a review of the different approaches used to develop this technology see [50].

The applications under which BMIs have been tested include computer cursor control in one [12,33,35,38,51–62], two [27,56,60,62–64], and three dimensions [63], text gen-
eration [35, 65, 66], letter selection [28, 29, 31, 35], simulated communication in a virtual environment [67, 68], augmentative and alternative communication [68, 69], control of a hand prosthesis [70], control of neuroprosthesis for grasping [23, 63, 71, 72], control of a hand orthosis [38, 73], navigation of a virtual environment [32, 74], control of a virtual wheelchair [75], control of a real wheelchair [66, 75], environmental control (electronic aids for daily living) [36, 62, 67, 68], robotic control [36, 66, 76], activation of a multi-finger robotic hand [77], control of a pong-like game [34, 78], and reconstruction of movement trajectories [79].

The work presented in this document was conducted using electrical recordings of brain activity obtained using subdural electrodes placed intracranially on the primary motor cortex as well as with standard non-invasive EEG technology. This chapter provides a review that complements the material covered in Chapters 3, 4, 5, and 6.

2.2 The nervous system

The human nervous system is divided into central and peripheral components. The brain, along with the spinal cord, forms the central nervous system (CNS). The peripheral nervous system (PNS) is constituted by nerves arising from the CNS and its role is to transmit signals to and from the CNS and receptor organs or body effectors (e.g., muscles and glands).

2.2.1 The neuron

The basic element of the nervous system is the nerve cell or neuron. Neurons can receive, process, and transmit information to and from other neurons. They can also receive information from sensory organs and transmit information to muscles and glands. Despite the wide variety of neurons that exist in the human body, most of them have three common anatomical components: 1) a dendrite (or several dendrites) which is typically
the site where information from other cells is received, 2) a body, which performs the homoeostatic functions of the cell, and 3) an axon which serves as the site for transmission of information.

The neuron’s ability to receive and transmit information is primarily due to the excitability of its cellular membrane. This membrane consists of two layers of lipid molecules and it prevents the movement of electrically charged molecules (ions). These ions include sodium ($\text{Na}^+$), potassium ($\text{K}^+$), chloride ($\text{Cl}^-$), and calcium ($\text{Ca}^+$). These ions can only move through the membrane using dedicated channels or with the help of a carrier molecule. The semipermeability of the membrane facilitates a concentration gradient of these ions between the intra and extracellular environments: in a normal resting state, the $\text{Na}^+$ concentration is higher outside of the neuron while the concentration of $\text{K}^+$ is higher inside the cell. This concentration difference in turn creates an electrical potential between the two sides of the membrane. This potential, known as resting potential, has an approximate value of -70 mV. Each neuron works constantly to sustain this ionic gradient and consequently this potential difference.

The permeability characteristics of the cell membrane can change in response to an external stimulus. These changes can cause the membrane to become more permeable to the ion molecules allowing their movement and subsequent changes in their concentrations. In turn, these concentration changes are reflected as changes in the electrical potential surrounding the membrane. An increase or decrease in the resting potential is referred to as depolarization or repolarization, respectively. The term hyperpolarization is used to describe a condition in which the membrane potential decreases beyond the resting potential.

### 2.2.2 The action potential

When the membrane potential along the initial segment of the axon is depolarized, the membrane becomes permeable to $\text{Na}^+$, allowing the entrance of this ion to the axon by
diffusion. This depolarizes the membrane potential even further, which results in the membrane becoming even more permeable to Na\(^+\). This accelerated inflow of Na\(^+\) into the cell creates a sudden reversal of the membrane potential so that it leaves its resting level to a new approximate value of +30 mV. Eventually the channels that allow the passage of Na\(^+\) into the cell become inactive and K\(^+\) ions flow toward the extracellular space contributing to a repolarization of the membrane to -70 mV. These changes in Na\(^+\) and K\(^+\) concentrations, and their corresponding changes in the membrane potential they produce, form an event denominated action potential. It is through action potentials that the nervous system can receive, process, and convey information to other parts of the body.

### 2.2.3 The synapse

When an action potential reaches the end of a neuron’s axon it can cause changes in the membrane potential of a second cell (i.e., another neuron or an effector cell within a muscle or a gland). This event takes place over a functional connection known as the synapse. The synapse is an anatomical structure where the axon terminal of a neuron comes in close proximity to the dendrite of a second neuron. The presynaptic and postsynaptic neurons are not in contact; there is a gap between the cells of approximately 10-15 \(\mu\)m known as the synaptic cleft. The communication across the synapses is possible due to chemical and, to a lesser extent, electrical coupling. The action potential releases neurotransmitters from the presynaptic neuron into the synaptic cleft which bind to the membrane of the postsynaptic cell. This in turn causes ion channels to open which allow the diffusion of ions often producing a depolarization known as an excitatory postsynaptic potential (EPSP). It is also possible for the binding of the neurotransmitters to cause a hyperpolarization of the postsynaptic membrane. This is referred to as an inhibitory postsynaptic potential (IPSP) as the membrane potential becomes even lower than the resting potential.
A single EPSP is unlikely to trigger an action potential on the postsynaptic neuron. Instead the effect of EPSPs is summed over time and space (different regions of the dendrite). An action potential is generated if this EPSP summation at the initial segment of the axon reaches its triggering threshold.

The EPSPs and IPSPs can generate electrical fields through the extracellular environment which acts as a volume conductor. These electrical fields can be recorded in the extracellular space from a small distance away from the neuron. With the electrical fields added linearly, it is possible to detect the activity of a group of neurons at even greater distances. Cortical potentials, like the ones recorded using EEG and electrocorticographic ECoG techniques, are a reflection of EPSPs and IPSPs of large populations of neurons [80].

The electrical activity of the brain is divided into main categories: spontaneous (ongoing) potentials and evoked potentials (EP) or event-related potentials (ERP) [81]. The spontaneous potentials have an oscillatory nature. The frequencies most commonly seen in the ongoing EEG and ECoG recordings are classified into arbitrary frequency ranges described in Table 2.1. EPs are the response to an external stimulus (e.g., a flashing light or an auditory tone) and their magnitude and latencies depend on the characteristics of the stimulus itself (e.g., loudness). ERPs, also known as endogenous or cognitive ERPs, represent the response to other events resulting from internal processing and their magnitude depends strongly on the attitude of the individual (e.g., attention, motivation, etc.) [80]. Both EPs and ERPs are stereotyped responses.

### 2.2.4 Voluntary movement and the cerebral cortex

The brain is divided into several anatomical and functional sections. Some of these sections include the brainstem, the cerebellum, and the cerebrum. The brainstem relays signals (action potentials) between the spinal cord and the higher centres in the brain. The cerebellum, is associated with fine control of muscle movements and coordination
Table 2.1: Most commonly observed frequencies in oscillatory activity of the brain.

<table>
<thead>
<tr>
<th>Designation</th>
<th>Frequency Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>$&lt; 4 \text{ Hz}$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>$4 \text{ Hz} \leq \theta &lt; 8 \text{ Hz}$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>$8 \text{ Hz} \leq \alpha &lt; 13 \text{ Hz}$</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$13 \text{ Hz} \leq \beta &lt; 30 \text{ Hz}$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>$&gt; 30 \text{ Hz}$</td>
</tr>
</tbody>
</table>

[81]. The cerebrum is the largest portion of the brain (approximately 80% of its mass) and it is primarily responsible for higher mental functions.

The cerebrum is divided into two halves, the right and left hemisphere, which are connected internally by a large tract (group of axons) called corpus callosum. The outer portion of the cerebrum is the cerebral cortex with an approximate thickness of 2 mm to 4 mm and contains a large number of neurons (approximately $10^{10}$) organized in columns perpendicular to the surface of the brain. The neurons in the cortex are highly interconnected. With its high number of synapses, it is believed that the cortex is responsible for generating most of the potentials measured by EEG and ECoG measurement techniques.

The cerebral cortex has numerous elevated and depressed folds called gyri and sulci (or fissures), respectively. The deep sulci create five subdivisions of the cerebrum, called lobes, on each hemisphere. These are the frontal, parietal, temporal, occipital lobes as well as the insula (which is covered by the frontal, parietal and temporal lobes).

The frontal lobe is the anterior portion of each hemisphere. A deep fissure, the central sulcus, separates the frontal lobe from the parietal lobe. The gyrus located just in front of the central sulcus, the precentral gyrus, is the primary area of the cerebral cortex responsible for motor control and it is known as the primary motor cortex (MI). While the motor areas of the cerebral cortex also include several premotor areas, the work presented here will only focus on the primary motor cortex.
Electrical or magnetic stimulation of the motor cortex produces movement on the opposite side of the body. This has made it possible to create maps that link sites of stimulation and the observed motor responses. These maps have different body parts that are consistently represented on the motor cortex and the size of representation of body parts involved in the movements requiring the highest amount or precision and dexterity have disproportionately large representations. These areas include the face, the fingers, and the hand [82].

2.2.5 Voluntary movement as an activation strategy

EEG and ECoG signals experience changes when voluntary movement is performed. These include changes in power at different frequency bands. More specifically, there is a decrease of power in the 8 Hz -13 Hz and 13 Hz -30 Hz frequency ranges that start before the execution of a movement and continue until the movement is completed. Almost simultaneously, there is an increase in higher frequencies (> 30 Hz) [83]. Once the movement is completed, there is an increase in the 13 Hz -30 Hz frequency band. ERPs are also elicited through voluntary movement.

Many of the changes in EEG and ECoG signals when performing a voluntary movement are also present when an individual is intending to perform the movement or even imagining it [7,8]. This makes the use of motor imagery a good candidate to elicit changes in brain activity voluntarily. For this reason, the use of imagined movements has been extensively used for the development of BMI technology.
2.3 Review of the BMI technology

2.3.1 BMI systems that use voluntary movement as a way to elicit changes in brain activities

There are several approaches for the development of BMI systems using voluntary movement as a strategy to elicit changes in the activity of the brain voluntarily. One approach consists of transforming the power level of EEG or ECoG signals into the position of a cursor on a computer screen. The estimation of the power level usually focuses on a specific frequency range and it is often estimated using autoregressive (AR) spectral estimation [56, 57, 59–62, 64] or with the Fourier Transform [84]. The estimated power is then transformed into a position of a cursor on a screen with a linear transformation [56, 62–64, 84]. Using this approach it has been possible to control cursors in one [33, 56–62], two [56, 60, 62–64], and three dimensions [63].

A different BMI implementation that uses voluntary movement as an activation strategy consists of identifying specific movements performed or imagined by an individual. This has been achieved either by identifying motor related ERPs in ECoG signals [85–87] or by identifying power changes in specific EEG [6, 24, 24, 88–90] or ECoG [91] frequency bands. The ERPs and the frequencies that undergo consistent power changes unique to specific movements are first identified, usually through averaging of the responses over several repetitions of a specific motor action. The identified responses (ERPs and/or frequency bands) constitute the features which an automatic classifier can use to identify the performance or imagination of a specific motor task. Some of the classification approaches that have been used to identify the different motor tasks include linear discriminant analysis [5, 10, 12, 24, 88, 90–94], support vector machines [24, 92], neural networks [92, 95], linear regression [95], nearest neighbour classification [24], signal space projection [88, 89], and template matching [85–87, 91]. These systems are often capable of identifying several movements for each user.
EEG and ECoG-based BMI systems can identify specific movements with good accuracies. For example, it is possible to find devices that are capable of discriminating between movements performed with the right hand and left hand [92,96–101], or between a hand and a foot [25,102–104].

In recent years, it has also been possible to extract kinematic parameters of a limb in motion from individual neurons or neuronal ensemble recordings. The activity of neurons is recorded using microelectrodes that penetrate the cerebral cortex of monkeys [16, 17, 19, 105–108] and humans [16, 105]. The firing frequency of nerve cells has been used to predict the direction and position of a hand moving in one [18], two [107,109], and three dimensions [18,107], to control computer cursors [16,17,105,106], and to control robotic arms [16,18,19].

Despite these impressive results, the implantation of microelectrodes to perform intracortical recordings is considered highly invasive and it is still necessary to understand the long term effects of using this technology.

2.3.2 The problem of asynchronous control in BMI

The systems described in the previous paragraphs can classify movements with high accuracies. However, most of them require that the user engages in motor activity (real, intended, or imagined), during a specific time period. In other words, the user can control the BMI only during temporal windows defined entirely by the BMI system itself. This is referred to as a synchronous mode of operation and it is used by almost all of the BMI devices developed to date, regardless of the strategy used to elicit changes in brain activities voluntarily.

The synchronous mode of operation is a good starting point for the development of BMI technology. However, the user’s need to wait for the appropriate time to operate the BMI decreases the usability of this system and restricts the use of this technology to applications that do not require immediate (or quick) responses. It is likely that the use
of a BMI outside of a research laboratory environment will require the implementation of asynchronous systems that would allow an individual to use the BMI at any desired instant.

Implementing an asynchronous BMI requires constant monitoring of brain activities to identify changes corresponding to specific mental states used to operate the system. This has been accomplished by classifying changes in amplitude of ongoing EEG signals in the 1 Hz - 4 Hz range \[34,110\] in real time according to whether or not a person is imagining a specific movement (e.g., finger flexion). Amplitude changes in the EEG can be used to perform the classification using a distance based classifier (nearest neighbour) \[34\] or a neural network \[110\].

A different approach to the asynchronous BMI implementation consists of the identification of ERPs \[85–87\] and power changes in different frequency bands that occur in ECoG recordings when an individual performs a specific movement \[91,111\]. ERPs are generated by averaging time-locked responses upon the performance of a particular movement. Detection of ERPs in ongoing ECoG recordings is performed by estimating the crosscorrelation between the ERP and the signal under analysis. If the value of the crosscorrelation reaches an experimentally defined threshold, the BMI indicates that it has identified the occurrence of the movement corresponding to the ERP used for the detection. The same threshold comparison is used when using power changes in EEG and ECoG frequencies. However, given that there is typically more than one spectral component that can be used to identify specific movements, these frequencies are often combined linearly into a single figure that can then be compared with a detection threshold \[91,111\].

Given the constant monitoring of brain activity required and the need to identify mental states (i.e., the performed, intended, or imagined movement) from a single occurrence of the event (i.e., without averaging several responses), today, development of asynchronous systems remains one of the most important challenges in BMI research.
Our primary area of research focuses on the rehabilitation of individuals who have sustained a spinal cord injury or stroke with a strong emphasis on the use of neuro-muscular stimulation for the facilitation of movement after paralysis. Like most of the groups conducting BMI research and development, we have identified this technology as an important access method to enhance function in people with limited mobility. All of the BMI systems described previously offer important features that could be used for the purposes of controlling assistive devices designed for the restoration of movement. Equally, they offer disadvantages that must be addressed before the integration of these two technologies can reach its full potential.

Perhaps the most obvious possibility for integrating BMI and neuroprosthetic or orthotic devices lies in the fact that BMI technology can be used to identify imagined movements. This suggests that it would be possible to create highly transparent interfaces to control assistive devices for the restoration of movement that would require little or no training before the user was able to operate the system. This notion has been explored through the control of a hand orthosis [73], prosthetic hands [16, 70, 77], and neuroprostheses for grasping [23, 63, 71, 72]. Besides providing groundbreaking BMI implementations, these systems have also uncovered one of the most important problems to address for the integration of BMI and prosthetic and orthotic devices: for most of these experiments, there is no correspondence between the movement identified by the BMI and the movement restored by the assistive device (i.e., the prosthesis or orthosis). For example, one system uses imagination of foot movements to operate a hand orthosis [73]. To achieve an optimal level of transparency in the control of prosthetic and orthotic devices the identified movement should match the facilitated movement. To strengthen further the integration of these two technologies, the BMI must be able to identify movements involving a single limb as these devices usually facilitate at least two motions of the same limb (an agonist and antagonist action). There are very few examples of BMI systems that are capable of identifying movements performed with the
same limb. Deng et al. successfully created a BMI to identify intended shoulder and elbow contractions [37] performed with a single arm. However, their system required the use of 163 EEG electrodes.

The transformation of power into the position of a computer cursor is often achieved using signals from a single electrode typically processed in a simple way. This may offer significant practical advantages over a BMI requiring many electrodes (e.g., 163), as the system would have less components and the setup time required would be reduced significantly. The simplicity of implementation of these systems comes, however, with an increased required training time: users of this technology have to undergo extensive training sessions, lasting up to several months [64, 84, 112–119], in order to achieve the self-regulation of brain oscillations necessary to operate the BMI. And even after training is completed, the operation of this technology is often very demanding for the user. This is true for EEG-based systems; recent experiments using self-regulation of brain oscillations to control a computer cursor have shown that the required training time is reduced to minutes when using ECoG signals [60].

2.4 Summary

Ideally, the identified imagined (or attempted) movement should match the movement facilitated by the prosthetic or orthotic device. This would require the development of a BMI system capable of identifying movements performed with the same limb. The device should also be able to be operated with minimum training time, using a small number of sensors, and in an asynchronous way allowing the user to use the BMI at any desired instant. In this work we have created BMI systems that meet these requirements.

In what follows, we have approached each one of the above discussed problems individually and independent from each other. First, we addressed the identification of movements involving a single limb. We focused specifically on the identification of real
movements performed with a single arm. This system was developed using ECoG recordings obtained from individuals who had undergone implantation of subdural electrodes for clinical reasons different than the work presented here. The number of reports describing BMI systems using ECoG recordings were limited when this project took place and it was an ideal opportunity to explore the differences in performance between intracranial recordings and EEG-based BMI systems. The identification of real movements would provide certainty on the involvement of the motor cortex and it would eliminate almost entirely, the need to train the experimental subject to achieve self-regulation of brain signals.

Once the system for identifying real arm movements involving a single limb was created, we then focused on its integration with a neuroprosthetic device. For this purpose, we created a neuroprosthesis for grasping controlled by the classification of ECoG signals. The acquisition of ECoG recordings poses several challenges. One very important difficulty lies in the fact that it is only possible to record these signals during a few days. Further, the application of electrical stimulation to individuals who are still under surgical recovery after the initial intracranial electrode implantation is difficult to justify. It is equally difficult to provide justification for the implantation of subdural electrodes when they are not required for diagnostic or therapeutic purposes. For these reasons, the signals used to control the neuroprostheses were obtained from one individual and classified off-line while a second person wore the neuroprosthesis which was triggered by the activation of a switch. The switch initiated a process in which an ECoG signal was selected randomly from a batch of ECoG signals recording during the identical arm and hand movements and classified according to the movement performed at the time of recording. The result of the classification determined the behaviour of the neuroprosthesis; only when an ECoG signal was classified correctly did the FES system deliver the stimulation necessary to facilitate a desired movement.

Finally, we explored the creation of an asynchronous BMI in a third set of experiments.
To do this, we combined a novel asynchronous control strategy for two-dimensional control with the implementation of a "brain switch." The method was first developed and tested using EEG signals resulting in a BMI that made it possible to control the direction of a miniature car controlled remotely. A second system was later created for the control of a computer cursor using ECoG signals. In both cases, it was possible to implement the system using a single sensor (EEG or ECoG).
Chapter 3

Identification of Arm Movements
Using ECoG Signals

The material presented in this chapter was published in the article:


The contents of this chapter are identical to the material presented in the publication except for the text formatting, which was done according to University of Toronto requirements, as well as Figure 3.5 which appeared incorrectly in the publication. This work was also presented at international conferences including The Third IEEE Conference on Neural Interfacing held on May 2nd-5th, 2007 in Hawaii, U.S.A., and the 13th Annual International Functional Electrical Stimulation Society Conference held on September 21st-25th in Freiburg, Germany.

3.1 Abstract

The purpose of this study was to explore the feasibility of using electrocorticographic (ECoG) recordings from subdural electrodes placed over the motor cortex to identify the
upper limb motion performed by a human subject. More specifically, we were trying to identify features in the ECoG signals that could help us determine the type of movement performed by an individual. Two subjects who had subdural electrodes implanted over the motor cortex were asked to perform various motor tasks with the upper limb contralateral to the site of electrode implantation. ECoG signals and upper limb kinematics were recorded while the participants were performing the movements. ECoG frequency components were identified that correlated well with the performed movements measured along 6D coordinates \((X, Y, Z, \text{roll}, \text{yaw}, \text{and pitch})\). These frequencies were grouped using histograms. The resulting histograms had consistent and unique shapes that were representative of individual upper limb movements performed by the participants. Thus, it was possible to identify which movement was performed by the participant without prior knowledge of the arm and hand kinematics. To confirm these findings, a nearest neighbour classifier was applied to identify the specific movement that each participant had performed. The achieved classification accuracy was 89%.

### 3.2 Introduction

Brain-computer interfaces (BCIs) use signals from the brain to control electronic devices such as computers. Public and scientific interest in this technology is based on the potential for these devices to assist individuals with severe mobility impairments such as advanced stages of amyotrophic lateral sclerosis (ALS), brain stem stroke, spinal cord injury and severe cerebral palsy [3,120].

There are three fundamental components of a BCI: an input (i.e. brain signal), and output (i.e. control command to an external device) and a translation stage that transforms the input into the output [3]. Brain-computer interfacing is an emerging field, and researchers are still asking fundamental questions such as which type of brain signals are most useful, how to decode or classify these signals, which features of these signals
to use to perform the classification or decoding and what the potential applications of BCI systems might be.

One of the most prominent questions in the field of BCI is which neuronal signal, or group of signals, is optimal for use as an input to a BCI [121]. The types of brain signals that have been used as input to a BCI can be classified as magnetic [39,40], metabolic [122] and electrical [3]. Of these, electrical signals have been used most extensively. The electrical activity of the brain is characterized by ongoing oscillatory activity that has been divided into frequency bands. Some of the primary oscillatory rhythms include the delta rhythm ($<4$ Hz), the alpha or sensorimotor mu rhythm (8-13Hz), the beta rhythm (13 Hz-35Hz), and the gamma rhythm ($<35$ Hz) [80].

The existing BCI systems can be generally divided into two main categories: 1) systems that require the user to produce a specific mental state to generate a desired command that can be used to trigger an event (e.g. move a cursor on a screen), and 2) systems that extract information about the movement kinematics from the brain signals and use this information to generate a similar or identical movement with a prosthetic or a robotic device. Currently, many examples of BCI systems that require the user to produce a specific mental state exist. The mental state produced by the user is not necessarily related with the behavioural outcome. For example a person imagines moving the tongue to move a computer cursor [123]. The different mental states are detected as changes in brain activity which can be recorded using different techniques such as electroencephalography (EEG) and electrocorticography (ECoG). EEG records the activity of the brain using scalp electrodes and ECoG signals are recorded with subdural electrodes. These are macroelectrodes placed surgically on the surface of the brain underneath the dura. The changes in brain activity convey the user’s intentions. Some of the features that have been used to detect different mental states include slow cortical potentials (SCP) [28,69,124,125], P300 potential [126–130], as well as changes in power (amplitude) of oscillatory rhythms [59,102,103,131]. These systems have been used
successfully to control computer cursors in one and two dimensions [3, 59, 60, 123, 131], generate text [4, 35, 69, 126], and to select from a small set of options (e.g., yes/no) [128, 130]. These implementations of BCI’s are characterized by a small communication bandwidth making them suitable for providing assistance in communication to individuals who have lost all ability to perform voluntary movement, such as individuals with locked-in syndrome.

Recently, there has been an increased interest in exploring the use of BCIs to restore movement in individuals with paralysis. This broadens the clinical population that can benefit from BCIs to include individuals with spinal cord injury or stroke. Inherently, this application carries the notion of using prosthetic devices, functional electrical stimulation systems, and external actuators (such as a robotic arm) as an extension or substitution of a body part that is affected by the disability. For a transparent and intuitive operation of these devices through a BCI, it would be ideal to use neural activity which is correlated with the desired output to command the device. For example, if the desired action was to open a prosthetic hand a BCI user would only have to focus on opening his or her own hand and the BCI would detect changes in brain activity resulting from the intention of opening the hand and would perform the desired action. It has been shown that this type of correlation between neural signals and behaviour can be found in an individual engaged in voluntary movement (performed, imagined, or during preparation to perform a movement).

The current challenges facing BCIs intended for restoration of movement are the detection and estimation of kinematic information as well as identification of specific movements. Some of the most important results in the detection and estimation of kinematic parameters in brain activity come from recordings of populations of single neurons using micro electrodes. The firing frequency of neurons in the primary motor cortex [17, 18, 106] has been decoded to generate continuous control signals using both linear and non-linear algorithms. With this approach it has been possible to control a computer cursor
in two [16, 106] and three dimensions [18](within a simulated/virtual three-dimensional space), and control a robotic arm [16, 18]. This work has been conducted with monkeys and more recently with human participants [16, 105].

There are still important concerns regarding the stability and reliability of long-term single neuron recordings. Two alternatives to recording the activity from individual neurons are local field potentials (LFP) and ECoG recordings. LFPs are recorded using the same microelectrodes used to record the activity of individual neurons but they record the activity of a group of neighbouring neurons. The analysis of LFPs and ECoG signals has shown that changes in amplitude of several frequency components in these signals reflect some kinematic aspects of arm movements. These kinematic parameters include amplitude (range of motion) [132], direction of movement [121, 132–135], velocity, and position [136].

The detection of specific movements has included imagined movements, performed movements, and the intention to perform these movements. Using EEG recordings it has been possible to discriminate between imagination of finger, tongue, left and right hand movements [137] as well as the intention to generate shoulder or elbow isometric contractions [37]. Using ECoG recordings, it has been possible to identify extension of the middle finger, palmar pinch, tongue protrusion and lip protrusion [91, 111], wrist extension, target tracking, finger sequencing and threading [138, 139] movements, hand and face movements as well as verbalization [86, 87]. It has also been possible to identify the body part (tongue, face, arm or leg) used to perform sustained contractions [140, 141].

Recently a system proposed by Pfurtscheller et al. was also capable of discriminating between imagined foot, tongue, left hand, and right hand movements using EEG recordings [103]. The same group has demonstrated that this type of BCI system can be used to control orthotic [73], prosthetic or neuroprosthetic [4, 23, 72] systems that would operate as state machines [142].

Today we can confidently say that recordings from micro electrodes implanted in the
motor cortex can be used to extract reliably, and in real-time, upper limb kinematics. However, it remains unknown if similar information can be extracted using a system that applies significantly less specific recordings, such as ECoG recordings. There are at least two advantages for using ECoG-based system. First, ECoG electrodes are minimally invasive, especially those with four or six contacts, and have been used extensively and reliably for diagnostic and treatment purposes in the past [48, 49]. Second, using four or six recording sites dramatically simplifies the BCI system design and makes the system more feasible from engineering and clinical perspectives. Few recent studies have tried to address this challenge. Some studies have been able to demonstrate that specific movements can be identified from ECoG recordings using 16 to 126 ECoG electrodes. Graimman et al. [91] were able to identify specific movements using a single ECoG electrode. However, they first had to implant a group of 63 to 126 electrodes and through an elimination system were able to select the single electrode used for motor task identification through the ECoG recordings.

The purpose of this study was to explore the possibility of identifying specific movements performed by an individual from four ECoG recordings. The movements were performed using the same upper limb and likely involved areas of the body with close or similar representations in the motor cortex. A feature extraction algorithm was developed that was able to determine which arm movement was executed based on ECoG recordings alone. The ECoG recordings were performed using standard subdural four-contact electrodes placed over the primary motor cortex (MI).

### 3.3 Materials and Methods

#### 3.3.1 Participants

Two individuals participated in this study. Subject 1 was a 73 year old male individual with Parkinson’s Disease, and subject 2 was a 65 year old female with Essential Tremor.
Both were recruited from the Movement Disorder Clinic of the Toronto Western Hospital. Neither subject exhibited action tremor or rigidity. They were both medicated at the time of testing. Subject 1 showed mild signs of tremor and subject 2 did not show any signs of tremor after the electrode implantation. The participants gave written informed consent to participate in the study, which was approved by the University Health Network Research Ethics Board. Both participants received a system for direct brain stimulation (DBI) for the treatment of tremor. This procedure began with the implantation of subdural electrodes followed by a period of several days in which the electrode leads were externalized and the characteristics of the electrical stimulation (i.e., amplitude, polarity, etc.) were fine tuned. Both subjects had electrodes implanted in the left hemisphere. This was followed by implantation of the pulse generator. The study presented in this article was conducted during the time period when the electrode leads were externalized and at least two days after the electrodes were implanted.

### 3.3.2 Electrodes

Each participant was implanted with subdural 'Resume' electrodes (Medtronic 3586, Minneapolis, MN) consisting of a single row of four platinum discs (contacts) of 4mm diameter and a centre-to-centre distance of 10mm embedded in a silicone membrane (Figure 3.1). Patients underwent craniotomy under local anaesthesia. The electrode strip was implanted over MI area associated with the upper extremity representation. The location of the electrodes was confirmed using electrical stimulation and by observing contractions of the muscles on the contralateral upper limb (100Hz, 100ms, monopolar, 3-10mA) [143]. Specifically, when stimulated subject 1 produced the elbow flexion movement and subject 2 produced the hand closing movement. For both participants, the electrodes were implanted for clinical and investigational reasons independent of the study presented here.
3.3.3 Experimental Setup

The study was conducted in the Epilepsy Monitoring Unit at the Toronto Western Hospital. The ECoG signals were acquired in a monopolar configuration referenced to Fz using an electroencephalographic digital system (XLTEK, Canada) on a dedicated personal computer with a sampling rate of 200 Hz and a bandwidth limited between 0.3-100 Hz. The movement of the upper limb was recorded using a six-dimensional (X, Y, Z, roll, pitch, and yaw) electromagnetic movement measurement system (Fastrak by Polhemus Inc., USA) and customized data acquisition software written in Visual Basic. One Fastrak sensor was placed over the dorsal aspect of the third metacarpal bone. Three-dimensional position and rotation of this sensor was recorded at 40Hz. The electromagnetic nature of the measurement system makes it vulnerable to interference from nearby large metallic objects and metallic objects placed between the transmitter and the receiver [144]. Metallic furniture was moved away from the experimental area in an effort to ensure that
the recordings were unaffected by these objects. Due to the constraints of working in a clinical environment it was not possible to verify that the kinematic recordings were free of artefacts. However, the temporal information of the movement, which is more important than the magnitude of the movements for the work presented here, was unaffected by near by metallic objects. Data collected by the motion recording system were synchronized with the data collected by the ECoG recording system using a temporal marker.

3.3.4 Experimental Protocol

ECoG signals and limb kinematics were recorded while each subject performed movements with the upper limb. The motor tasks for subject 1 included elbow flexion (EF) as well as reaching to targets placed 30 cm to the right (RTR) and left (RTL) of the midline. Subject 2 performed reaching tasks RTR and RTL, as well as closing of the hand task (CH). Figure 3.2 shows the motor tasks that were performed by both subjects. Table 3.1 shows the ranges of the performed movements. Since the ECoG electrodes were placed in the MI areas responsible for EF (subject 1) and CH (subject 2) tasks, it was an obvious choice to add tasks RTR and RTL to the pool of tasks tested because they involve muscle groups with cortical representations either in the same location or in close proximity to cortical representation of tasks EF and CH.

All the movements were performed with the upper extremity contralateral to the site of electrode implantation while the subjects were sitting comfortably. The users received an auditory warning cue (ready) followed by an auditory execution cue (go). The time between the ready and go signals was randomized between one and three seconds to avoid anticipation by the subjects. After the go cue was issued participants performed one of the tasks mentioned above (EF, RTR, RTL and CH). From the moment the ready cue was given until the participant completed the task the ECoG signals and movement kinematics were recorded simultaneously. Each movement was repeated 30 times. The
### Table 3.1: Duration of movement, Available Trials, and Movement ranges for all kinematic dimensions recorded.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Task</th>
<th>Duration (s)</th>
<th>No. of good trials</th>
<th>Range of Motion (Mean±SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>1</td>
<td>EF</td>
<td>0.94±0.26</td>
<td>13/30</td>
<td>17.4±3.4</td>
</tr>
<tr>
<td>1</td>
<td>RTR</td>
<td>0.94±0.45</td>
<td>8/30</td>
<td>30.2±19.6</td>
</tr>
<tr>
<td>1</td>
<td>RTL</td>
<td>0.87±0.4</td>
<td>8/30</td>
<td>35.4±4.9</td>
</tr>
<tr>
<td>2</td>
<td>CH</td>
<td>0.99±0.39</td>
<td>13/30</td>
<td>7.3±1.1</td>
</tr>
<tr>
<td>2</td>
<td>RTR</td>
<td>0.74±0.14</td>
<td>9/30</td>
<td>31.8±8.9</td>
</tr>
<tr>
<td>2</td>
<td>RTL</td>
<td>0.83±0.15</td>
<td>10/30</td>
<td>29.2±10.4</td>
</tr>
</tbody>
</table>
Chapter 3. Identification of Arm Movements Using ECoG Signals

(a) Elbow Flexion (EF)  
(b) Closing Hand (CH)

(c) Reaching to a target placed 30 cm to the right of the individual’s midline (RTR)  
(d) Reaching to a target placed 30 cm to the left of the individual’s midline (RTL)

Figure 3.2: Movements performed by the participants of this study.
Figure 3.3: Example of the data recorded in our experiments. The onset of movement (t=0 sec) was defined as the moment in which the magnitude of the movement reached 5% of its total amplitude.

durations of each of the motor tasks are shown in Table 3.1.

### 3.3.5 Analysis

The kinematic recordings were up-sampled to 200Hz using cubic spline interpolation and then synchronized with the ECoG signals. The onset of movement was determined by observing the instant at which the magnitude of the movement recordings exceeded a threshold of 5% of the total movement range. The initial position and orientation were defined as the value of the motion recorded at this instant. For the purpose of analysis, each trial consisted of data starting 1500ms prior and ending 3000ms after the beginning of the kinematic recording. A typical trial is shown in Figure 3.3.

Each trial was visually inspected to identify mistrials. A mistrial was defined as: 1)
a trial in which the individual had performed a movement different to what had been instructed; 2) the participant had started moving before the go auditory signal; 3) the movement had lasted more than three seconds; or 4) it was not possible to identify the onset of the movement. Mistrials were excluded from the analysis. The total number of trials available for analysis after removing the mistrials is shown in Table 3.1. Labelling contacts 1, 2, 3 and 4 of the ECoG electrodes as ECoG1, ECoG2, ECoG3 and ECoG4, respectively, the following combination of signals were subjected to our analysis:

- four Monopolar (MP) signals: ECoG1, ECoG2, ECoG3 and ECoG4
- three Differential Adjacent (DA) signals resulting from subtracting potentials of the adjacent electrodes: ECoG1 - ECoG2, ECoG2 - ECoG3 and ECoG3 - ECoG4
- three Differential Nonadjacent signals (DN) representing the difference between potentials of the non-adjacent electrodes: ECoG1 - ECoG3, ECoG1 - ECoG4 and ECoG2 - ECoG4

### 3.3.6 Feature Extraction

The time-frequency distribution for each ECoG signal was estimated using the following method [132, 145]. Each signal was divided into segments of 640msec (128 samples) by applying a Hamming window. A Fourier transform was then computed for the windowed ECoG signal resulting in a spectrum with a resolution of 1.56Hz. Then the window was shifted to the right by one sample and the procedure was repeated until the end of the ECoG signal was reached. This resulted in a spectrogram consisting of a matrix in which each row represented the power spectrum of a windowed signal. Each column of this matrix represented a time series of the changes in power at different frequencies. A Pearson correlation coefficient was calculated between each one of these time series and each of the six kinematic signals (X, Y, and Z, roll, yaw and pitch). Any correlation coefficient with absolute value greater than 0.1 was considered significant (p<0.01; degrees of freedom of
statistics were 600). For each of the kinematic components, we identified the frequency components with the highest absolute correlation coefficients. The frequencies that were found to be significantly correlated with movement were grouped in a histogram. A different histogram was created for each one of the six kinematic coordinates of the executed movement. We explored four cases for the creation of the histograms: 1) the columns of the histogram had bin widths of 3Hz (i.e., 0-3Hz, 3-6Hz, . . . , 96-99Hz); 2) the columns of the histogram had bin widths of 5Hz (0-5Hz, 5-10Hz, . . . , 95-100Hz); 3) the columns of the histogram had bin widths of 7Hz (0-7Hz, 7-14Hz, . . . , 91-98Hz); and 4) the columns of the histogram had bin widths of 10Hz (0-10Hz, 10-20Hz, . . . , 90-100Hz). These widths defined the spectral resolution of the histogram. An attempt was made to use bin widths that would be either narrower or wider than the bandwidth of a common oscillatory rhythm. For example, a 3Hz bin width had a smaller bandwidth than any of the four frequency bands (delta (< 4 Hz), alpha (8Hz-13Hz), beta rhythm (13Hz-35Hz), and gamma (>35 Hz)), while a 5Hz bin width would cover completely some of the frequency bands.

The magnitude of each bin in the histogram indicated the probability that the frequency it represented was correlated with the movement performed by the subject at the time of the recordings. The probability estimate was defined as the number of times a frequency bin was found to be correlated divided by the number of frequency components included in the histogram:

\[ P_{Kin_{jk}}^{Freq_{Bin_i}} = \frac{|Freq_{Bin_{ijk}}|}{L} \]  

(3.1)

where \(|Freq_{Bin_{ijk}}|\) is the number of spectral components in the \(i\)-th frequency bin \(Freq_{Bin}\) found to be correlated with the \(j\)-th kinematic dimension \(Kin\) of the \(k\)-th motor task and \(L\) is the number of spectral components used to create the histogram. Figure 3.4 shows an example of the end result of this process. The entire histogram for kinematic dimension \(j\) of motor task \(k\) can then be represented as a vector of probabilities as:
Figure 3.4: Distribution of ECoG frequency components correlated with the X-coordinate while subject 1 was performing elbow flexion (EF). The magnitude of each bin in the histogram indicates the probability that the frequency it represents is correlated with the kinematic dimension. The probabilities of each ECoG signal for each configuration tested (MP, DA, and DN) signal combinations have been averaged.

\[
\overline{P_{\text{Kin}}}_{jk} = \begin{bmatrix}
    P^K_{\text{FreqBin}_1} & P^K_{\text{FreqBin}_2} & \cdots & P^K_{\text{FreqBin}_N}
\end{bmatrix}^T
\]  

(3.2)

3.3.7 Classification Test

We created a system to identify off-line which movement was performed by an individual during the recordings. Our goal was to determine the type of movement (i.e. EF, CH, RTR, RTL) that was performed by the individual by observing the ECoG features of a single trial using the process described above. This was accomplished using a nearest neighbour classifier (NNC), which is an algorithm commonly used in automatic classi-
Chapter 3. Identification of Arm Movements Using ECoG Signals

The NNC is capable of determining if an item belongs to any previously defined classes, each containing objects with similar characteristics or features. The item’s membership is determined by measuring the similarities between its own features and the features of each one of the classes, selecting the class found to have the most similarity. If each one of the features is considered to be a dimension in a multidimensional space it is possible to use geometrical distances, such as the Euclidean distance, to establish similarities. In other words, the class with the shortest distance to the item that is classified is the most similar one. The magnitude of each column in the histograms was defined as a feature for the NNC; for any given motor task \( k \), all of the features for each kinematic signal (X, Y, Z, roll, yaw and pitch) were concatenated to form a single feature vector \( \theta_k \):

\[
\theta_k = \begin{bmatrix} P_{Kin1k} & P_{Kin2k} & \cdots & P_{KinMk} \end{bmatrix}^T
\]

(3.3)

where \( P_{KinMk} \) is defined by 3.2.

For each one of the movements performed we selected \( n \) trials and created their feature vectors (as defined by 3.3). These vectors were averaged and used to create the classifier. This process represented the training method for our classifier. The remaining \( m-n \) trials, where \( m \) represents the total number of trials available for a specific movement, were used to test the classifier (i.e., the trials used to create the classifier were not used to test it). Since the classification accuracy can depend greatly on the specific trials used to create the classifier, we repeated this process of developing a classifier 100 times, each time selecting at random the actual \( n \) trials used to create the classifier [146]. The reported accuracy was defined as the average accuracy of the individual accuracies of the 100 classifiers developed as part of this process. The following five effects were statistically analyzed: 1) effect of the number of trials \( n \) used to train the classifier; 2) effect of the number of frequency components used to train the classifier; 3) effect of the kinematic dimensions used (X, Y, and Z only, or X, Y, Z, roll, yaw and pitch) to train
the classifier; 4) effect of the type of ECoG signals used for the training, i.e., monopolar, differential adjacent, or differential nonadjacent signals; and 5) effect of the bin width used to generate the histograms. A Kruskal-Wallis nonparametric analysis of variance was performed on the classifier accuracy to test for dependence against each of the six factors. Statistical significance was set at \( p < 0.05 \). Then, a multiple comparison test was performed within each factor to identify groups that yielded similar levels of accuracy. Confidence intervals of 95% were constructed for each factor value and compared.

**Effect of the number of trials used to train the classifier**

We tested the accuracy of the classifier versus the number of trials \( n \) used to create the feature vectors for training. More specifically, we started by training the classifier with feature vectors created using a single trial (\( n=1 \)) for each one of the performed movements and tested the classifier accuracy using the remaining data (\( m-n \) trials). Once this process was completed, we created a classifier using feature vectors averaged over two trials (\( n=2 \)) and the accuracy was estimated. This process was repeated until the classifier was trained with feature vectors created with five trials (\( n=5 \)). The data used for testing included trials for all of the movements and was classified off-line. The classification accuracy was defined as the number of trials correctly classified divided by the total number of classified trials.

**Effect of the number of frequency components used to train the classifier**

We also explored the effect of the number of frequency components on the performance of the classifier. To do this, we trained the classifier using a different number of spectral components (5, 10, 15, 20, 25, 30, 35 and 40), selected according to the magnitude of their correlation coefficient with the different kinematic signals. For example, when five spectral components were used to train the classifier the five frequencies with the highest absolute correlation values were selected to create the histograms. Likewise, the frequency
components with the ten highest absolute correlation coefficients were selected when the classifier was trained with ten spectral components. The different values tested for the number of spectral components as well as number of trials used to train the classifier resulted in 40 different tested combinations.

**Effects of the kinematic dimensions used**

We also investigated the effects of using different kinematic components on the accuracy of the classifier. In other words, we determined if using all of the kinematic components for training and testing the classifier would result in higher accuracy or if better performance would be obtained by using only the X, Y, and Z coordinates. This was done to test the performance of the classifier using a smaller feature set. Note that in a very limited number of experiments where the arm was moving in one plane (for example one of the X, Y and Z coordinates did not change at all), the correlation between at least one coordinate and ECoG signals was poor. Although, in this case one may be tempted to remove the coordinate that has poor correlation to ECoG signals, it is our opinion that these particular cases actually help the classifier identify them.

**Effects of the type of ECoG signals**

We compared the effect of using monopolar (MP) ECoG signals against differential ECoG signals (DA and DN) electrodes. This allowed us to determine if using monopolar signals or differential signals (representing differences between different monopolar signals) had any impact on the performance of the classifier.

**Effects of histogram bin width**

We also explored the effect of using bins representing different bandwidths to generate the histograms. This gave us an opportunity to determine if the performance of the classifier was dependent on the bandwidth used to group spectral components.
3.4 Results

3.4.1 Correlation between ECoG spectral components and kinematic recordings

The correlation coefficients between the kinematic recordings and ECoG spectral components used were in the range of 0.15±0.006 to 0.63±0.01 (mean±SD). These values were obtained averaging all of the available trials, movements and subjects. Figure 3.5 shows an example of three spectral components with the highest correlation coefficients against position recordings (X,Y,Z) for a single RTR trial.

3.4.2 Representation of correlated frequency components using histograms

The histograms revealed consistent and unique distributions that were representative of the individual upper limb movements. As shown in figures 3.6 and 3.7, each one of the movements generated a unique histogram for each of the kinematic dimensions. The histograms were also subject specific (i.e., histograms corresponding to the same movement were different for both subjects).

3.4.3 Classification tests

Effect of the number of trials used to create the training vectors for the classifier

The classification accuracy was highly dependent on the number of trials used for the classifier (p<0.0001), as can be seen in Figure 3.8. The lowest accuracies were obtained when using a single trial to train the classifier, while using 5 trials to generate the training feature vectors for the classifier yielded the highest accuracies.
Figure 3.5: Example of correlated spectral components and kinematic recordings. The spectral components shown were found to have the highest correlation coefficients for a single trial (reaching to the right - RTR). Consistent with observations in the time domain, the spectral component (10.93 Hz) correlated with the Y component of movement contains more power than the other two shown spectra (57.81 Hz and 51.56 Hz).
Figure 3.6: Histograms obtained using frequency bins of 10 Hz for Subject 1. Each one of the movements generated a different histogram for each one of the coordinates.
Figure 3.7: Histograms obtained using frequency bins of 10 Hz for Subject 2. Each movement generated a different histogram for each one of the coordinates.
Figure 3.8: Classification accuracy obtained with different number of trials used to create the feature vectors used to train the classifier. The graph was generated using all of the frequency bin widths (3 Hz, 5 Hz, 7 Hz and 10 Hz) to group the spectral components in the histogram and all kinematic information (X, Y, Z, roll, yaw and pitch). The values shown represent the accuracies obtained averaged across all of the frequency components (5, 10, ..., 40). The classification accuracy was highly dependent on the number of trials used for the classifier (p<0.001). The difference in classification accuracy between using four and five trials to train the classifier was found to be insignificant by the multiple comparison test. Accuracy prediction using a quadratic model of the data revealed that accuracy did not improve significantly beyond 5 trials.
Effect of the number of frequency components used to create the training vectors for the classifier

The number of spectral components used to create feature vectors to train the classifier had a positive effect on the classification accuracy, as shown in figure 3.9, up to 20 spectral components. Increasing the number of spectral components used to train the classifier beyond 20 did not improve the classification accuracy, as confirmed by the multiple comparison test. This was tested for various ECoG signals namely monopolar, differential adjacent, differential nonadjacent, and combination of monopolar and differential adjacent signals.

Effects on the kinematic dimensions used

There was no significant difference in classification accuracy as a result of using only X, Y and Z kinematic data versus all kinematic data, i.e., X, Y, Z, roll, yaw and pitch, to perform the classification (p<0.01). The averages were estimated over all number of trials to train the classifier (1 to 5) and all number of spectral components tested (5 to 40).

Effects on the type of ECoG

The accuracies obtained using monopolar, differential adjacent, differential nonadjacent, and combined monopolar AND differential adjacent AND differential nonadjacent signals were different (p<0.0001) (see figures 3.8 and 3.9). The accuracies achieved using differential adjacent and differential nonadjacent signals were significantly greater than those achieved using monopolar signals. The difference between the accuracy obtained using differential adjacent and differential nonadjacent was not significant by the multiple comparison test. The best accuracies were obtained using four or five trials to create the training vectors using differential nonadjacent differential signals.
Figure 3.9: Classification accuracy obtained with different number of spectral components to create the feature vectors to train the classifier. The graph was generated using 5 Hz and 10 Hz frequency bins to group the spectral components in the histogram and all kinematic information (X, Y, Z, roll, yaw and pitch). The values shown represent the accuracies obtained averaged across all of the number of trials tested (1 through 5). The number of spectral components used to create training vectors to train the classifier had a positive effect on the classification accuracy. For all of the cases (DA, DN, MP, and MP & DA) the differences in accuracy were not significant when 20 or more spectral components were used to train the classifier, which was confirmed by the multiple comparison test.
Effect on the size of the frequency bins used for the generation of the histogram

The size of the frequency bins used to create the histograms was found to have a positive effect on the classification accuracy, as can be seen in figure 3.10. The highest accuracies were obtained using frequency bins of 10Hz and differential nonadjacent and differential adjacent signals (84.4% and 81.2%, respectively). Using a frequency bin of 3Hz resulted in the lowest accuracies. The multiple comparison test showed all of the accuracies obtained with different frequency bins to be significantly different except for frequency bins of 7 and 10 Hz.

3.4.4 Summary

Significant correlations were found between the spectral changes of ECoG signals and kinematic recordings. The frequencies significantly correlated with movement forming consistent and unique distributions when grouped in a histogram, making it possible to classify specific movements. The classification accuracy was dependent on the number of trials and number of spectral components to create the classifier. The performance of the classifier was also dependent on the type of ECoG signals and the size of the frequency bins used by the classifier.

3.5 Discussion

We presented a novel method for the identification of specific motor tasks from ECoG signals. The process described here is based on creating histograms representing the probability of correlation between spectral components of ECoG signals within predefined frequency bands and kinematic components of movement. The distribution of the spectral components was found to be unique for the different motor tasks. This allowed the use of the histograms as features to classify ECoG signals according to the specific
Figure 3.10: Effect of the size of the frequency bins used to group spectral components on the classification accuracy. The size of the frequency bins used to create the histograms was found to have a positive effect on the classification accuracy. The multiple comparison test showed all of the accuracies obtained with different frequency bins to be significantly different.
movement that an individual had performed. The distributions of ECoG spectral components correlated with movement were different for the two participants in this study. This was especially evident on the histograms generated while both individuals performed the same motor tasks (RTR and RTL). As expected, this finding suggests that the ECoG features that can be used for the identification of specific motor tasks are subject specific. As expected, we showed that classification accuracy improved proportionally to the number of trials used to train the classifier. However, our results suggest that it may be possible to achieve very good recognition accuracies using only 4 or 5 trials to create feature vectors to train the classifier. We determined that a higher number of spectral components used to create the vectors for training and classification increased the accuracy of the classifier. The classification range of values tested (5, 10, ..., 40) allowed us to see a plateau in the recognition accuracy. This suggests that there is a maximum number of spectral components that can be used to train the classifier after which no significant improvements in recognition can be achieved. In our results, the recognition accuracy reached a maximum value after approximately 20 spectral components. The spectral components correlated with the different kinematic components of each movement were grouped in histograms with bins of 3Hz, 5Hz, 7Hz and 10Hz. We observed a proportional increase of classification accuracy, with the highest values obtained for the frequency bins of 10Hz. The accuracy was not affected by the kinematic recordings used to conduct our classification tests. Our results demonstrate that it is possible to use signals obtained with subdural electrodes with only four contacts placed over the motor cortex to classify movements performed by an individual. We were able to determine that using differential signals representing differences between monopolar signals greatly increases the performance of the classifier as compared to monopolar signals. This is likely because a large component of the monopolar signal is related to activities of the reference electrode rather than activities of the motor cortex. In addition, the accuracy among the differential signals was greater when differential nonadjacent signals were used. This may be
due to the fact that differential nonadjacent signals conveyed information over a larger area of the motor cortex as compared to differential adjacent signals. One advantage of using subdural electrodes in the context of brain-computer interfacing over systems that use scalp electrodes is an increased ability to record activity above 30 Hz. From the work presented here it was evident that frequencies greater than 40 Hz played an important role in the identification of the individual motor tasks. This is consistent with results obtained by others [59,60,111,136,138,147,148]. In particular, there is mounting evidence that ECoG signals with frequencies between 100 and 200 Hz may contain useful information pertaining to BCI applications [59,60]. Technical limitations of the equipment used in our study did not allow us to acquire the ECoG signals at a higher rate than 200 Hz (traditional in clinical settings) and explore frequencies greater than 100 Hz. The fact that the participants of the study were not part of the target population of BCI technology may raise the question of whether or not the work presented here would be applicable to the targeted patient population. The method presented here is based on establishing similarities, estimated by a correlation coefficient, between changes in power of frequency bands of ECoG signals and kinematic recordings. It has been reported that in subjects with Parkinson’s Disease, changes in power in the 8-12 Hz band begin closer to the onset of hand movements when compared to control subjects [149]. Although it is unknown what specific effect this would have on the performance of the procedure presented here, there is the possibility that this difference in the temporal evolution of spectral changes, as related to voluntary movement, might affect the correlation values on which the presented method is based. This might require modifications to the feature extraction process yet we feel confident that this classification method would work with diverse patient populations. In this particular study we had two patients with different diagnoses, namely Parkinson’s Disease and Essential Tremor, and the proposed classification method worked well with both individuals and achieved identical classification accuracy. To achieve the highest classification accuracy with the proposed BCI method
one should use 10Hz bins, five trials for training, and differential adjacent or differential nonadjacent ECoG signals. If these conditions are satisfied one should expect to have classification accuracies of 89% or higher. It is worth mentioning that this method requires a very low number of training trials (maximum five) to generate the classifier with such high classification accuracy. Furthermore, the method of classification, namely nearest neighbour classifier, is transparent, easy to implement and intuitive. The only deficiency of this method is that it requires an individual to complete the kinematic task before the classification can be carried out. Our immediate future work will be focused on developing a classifier that will be able to perform the classification while the task is being executed. Our long-term goal is to apply this classification method to imagined movements. If successful, either of these two approaches will allow us to apply this classifier in real-time BCI applications.

3.6 Acknowledgement

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Chapter 4

ECoG Controlled Neuroprosthesis for Grasping

The material presented in this chapter appeared in the publication:


The contents of the chapter are identical to the material presented in the publication except for formatting, which has been modified to meet the requirements established by the University of Toronto, as well as a label in Table 4.2 which appeared incorrectly in the publication.

4.1 Abstract

4.1.1 Study design

Proof of concept study to control a neuroprosthesis for grasping using identification of arm movements from ECoG signals.
4.1.2 Objective

To test the feasibility of using electrocorticographic (ECoG) signals as a control method for a neuroprosthesis for grasping.

4.1.3 Setting

Acute care hospital, Toronto Western Hospital and spinal cord injury (SCI) rehabilitation centre, Toronto Rehabilitation Institute, Lyndhurst Centre. Both hospitals are located in Toronto, Canada.

4.1.4 Methods

Two subjects participated in this study. The first subject had subdural electrodes implanted on the motor cortex for the treatment of essential tremor (ET). ECoG signals were recorded while the subject performed specific arm movements. The second subject had a complete SCI at C6 level (ASIA B score) and was fitted with a neuroprosthesis, capable of identifying arm movements from ECoG signals off-line, for grasping. To operate the neuroprosthesis, subject 2 issued a command that would trigger the release of a randomly selected ECoG signal recorded from subject 1, associated with a particular arm movement. The neuroprosthesis identified which arm movement was performed at the time of recording and used that information to trigger the stimulation sequence. A correct ECoG classification resulted in the neuroprosthesis producing the correct hand function (that is grasp and release).

4.1.5 Results

The neuroprosthesis classified ECoG signals correctly delivering the correct stimulation strategy with 94.5% accuracy.
4.1.6 Conclusions

The feasibility of using ECoG signals as a control strategy for a neuroprosthesis for grasping was shown.

4.2 Introduction

Functional electrical stimulation (FES) elicits muscle contraction using electrical impulses and is used as a motor neuroprosthesis to facilitate movement after SCI. The term neuroprosthesis will be used here to refer to a motor neuroprosthesis.

Neuroprostheses are controlled using switches, linear variable resistors, joysticks, position sensors, electromyographic signals, and speech [142]. A more intuitive method for controlling neuroprosthetic devices would be to use brain activity. Brain-machine interfaces (BMIs) translate brain signals into control commands for electronic devices.

Electrical signals reflecting brain activity have been used most extensively to develop BMI systems. Non-invasive techniques for recording the electrical activity of the brain include electroencephalography (EEG). Invasive techniques allow the recording of local field potentials (LFPs) reflecting the activity of a group of neighbouring neurons. LFPs can be recorded using macroelectrodes placed on the surface of the brain, resulting in electrocorticographic (ECoG) signals, and using microelectrodes placed intracortically. These microelectrodes can also record the activity of individual neurons.

Operating an EEG based BMI requires the user to change brain activities voluntarily. For this, the user is often trained for up to several months. Therefore, an important challenge in the development of BCIs is minimizing the required training. For example, by using ECoG signals the training time can be reduced to the order of minutes [60].

Spectral and temporal changes in brain activity elicited by voluntary movement have been used to reduce the training time of a BCI user. These changes have allowed the identification of specific movements and the detection and estimation of kinematic pa-
rameters of the motion performed [150].

Single cell recordings in monkeys and humans have yielded important results in the detection and estimation of kinematic parameters from brain activity making it possible to control computer cursors and robotic arms using the activity from a group of neurons [16, 151]. However, there are concerns regarding the reliability and long term stability of single neuronal recordings [152].

LFPs, including ECoG recordings, offer alternatives to single neuron recordings. The changes in power of LFPs frequency components reflect kinematic information of arm movements [121, 133, 135, 136] and recently it was possible to predict hand position from ECoG signals [152].

The convergence of the fields of neuroprosthetics and BCI appears to be a natural next step in the development of these two fields. Using BCI technology, a neuroprosthesis could detect the intention to perform a specific movement and deliver the electrical stimulation to produce that exact movement. The benefit of such a system would be enhanced further if the user required little or no training to use this device.

Upper limb neuroprostheses [4, 22, 153, 154] have been controlled by individuals with quadriplegia using single cell recordings (15) and EEG signals after training lasting between three days and four months [153]. To generate control commands, the EEG-based BCI users employed motor imagery [4], closing and opening of the eyes [22], and self regulation of power in specific frequency bands [153]. The accuracies reported for these systems range from 76% [22] to 94.2% [153].

The purpose of this study was to test the feasibility of using ECoG signals as a control strategy for a neuroprosthesis for grasping. A neuroprosthetic device was created and controlled using ECoG signals acquired previously. In the following section it will be shown that an ECoG driven neuroprosthesis can be implemented using a 4-channel ECoG electrode and minimal training time to achieve 94.5% accuracy.
4.3 Materials and Methods

To test the integration of a BMI system and a neuroprosthesis for grasping it is necessary either to: a) implant an individual with SCI with an ECoG electrode or b) use ECoG signals recorded from another individual, already implanted with a subdural electrode, to control a neuroprosthesis instrumented on an individual with SCI. Since we could not justify implantation of the ECoG electrode solely to test the system feasibility, we used the second approach.

4.3.1 Subjects

Two subjects participated in this study. Subject 1 was a 67-year-old woman implanted with subdural (i.e., ECoG) electrodes for the treatment of essential tremor (Fig. 4.1(a)). The subject was recruited from the movement disorder clinic at the Toronto Western Hospital and gave informed consent to participate. The study was approved by the University Health Network Research Ethics Board. Subject 2 was a 35 year-old man with a complete cervical SCI (C6 level/ASIA B) and had received four weeks of FES therapy treatment for restoring grasping function, as part of another study [155]. He was able to use his arms and wrists but had no hand movement. Subject 2 gave written and informed consent to participate in this study as required and approved by the Toronto Rehabilitation Institute Research Ethics Board. Figure 4.1(b) subject 2 wearing the neuroprosthesis for grasping. We certify that all applicable institutional and governmental regulations concerning the ethical use of human volunteers were followed during the course of this research.

4.3.2 ECoG and Motion Recordings

ECoG signals and arm movements were recorded simultaneously from subject 1 during a single one-hour session three days after the initial implantation of the subdural electrode.
Chapter 4. ECoG Controlled Neuroprosthesis for Grasping

(a) X-ray image of subject 1 with subdural electrodes implanted on the motor cortex over the representation of the upper limb.

(b) Subject 2

(c) Surface stimulation electrodes used to elicit palmar and lateral grasps

(d) Surface stimulation electrodes used to elicit palmar and lateral grasps

Figure 4.1: Participants of this study.
The subdural electrode (RESUME, Medtronic3586, Medtronic, USA) had a single row of four platinum-iridium disc contacts (4 mm diameter and 10mm center to center distance). The electrode was implanted over the arm representation of the left motor cortex, which was confirmed intra-operatively using electrical stimulation delivered directly to the brain and observing contractions of the right upper limb. Monopolar ECoG signals were band limited (0.5 Hz - 500 Hz) and recorded (sampling rate = 2 kHz, SynAmps2, Compumedics, USA). The ECoG signals were down-sampled to 200 samples per second and subtracted from each other to create differential signals using the recordings from non-adjacent electrodes (e.g., contact 3 and contact 1) [2]. Using only the right upper limb, subject 1 performed wrist flexion (WF), reaching to the right (RTR) and reaching to the left (RTL) after an auditory cue and held the final position of the movement until a second auditory cue. A motion sensor was placed over the dorsal aspect of the third metacarpal of the right hand to record the movement using a six-dimensional (X, Y, Z, roll, yaw and pitch) motion capture system (Fastrak, Polhemus Inc., USA). Only position recordings (X, Y and Z) were used for this study [2]. Each movement was repeated at least 35 times and each trial was visually inspected to identify mistrials, defined as: 1) a trial in which the individual had performed a movement different from what had been instructed; 2) the participant had started to move before the auditory cue; or 3) the movement was not completed. Table 4.1 and Figure 4.2 show the movements performed along with the number of trials used to conduct this study.

We created a nearest neighbour classifier (Matlab, Mathworks, U.S.A.) using five trials of each motor task to identify the performed arm movements by analyzing the ECoG signals. The remaining trials were used to test the neuroprosthetic system. To classify the subdural signals we identified ECoG spectral components correlated with the kinematic components of the arm movement (Pearson correlation coefficient $> 0.1$; statistics degrees of freedom = 600). The time resolved spectra were obtained using a spectrogram (128-sample Hamming window, 128-FFT, and 127 point overlap). The
(a) Wrist Flexion (WF)  
(b) Reaching to the right (RTR)  
(c) Reaching to the left (RTL)

Figure 4.2: Movements performed by subject 1.
Table 4.1: Movements performed by subject 1 along with duration of movement, available trials and movement ranges. The movements included wrist flexion (WF), reaching to the right (RTR) and reaching to the left (RTL).

20 frequency components with the highest correlation coefficients were grouped using a histogram with bins representing frequency bands of 10 Hz. Details of this process can be found in [2].

4.3.3 Neuroprosthesis for Grasping

The right hand of subject 2 was fitted with a neuroprosthesis to generate palmar and lateral (key pinch) grasps (18) [1]. The neuroprosthesis was designed and created specifically for this study using a Compex Motion four-channel transcutaneous electrical stimulator (Compex S.A., Switzerland).

The grasping movements were achieved by stimulating: 1) flexor digitorum superficialis and flexor digitorum profundus using two electrodes connected in parallel to channel 1 (20 mA) to generate finger flexion; 2) flexor pollicis brevis using channel 2 (14 mA) to generate thumb opposition; and 3) extensor digitorum communis using channel 3 (22 mA) to generate opening of the hand. Palmar grasp was obtained by stimulating channels 1 and 2, simultaneously. By stimulating channel 1 followed by channel 2, 500 msec later, the lateral grasp was achieved. Stimulation of channel 3 generated hand opening.
In all cases, the stimulation frequency was set to 40 Hz and the pulse duration was 300 \( \mu \text{sec} \). Figure 3 depicts the stimulation profiles to elicit the grasping synergies.

The neuroprosthesis had three accessible buttons (Buddy Button 5700 Series, Tash Inc., Canada) that subject 2 could activate with the dorsal aspect of his left hand. Pressing button 1 or 2 elicited palmar grasp or lateral grasp, respectively. A second activation of either of these switches generated hand opening. Button 3 was used to turn the neuroprosthesis on and off. A two-hour training period allowed the user to become comfortable using the neuroprosthesis commanded with the three buttons.

Later, the accessibility buttons were disconnected from the stimulator and reconnected to the ECoG classifier. With this modification, pressing buttons 1, 2, and 3 resulted in the random selection and classification of an ECoG signal recorded when subject 1 had performed WF, RTR, and RTL, respectively. The classified trials excluded the recordings used to create the classifiers. After the classifier determined which ECoG signal had been extracted it commanded the neuroprosthesis to perform the desired hand function or turn on/off the stimulator. Correct classification of the ECoG signals resulted in the correct stimulation sequence delivered by the neuroprosthesis. A diagram depicting the complete implemented neuroprosthetic system is shown in Figure 4.4.

Subject 2 picked up 18 objects \([156]\), shown in Table 4.2, requiring palmar and lateral grasps. Each object was grasped and lifted from a table using the neuroprosthesis. The participant held the objects in pronation and supination and then released them. To test all of the available classes (ECoG signals), the user was asked to turn the neuroprosthesis off and on after grasping two objects consecutively.

### 4.3.4 Classification Tests

The accuracy of classification (as the number of trials in which the system performed the action required by the user divided by the total number of activations of the neuroprosthesis) was measured. The time between the activation of a user switch and the issuing
Figure 4.3: Stimulation sequences for (a) palmar and (b) lateral grasps. Both stimulation sequences used three stimulation channels. Each channel stimulated a different muscle or nerve at different times for generating synergistic movements. (I) Pressing button 3 was used to turn the stimulator on through a random selection and classification of electrocorticographic (ECoG) signals recorded while subject 2 was reaching to the left (RTL). (II) Pressing buttons 1 or 2 caused the system to classify randomly selected ECoG signals recorded while subject 2 was performing wrist flexion (WF) or reaching to the right (RTR), respectively. The result of the classification triggered a specific stimulation sequence to elicit palmar or lateral grasps. (III) Grasping was sustained until either button 1 or 2 was pressed a second time, which resulted in a change in the stimulation delivered to facilitate hand opening. (IV) After 3 s, the stimulation stopped and the neuroprosthesis returned to an idle state. (V) Button 3 could also be used to turn the stimulator off through the classification of a randomly selected ECoG signal recorded when subject 2 was reaching to the left. This figure was adapted from [1].
Figure 4.4: Complete experimental setup. The user pressed one of three buttons to control the neuroprosthesis. Each button was associated with a dataset of ECoG signals recorded earlier. The system randomly extracted a single trial of the corresponding dataset, which was classified using a nearest neighbour classifier. The result of the classification process was then used to trigger a stimulation sequence. When the classification was successful, the correct stimulation sequence was delivered by the neuroprosthesis. Conversely, an incorrect classification would result in an incorrect action taken by the neuroprosthesis. ECoG, electrocorticographic; WF, wrist flexion; RTR, reaching to the right; RTL, reaching to the left.

<table>
<thead>
<tr>
<th>Required grasping approach</th>
<th>Object</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palmar</td>
<td>Mug, book, 355 ml soft drink can (full), mobile phone,</td>
</tr>
<tr>
<td></td>
<td>wooden blocks with high friction surface (100, 200 and 300 g),</td>
</tr>
<tr>
<td></td>
<td>wooden blocks with wooden surface (100, 200 and 300 g),</td>
</tr>
<tr>
<td></td>
<td>wooden blocks with low friction surface (100, 200 and 300 g)</td>
</tr>
<tr>
<td>Lateral</td>
<td>Sheet of paper, paper bag, die, credit card, pencil</td>
</tr>
</tbody>
</table>

Table 4.2: Objects used to test the neuroprosthesis. The different objects required the use of both palmar and lateral grasp.
of the classification result was also recorded.

### 4.4 Results and Discussion

We confirmed the presence of ECoG spectral components correlated with each one of the kinematic dimensions of the movements performed by subject 1 (Table 4.3). Figure 4.5 shows histograms created by grouping 20 spectral components identified as the most strongly correlated with kinematic recordings. The distribution of correlated frequencies was found to be dependent on the type of movement performed by subject 1 ($p<0.001$, chi-squared statistic) suggesting that the recorded LFP activity is distinct for each arm movement performed.

Subject 2 was able to use the neuroprosthesis with an accuracy of 94.5%. Most of the incorrect classifications occurred when the system was attempting to classify trials corresponding to WF, as the confusion matrix provided in Table 4.3 shows. Closer inspection of the kinematic recordings revealed that the wrist flexion motion was less consistent than the reaching movements. This was likely the cause of the misclassification. The average time elapsed between the ECoG classification to the activation of the neuroprosthesis was $1,870 \pm 109$ msec.

There are seven grasping styles and dozens of combinations which can be generated using today’s FES technology. However, providing a user interface to control these functions independently remains a challenge, regardless of the user’s motor abilities. This is an unsolved problem in the FES field. A BMI capable of identifying multiple movements has the potential to command multiple grasps using a single interface. In this work we presented a BCI system that uses ECoG signals to control a neuroprosthesis for grasping. Activation of the neuroprosthesis triggered an off-line classification process of a single ECoG trial. The result of this classification triggered specific electrical stimulation sequences to perform palmar and lateral grasps as well as turning the electrical
Figure 4.5: Histograms resulting from grouping the 20 spectral components identified as the most strongly correlated with kinematic recordings. Each bin in the histogram corresponds to a frequency range of 10 Hz. Values are expressed as probabilities after dividing the magnitude of each column by the total number of spectral components used for each plot [2]. The amplitude of each column represents the probability that a spectral component within the frequency range defined by the bin is correlated with movement. Each histogram was different and unique for each one of the movements performed by subject 1.
Table 4.3: Abbreviations: RTL, reaching to the left; RTR, reaching to the right; WF, wrist flexion. Each element in the matrix shows the percentage ratio between the number of trials available for each movement performed by subject 1 and the outcome of the classifier. The classifier had the greatest number of misclassifications of ECoG signals recorded when subject 2 was performing WF and classified as RTR. The second category with the largest classification errors was RTL misclassified as RTR. However, the classifier performed well by identifying the ECoG signals recorded while the subject was performing RTR.

<table>
<thead>
<tr>
<th></th>
<th>WF</th>
<th>RTR</th>
<th>RTL</th>
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<tbody>
<tr>
<td>WF</td>
<td>91.67%</td>
<td>8.33%</td>
<td>0%</td>
</tr>
<tr>
<td>RTR</td>
<td>0%</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>RTL</td>
<td>0%</td>
<td>5.45%</td>
<td>94.55%</td>
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stimulator on and off. We believe that the short time required to create the system (less than 60 minutes, including both the neuroprosthesis and BMI design) along with the small number of trials used to create the classifier (i.e., five) using activity from only four contacts to identify three different movements performed with the same limb make this system unique. The technology and procedures used in this study have a good record of stability and reliability in clinical applications resulting in an increased interest in the development of BCIs using ECoG signals. However, it is still necessary to verify the long term performance of subdural electrodes in BCI applications. This work allowed us to explore our ideas of the integration of BMI systems and FES, and run a true end-to-end system test on the use of ECoG signals to control a neuroprosthesis for grasping. While several reports describe the control of robotic or virtual systems with brain activities, we selected this application due to its clinical prevalence; FES is technology currently used to facilitate movement in persons with SCI. However, to conduct our tests we could not justify implantation of subdural electrodes or the instrumentation of an arm with a
neuroprosthesis when these interventions were not required for medical reasons. Because of these ethical challenges the only possible solution was to use two subjects which is why the ECoG signals used to trigger the neuroprosthesis were not recorded from the same individual instrumented with the neuroprosthetic system. Although the movements identified from subject 1 were different from the movements produced by the neuroprosthesis in subject 2, we believe that this work brings us closer to a situation in which individuals will be able to elicit a movement in their paralyzed limbs by attempting or imagining that same movement. We feel confident that in future implementations this discrepancy can be overcome and that the neuroprosthesis will be able to produce the exact movement identified from ECoG recordings. By doing this, the level of transparency of interaction between the user and a neuroprosthetic device will increase dramatically. Voluntary movement-related changes in power in the beta band appear to show temporal differences [157] in patients with ET. These differences may affect the correlation values on which the classification method is based. However, we have tested successfully the presented method with individuals with Parkinson’s disease and essential tremor and we are confident that the employed method will work with different patient populations. While our system operates on ECoG signals recorded while actual arm movements were performed, our immediate work will focus on developing a classifier able classify imagined and/or intended movements to control the neuroprosthesis. We also plan to develop a system capable of identifying in real-time specific arm movements from ECoG recordings.

4.5 Acknowledgements

We would like to thank Ms. Carolyn Gunraj and Dr. Kei Masani for their assistance. This study was financially supported by the Toronto Rehab Student Scholarship Fund, Natural Sciences and Engineering Research Council of Canada (# 480588), Canadian Fund for Innovation (# 7313), Ontario Innovation Trust (# 7313), Ontario Ministry of
Health and Long-Term Care and the Canadian Institutes of Health Research.
Chapter 5

EEG Real-Time Two-Dimensional Control

The material presented in this chapter appeared in the publication:


The contents of the chapter are identical to the material presented in the publication except for formatting which has been modified to meet the requirements established by the University of Toronto.

5.1 Abstract

A brain-computer interface (BCI) can generate control commands using signals from the brain. These devices have a great potential to assist individuals with severe mobility impairments. Despite enormous advances in this field, most BCI systems have restricted information transfer rates limiting the potential applications that this technology may have. A defining factor for this limited information transfer rate is a synchronous (cue-based) mode of operation, currently used by most BMI systems. We present a novel
approach for using electroencephalographic signals from a single electroencephalographic (EEG) electrode to control asynchronously a remote controlled vehicle moving in two dimensions.

5.2 Introduction

A brain-machine interface (BMI) uses signals from the brain to control electronic devices. A BMI system has three fundamental components: an input (i.e., a signal from the brain), and output (i.e., a command that controls an external device), and an intermediate translation state that transforms the input into the output. This technology has great potential to assist individuals with severe mobility impairments, especially those who have lost all ability to move voluntarily and communicate.

In the last decade researchers around the world have created numerous BMI systems. The majority of these devices use electrical recordings acquired from the brain in a non-invasive way using electroencephalographic (EEG) techniques. To operate, these EEG-based BMI systems require that the user adopts different mental states, which are detected by specific temporal or frequency changes in the brain activities. Some of the features that have been used to detect different mental states include slow cortical potentials (SCP) [69,125,158], P300 potential [126,130], and changes in power (amplitude) of oscillatory rhythms [4]. When a change in the brain activity is detected, it is then possible to trigger a specific action effectively producing the interface between the brain and an external device. EEG-based BMIs have been used successfully to assist the communication of individuals who have lost all ability to perform voluntary movement (locked-in syndrome [69]).

Despite tremendous advances in the development of EEG-based BMI technology most of these devices suffer from a limited communication rate (information throughput). This has restricted the number of applications that could take advantage of EEG-based BMI
technology. An increase in communication rate would likely expand the population that can benefit from these devices. In fact, it has recently become evident that this technology may also benefit individuals with spinal cord injury [16, 23, 72, 73, 159]. An important challenge for researchers in the field of BMI is therefore to increase the communication rate of this technology.

One factor with a negative impact on the communication rate of BMIs is the use of synchronous modes of operation. With this style of interaction between the user and the BMI, used by the majority of current EEG-based BMIs, a person can issue commands (i.e., adopt a particular brain state) only during specific time instances determined by the BMI itself and not by the user. In turn, this mode of interaction to a large extent determines the rate at which commands can be generated. Most of the existing work on EEG-based BMIs uses a synchronous mode of operation.

To create practical BMIs that can be used outside a laboratory setting it is necessary to implement asynchronous systems that would allow the user to generate commands at any given time. Such a device could potentially allow for a more natural and faster way of interaction with the user. The implementation of an asynchronous BMI is a challenging problem as it requires that the brain activity be monitored constantly to identify specific EEG patterns indicating that a user wishes to generate a command. While only a few research groups have tried to address this problem in the past [66, 78, 160] there has been a recent increase in the creation of asynchronous BMIs. The application of asynchronous EEG-based BMIs have included control of functional electrical stimulation systems [71], virtual and simulated wheelchair navigation [32, 75], upper limb prosthesis [70], and a virtual keyboard [5].

We present here a proof of concept study where we use a single EEG electrode to perform asynchronous control of a miniature remote control vehicle moving in two dimensions. The proposed method operates on the identification of a single mental state used to create a “brain-switch”. This work is the implementation of the work presented
5.3 Materials and Methods

5.3.1 Participants

There was a single participant in this proof of concept study. The subject was a 24 year old man with no neurological disorders. He gave informed written consent to participate in this study and had no previous experience using a BMI.

5.3.2 Experimental Setup

EEG was recorded from the subject using a single EEG electrode placed at C3 according to the 10-20 reference system. The signals were band-limited between 0.5 Hz and 30 Hz and amplified using a dedicated EEG amplifier (IP511, GRASS Technologies, West Warwick, U.S.A.). The amplified signals were then digitized using a portable USB data acquisition system (NI-DAQPad-6016, National Instruments, Texas, U.S.A.).

A real-time “brain-switch” was implemented to create the BMI. This was done by first filtering the digitized signals between 7 Hz and 13 Hz [117]. The absolute value of a 250 msec segment was integrated twice and the mean value of this segment was then used to calculate a moving average with the last 5 estimated mean values. Whenever the value of this moving average decreased and remained below an experimentally determined threshold for a pre-specified duration, the switch would be considered activated (closed). The threshold value as well as the amount of time in which the signal had to remain under the threshold could be changed at any point during the operation of the BMI.

The “brain-switch” was then used as an input to a control strategy that allowed the control of two-dimensional movements with a single switch [161]. With this strategy, rather than using a single switch to indicate a desired behavior from an object under
control, the activation of the switch is used to indicate that the current behavior of the
device under control is not the desired one.

To operate the remote controlled car the subject activated the switch repeatedly. Each
time the switch was activated the behavior of the device under control (e.g., the direction
of the object moving in two dimensions) changed randomly. At the same time each time
the device changed its behavior, the control system eliminated the rejected behavior
(direction) temporarily so that it was not selected again in subsequent switch activations.
This ensured that the control system would ultimately converge to the direction desired
by the user.

Formally, each switch activation $n$ changed the direction of the moving car according
to

$$C_{[n]} = \text{argmin}(\gamma(n)(c))$$

(5.1)

Where

$$\gamma(n)(c) = H_{[n]}(\Delta t)\gamma(n-1)(c) + \chi_{[n]}(c) \left\{ 1 - H_{[n]}(\Delta t)\gamma(n-1)(c) \right\}$$

(5.2)

The weighing factor $H_{[n]}(\Delta t)$ reduced the probability that a rejected behavior was
selected in subsequent switch activations and it was defined as

$$H_{[n]}(\Delta t) = \ell^{\Delta t/\tau}$$

(5.3)

Where $\Delta t$ is the time between the last two switch activations.

The function $\chi_{[n]}(c)$ was a weighting factor reducing the probability that directions
similar to a rejected one were selected. It was defined as

$$\chi_{[n]}(c) = \begin{cases} 
1 - \frac{r}{\alpha_s} & \text{if } r \leq \alpha_s \\
0 & \text{if } r > \alpha_s 
\end{cases}$$

(5.4)
Where \( r \) was the distance between a rejected direction and neighboring directions. The parameter is an arbitrary constant that defines the spatial effect (domain) of the function. Details of this work can be found in [161] and the open source software libraries for the control strategy are available at http://komodoopenlab.com/index.php/Portfolio/Aibicom.

We defined the following states as the set from which the control system could select a behavior: 1) move forward, 2) move backward, 3) move forward right, 4) move forward left, 5) move backward right, 6) move forward left, and 7) stop. The control strategy was used to command a miniature remote control car (ZipZaps\textsuperscript{TM}, The Source, Canada) (Figure 5.1). This car was modified so that it could receive digital control input signals making it possible to operate it with a personal computer. The actual control signals were delivered to the remote control car using the same data acquisition system used to collect the EEG signals.

### 5.3.3 Participant Training

The participant of this study received training lasting 5 days. During this training time the user first became familiar with the single-switch control strategy. He was instructed on how to operate single switch interface and asked to control the remote controlled car by activating an actual switch.

The training time also allowed the person to learn how to induce changes in their brain oscillations in the selected frequency band (7 Hz -13 Hz). The initial attempts to achieve this self-regulation of EEG signals were done using motor imagery of the right hand. The participant was shown the moving average of the processed EEG signal as a continuous graph displayed on a computer screen as well as a visual indicator that was turned on whenever the brain switch had been activated. The user was given the opportunity to ask for adjustments in the threshold value (increase or decrease) and the time duration (shorter or longer) during which the EEG signal had to be sustained below the threshold level for the “brain-switch” to be activated.
Figure 5.1: Remote-controlled car used to conduct this study. Custom modifications to the car and the controller box made it possible to operate it through a personal computer. The direction of the car was controlled using a novel single-switch asynchronous access method.
5.3.4 Experimental Tasks

The participant was asked to control the remote control car from an initial point to a final point. To do this, three targets were marked on the floor, which indicated the possible starting and ending points. The targets were arranged in the manner displayed in Figure 2. The data collected for these experiments included 1) number of activations required to complete the task, and 2) the time required to move from one target to another.

5.4 Results

The EEG signals revealed changes in power in the selected frequency bandwidth (7 Hz to 13 Hz). Subject 1 was able to gain control over the power of his brain oscillations after three days of training. He was able to drive the remote control car successfully for 11 minutes during which he drove the car to 7 targets. The average time required to move between targets was 90.71 seconds (±85.28) with an average of 13.85 switch activations (±13.33).

5.5 Conclusions and Discussion

We presented a methodology for two-dimensional asynchronous control using a single EEG electrode. We believe that the work presented here proposes a simple approach to BMI implementation in which the user is capable of issuing commands at any given time to control a two-dimensional task.

One factor that limits the communication rate of BMI devices include a small number of brain states that these devices can identify. With one identifiable brain-state it is possible to generate one command, which is ideal for controlling devices that offer only two possible outcomes/states (e.g., a light that can be turned on or off) or to answer YES or NO questions. Therefore, one of the methods used to increase the information
throughput of BMIs has been enhanced by increasing the number of brain-states that the BMI can identify. Today it is possible to find BMIs that recognize up to four different mental states [162]. This recognition of multiple brain states has been possible through the use of sophisticated computational methods [75] and/or by increasing the features in brain signals that a person can control voluntarily [64].

A different approach to increase the communication rate of the BMIs has concentrated on identifying and using different neural signals with richer information content. Examples of this approach include BMI systems that record the activity of the brain directly from small populations of individual neurons acquired with invasive techniques (i.e., intracortical electrodes). Using this approach, it has been possible to control computer cursors in two dimensions, robotic arms, and assistive devices. However, the stability and long-term viability of these highly invasive systems still needs to be investigated.

The approaches taken to increase the communication rate of the BMI systems also increase the demands placed upon the user as well as increase the complexity of the BMI systems. This can result in systems that are: 1) difficult to use, or 2) require extensive training, or 3) are not suitable for applications outside a laboratory.

The approach that we present in this article uses self-regulation of oscillatory rhythms of the motor cortex and identifies moments when this activity is above or below predefined threshold level. This application of the EEG signals has a proven track record in the field of BMI applications. What is unique about our method is that it uses this very simple EEG signal processing technique and integrates it with new real-time two-dimensional asynchronous control technique proposed by Silva et al. [21]. This new control technique allowed us to create a sophisticated control tool that was able to regulate movement of the remote controlled toy car in two-dimensional space using simple EEG threshold detection approach. We believe that this BMI system gives users more time to concentrate on the task they need to perform instead of focusing their attention on operating the BMI system itself.
The system presented here can be improved by increasing the speed at which the user can change direction. In our work, this is not dependent on the control mechanism presented here but rather on the EEG feature detection, and methods to extract them as a prerequisite for the BMI. The use of other feature identification and extraction approaches will likely result in an increase in the overall operational speed of the system. It is also highly probable that the speed of the system will increase as the user gains more experience with the proposed BMI system.

Our future directions include the exploration of the control methodology presented here for the control of three-dimensional movements. In parallel we will also focus on identifying new features that can be used to create a brain-switch as well as the techniques required to extract and process these features.

5.6 Acknowledgement

This project received financial assistance from the Toronto Rehabilitation Institute Student Scholarship Fund, Ontario Graduate Scholarships in Science and Technology, University of Toronto Open Fellowship, Natural Sciences and Engineering Research Council of Canada (#249669), Canadian Fund for Innovation (# 7313), Ontario Innovation Trust (#7313), and Ontario Ministry of Health and Long-Term Care.
Chapter 6

ECoG Real-Time Two-Dimensional Control

The material presented in this chapter has been submitted for publication to the peer reviewed journal Medical Engineering & Physics under:


6.1 Abstract

This document describes a brain-machine interface used to asynchronously control the real-time two-dimensional movement of a computer cursor using a single subdural electrode. Power changes in the ECoG signals were used to implement a “brain switch”. To activate the switch the subject had to decrease the power in the 7 Hz-13 Hz frequency range using motor imagery of the left hand. The brain switch was connected to a system for asynchronous control of movement in two dimensions. Each time the user reduced the amplitude in the 7 Hz- 13 Hz frequency band below an experimentally defined threshold the direction of cursor changed randomly. The new direction was always different to those previously rejected ensuring the convergence of the system on the desired direction. The
user was able to control the cursor to specific targets on the screen after only 15 minutes of training. Each target was reached in 51.7 ± 40.2 seconds (mean ± SD) and after 9.4 ± 6.8 switch activations. Information transfer rate of the system was estimated to be 1.1 bit/s.

6.2 Introduction

Brain-machine interfaces (BMIs) use signals from the brain to control electronic devices. This technology represents a new opportunity to communicate and interact with the environment for people with limited or no ability to move voluntarily. Some of the individuals that may benefit directly from this technology include people with advanced stages of amyotrophic lateral sclerosis (ALS), brain stem stroke, cerebral palsy, and spinal cord injury [64].

The type of signals used to implement BMI systems are as diverse as the techniques that exist to monitor brain activity. However, most BMIs use electrical recordings from the brain which can be obtained non-invasively using electroencephalographic (EEG) techniques. Alternatively, electrocorticography (ECoG) is an example of a minimally invasive measurement technique which uses electrodes placed underneath the dura mater allowing recordings directly from the surface of the brain.

The operation of a BMI often requires users to adopt specific mental states which can be identified by temporal or spectral changes in their brain activities. With EEG-based BMIs, these changes have included slow cortical potentials [69, 125, 158], P300 potential [126, 130], and changes in power of oscillatory rhythms [4]. Upon detection of a predetermined change in brain activity, a specific action is triggered effectively creating the interface between the brain and an external device. EEG-based BMIs have been used successfully to facilitate communication for individuals who have lost all ability to perform voluntary movement (e.g., as a result of locked-in syndrome [69]).
Chapter 6. ECoG Real-Time Two-Dimensional Control

The development of BMIs has frequently implemented synchronous control strategies. Under this mode of operation, the user can issue commands (e.g., adopt a brain state) only during specific time periods determined by the BMI itself. Consequently, the rate at which commands can be generated is determined by the BMI system, and not the user. This control strategy has confined the use of this technology to applications in which the time of response is not critical (e.g., face to face communication).

An important step to expand the applications of BMI technology, and create devices that can be used outside a laboratory environment, is the implementation of asynchronous control strategies. This would allow the user to generate a command at any desired instant without the mediation from the BMI. Such a device would likely result in a more natural and intuitive mode of interaction between the user and the BMI.

Asynchronous BMI systems require constant monitoring of brain activity to identify changes indicating the desire to issue a command. Until recently, only a handful of research groups worldwide had addressed the development of asynchronous BMI systems [66, 78, 160]. Despite an increase in the study of asynchronous BMIs, their implementation still remains as one of the most important challenges in the development of BMI technology.

A strategy to implement asynchronous BMIs has been the use of steady state visual evoked potentials (SSVEP) [163] generated with a set of light sources flashing at known (and distinct) frequencies. To issue a command, the BMI user looks at a specific flashing source. The BMI detects the presence of the stimulation frequency (and harmonics) in the EEG activity recorded over the visual cortex. A fundamental drawback of this approach is that it relies on the user’s ability to perform reliable ocular movements which may not be assumed for every potential user of this technology. However, there is evidence suggesting that SSVEP can be used for BMI control even without reliable gaze function [164]. Using this approach it has been possible to control a prosthetic hand [70], a simulated telephone [165], computer cursor control [166], and virtual car...
navigation [167].

A second approach used to create asynchronous BMIs consists of the identification of specific features in EEG or ECoG signals, including changes in power of specific frequency bands [91], motor potentials (ERPs) [85–87] or a combination of both power changes and ERPs [111] generated internally (i.e., not elicited using an external stimulus). These features have been detected using a variety of signal processing techniques including correlation values [85–87], wavelet coefficients [34, 110, 160, 168, 169], and adaptive autoregressive parameters combined linearly and compared to a predetermined threshold [91]. When one of these features is identified in the brain activities the BMI responds accordingly. Devices implemented in this way have been used to control a video game [169], a functional electrical stimulation systems [71], simulated wheelchair navigation [32, 75], upper limb prosthesis control [70], and virtual keyboard operation [5].

Finally, a different approach to asynchronous BMI implementation requires the user to exert continuous control over certain aspects of the activity of the brain. An example of this approach uses the self-regulation of $\mu$ oscillatory rhythm amplitude translated directly into the position of a computer cursor on a screen [33, 57, 63, 64]. While this approach has proven to be effective, the ability to control the oscillatory rhythm with the necessary accuracy requires several weeks or months of training [64] and demands constant attention from the user.

In this paper, we introduce a novel approach for the implementation of an asynchronous BMI system to control the two-dimensional movements of a computer cursor using a single subdural electrode. We do this by implementing a brain switch (i.e., an ECoG activity level detector) in combination with a novel algorithm for two-dimensional control using a single switch. The result of this proof of principle study is a system that uses simple signal processing, requires little training, and is minimally intrusive allowing the user to concentrate on the task at hand.
6.3 Materials and Methods

The single subject of this study was an 68 year old woman with a subdural electrode implanted for the treatment of essential tremor (ET) using direct brain stimulation of the primary motor cortex (MI). She was recruited at the Movement Disorders Clinic of the Toronto Western Hospital and gave her written informed consent to participate. These experiments were approved by the University Health Network Research Ethics Board, Toronto, Canada.

The subdural electrode (model Resume II, Medtronic, MN, U.S.A.) was placed over the right motor cortex and had four recording contacts (platinum-iridium, 4 mm diameter, 10 mm center to center distance). The electrode connector remained externalized for two days after implantation to optimize stimulation parameters. This time also made it possible to record using the same subdural electrode. The work presented here was conducted one day after the initial electrode implantation.

6.3.1 Stimulation of the Primary Motor Cortex

Electrical stimulation was applied directly through the subdural electrodes in a monopolar configuration to determine their exact functional location of each contact by observing contra-lateral contractions using 9 mm Ag-AgCl disposable EMG electrodes. The stimulation frequency was varied from 3 Hz to 20 Hz using a pulse width of 60 microseconds. Stimulation amplitude was increased gradually to 10.5 V. The recorded muscles included right and left frontalis, orbicularis oculi, triangularis (also known as depressor anguli oris), first dorsal interrosseus and tibialis anterior. Band-limited EMG signals (2 Hz to 2.5 kHz) signals were amplified (Intronix Technologies Corporation, model 2024, Canada) and digitized at a rate of 5000 samples per second (Micro 1401, Cambridge Electronics Design, UK). The stimulation revealed the contact closest to the cortical representation of the contra-lateral upper extremity. Only signals from this single electrode were used
for the development of the project presented here.

### 6.3.2 Experimental Setup

The activity from the subdural contact was band-limited (1Hz - 100 Hz) and amplified (100,000 times) using a high performance amplifier (Model P511, Grass Technologies, U.S.A.). The preprocessed ECoG signal was then digitized using a portable data acquisition system (model NiDAQPad-6016, National Instruments, U.S.A.).

The subject sat comfortably, approximately 50 cm away from a computer monitor. The monitor displayed a single square target (3.5 cm x 3.5 cm) and a rectangular computer cursor (2 mm x 2 mm), both contained in a rectangular area of 16.5 cm x 14.5 cm (Figure 6.1). The cursor and the target could only move within the boundaries of this area. The monitor also showed a needle dial displaying the cursor’s direction of movement and a bar that gave a visual indication of the estimated power in the ECoG activity. Finally the display also contained a virtual LED that indicated if the ECoG power was below a threshold for a determined period of time. Both the threshold and the time required for the signal to be below the threshold level could be set at run time. The software was implemented using the LabView programming language (National Instruments, TX, U.S.A.)

### 6.3.3 Signal Processing

The BMI was implemented as a “brain switch”. To do this, the activity recorded with the subdural electrode was first band-pass filtered between 7 Hz and 13 Hz. A 250 ms segment was then squared and integrated twice. The mean value of this segment was then used to calculate a moving average with the last 5 estimated mean values. A switch activation was generated whenever the value of this moving average was maintained below an experimentally determined threshold for 1.25 seconds. Additionally, the system incorporated a “refractory period” of three seconds in which the system could not be
Figure 6.1: Experimental task display. The participant was asked to direct the cursor (small black square) toward a target (large grey square) of 3.5 cm x 3.5 cm in size. The target moved to a different location, selected randomly, every time it was reached by the cursor. The direction of the cursor changed each time the brain switch was activated and it could only move within a rectangular 16.5 cm x 14.5 cm area.

activated again after a first activation.

6.3.4 Experimental Task

The subject was asked to control a computer cursor in two dimensions towards a target. The target disappeared and reappeared in a random location when it was reached by the cursor. The participant completed three trials. The subject navigated the cursor to four (trial 1) or five (trials 2 and 3) different positions.

Our experimental measurements included: a) the number of activations required to
complete each trial, b) the number of activations required to reach a specific target, 
c) the time required to complete a trial, and d) the time as well as the number of activations 
required to reach each one of the targets were measured.

6.3.5 Asynchronous Control Strategy

A new asynchronous control strategy was implemented to control the two-dimensional 
movement of the cursor on the screen using the brain switch. This strategy was presented 
in [161]. With this strategy, the activation of the switch is used to indicate that the 
current behaviour of the device under control is not the desired one. This differs from 
a traditional function given to single switches were they are used to initiate a desired 
behavior from the device.

To control the cursor on the screen, the participant had to activate the switch re-
peatedly. The participant would activate the switch only if she was not satisfied with 
the direction of the cursor at any moment. Each time the switch was activated the cur-
 sor changed its direction. The new direction of cursor movement was determined in the 
following way: first, the screen was divided into a matrix of 8 rows and 8 columns. When-
ever the switch was activated, the control algorithm would select a target described by an 
x,y pair corresponding to the column and the row towards which the cursor should move. 
Each x and y value was selected independently on the n\textsuperscript{th} switch activation according to 

\[
c_{[n]} = \text{argmin}(\gamma_{[n]}(c))
\]

where

\[
c = c_x = c_y = \{0, 1, 2, 3, 4, 5, 6, 7\}
\]

was the set of all possible values that x and y could adopt representing the rows and 
columns into which the screen was divided,
and

\[ \gamma[n](c) = H[n](\Delta t)\gamma[n-1](c) + \chi[n](c) \left\{ 1 - H[n](\Delta t)\gamma[n-1](c) \right\} \] (6.3)

Equation 6.3 describes a temporo-spatial exclusion mask used to ensure that the control system eliminated the rejected direction temporarily each time the cursor changed its behaviour, so that it would not be selected in subsequent activations. This was accomplished with the temporal weighting factor \( H[n](\Delta t) \) in equation 6.3 defined as:

\[ H[n](\Delta t) = \exp\left(-\frac{\Delta t}{\tau}\right) \] (6.4)

Where \( \Delta t \) is the time between the last two switch activations (\( n \) and \( n - 1 \)). The time constant \( \tau \) was set to 250 seconds.

The function \( \chi[n](c) \) was a spatial weighting factor reducing the probability that any directions similar to a rejected one were selected. It was defined as

\[ \chi[n](c) = \begin{cases} 1 - \left(\frac{r}{\alpha_s}\right) & \text{if } r \leq \alpha_s \\ 0 & \text{if } r > \alpha_s \end{cases} \] (6.5)

Where \( r \) is the distance between a rejected direction and neighboring directions. The parameter \( \alpha_s \) is an arbitrary constant defining the spatial extent of the effect of equation 6.5. \( \alpha_s \) was set to 8 extending the effect of equation 6.5 to the entire screen.

Figure 6.2 depicts the access strategy used. Additional details can be found in [161] and the open source software libraries for the control strategy are available at http://jsilva.komodoopenlab.com/index.php/Projects/Access.

Once the new values of \( x \) and \( y \) were selected, the direction of movement was determined by first estimating \( \lambda \) according to:

\[ \lambda = \left\lfloor \text{sig}(x) + 1 \right\rfloor + \left\lfloor 10(\text{sig}(y) + 1) \right\rfloor \] (6.6)

The value of \( \lambda \) was then translated to an angle according to Table 6.1. The angle
Figure 6.2: Temporo-spatial exclusion mask described by equation 6.3. This function ensured that rejected directions of movement, as well as neighbouring directions, were eliminated temporarily to avoid their selection. The figure shows three switch activations at instants \( n - 3 \), \( n - 8 \), and \( n - 11 \).

determined the direction (out of the 44 possible options) of the moving cursor. Using this approach, it was ensured that the motion of the cursor always converged to the direction intended by the participant.

### 6.4 Results

The participant was able to operate the brain-switch after 15 minutes of usage. Consequently, it was possible for the participant to control the movement of the cursor and reach all of the targets successfully. Figure 6.3 shows several activations of the switch along with the processed ECoG activity.

The participant was able to reach all targets and the average time needed to reach each target was 51.7 ± 40.2 s. She needed 53 ± 5.6 activations to reach an individual target and each activation required 5.5 +/- 3.41 s. Each trial was completed in 250.4 ±
Table 6.1: Estimation of Direction of Movement. The value of $\lambda$, estimated according to equation 6.6, was used to determine the direction of movement of the cursor according to the values presented in this table.

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>Estimated direction</th>
<th>$\lambda$</th>
<th>Estimated direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>$\tan(x/y) + \pi$</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>$3/2\pi$</td>
<td>20</td>
<td>$\tan(x/y) + \pi$</td>
</tr>
<tr>
<td>2</td>
<td>$\tan(x/y) + 2\pi$</td>
<td>21</td>
<td>$\pi/2$</td>
</tr>
<tr>
<td>10</td>
<td>$\pi$</td>
<td>22</td>
<td>$\tan(x/y)$</td>
</tr>
</tbody>
</table>

Figure 6.3: Brain switch Activation. The figure shows five activations of the switch along with the ECoG power in the 7 Hz - 13 Hz bandwidth and the processed signal used for switch activation. The vertical dotted lines show the time required for the processed signal to be below the threshold before an activation could be generated. After an activation, the system could not be activated again for three seconds.
9.6 s

While a single activation of the brain switch carries a single bit of information, the control strategy made it possible to select one of the 44 possible directions in which the cursor could move. This selection process would typically require the use of six bits. With an average time of 5.5 s between each activation, the estimated information transfer rate was 1.1 bit/s.

Table 6.2: Results for individual trials. Figures describing performance of the BMI during three experimental trials.

<table>
<thead>
<tr>
<th>Trial #</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Number of Targets acquired</td>
<td>4</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Time required to complete trial (s)</td>
<td>257.3</td>
<td>254.6</td>
<td>239.3</td>
</tr>
<tr>
<td>Activations required to complete trial</td>
<td>59</td>
<td>52</td>
<td>48</td>
</tr>
<tr>
<td>Average time between activations (s)</td>
<td>5.1 ± 3.1</td>
<td>5.8 ± 3.5</td>
<td>5.6 ± 3.7</td>
</tr>
<tr>
<td>Average number of activations per target (s)</td>
<td>12.5 ± 9.7</td>
<td>8.2 ± 6.1</td>
<td>8.2 ± 6.1</td>
</tr>
<tr>
<td>Average time between reaching targets (s)</td>
<td>64.3 ± 58.2</td>
<td>47.9 ± 32.2</td>
<td>45.9 ± 37.7</td>
</tr>
</tbody>
</table>

6.5 Discussion

We presented a novel approach to provide two-dimensional asynchronous cursor control using a single electrocorticographic electrode. A single subdural electrode was used to implement a brain-switch using comparison of the power levels of 7 Hz - 13 Hz with an experimentally determined threshold. The single participant of this research was able to control the direction of the cursor to reach targets on a computer screen.

The control strategy used changed the direction of the cursor in movement with each brain-switch activation. The movement of the cursor converged to the direction desired
by the user after an average of 8-12 activations. This represented less than 30% of the 44 possible directions in which the cursor could move.

To this day, one of the limiting factors of the information transfer rate of BMI systems is the small number of commands that these devices can generate. With a single identifiable brain-state it is possible to generate one command. For this reason, increasing the number of brain states that can be identified has been a strategy to increase the information throughput of BMI systems [162]. This has been done by implementing sophisticated computational methods [75] and/or by increasing the features in brain signals that a person can control voluntarily [64].

A second strategy to increase the information transfer rate of BMIs has been to use neural signals with richer information content. This had lead to the development of BMI systems that use small populations of neurons acquired invasively. While it has been possible to control robotic arms and computers using this approach, many of these systems rely heavily on various constraint equations to restrict the movement of the device beyond the desirable envelope. Another concern, that is still an issue, which most likely will be resolved with new technology and surgical techniques, is that it is still necessary to assess the long-term viability of these highly invasive systems.

The methods used to improve the communication transfer rate of BMI systems often result in devices that are difficult to use, or require extensive training. The system that we presented here uses self-regulation of oscillatory rhythms at 7 Hz -13 Hz detected via comparison of a threshold. The use of this approach has been reported extensively for BMI applications. What is unique about this work is that it showcases the integration of very simple ECoG processing method combined with a technique for real-time two-dimensional asynchronous control. Our goal was to test this combination. We believe that the system presented allows the user to concentrate on the task at hand. The attention of the user is not divided between the goal (the intended action) and the cues provided by the interface for its operation. In addition, the timing of the interaction is
not determined by an automatic agent. Instead the user decides when to use the system.

While the processing of the ECoG signals that we implemented had a dwell time of 1.25 s and a refractory period of three seconds, both representing a limiting factor in the communication rate of this system, it is important to mention that the control strategy has no restrictions over the time at which a switch activation may occur or the number of directions that can be made available to the user. In this work, the speed at which the cursor can change direction is not dependent on the control mechanism but rather on the methods used to detect the power changes in the ECoG signals. It is very likely that the combination of the control strategy presented here with different strategies for implementing a brain switch results in an increase in the speed at which control commands can be generated increasing the usability of this system.

We had previously tested the control strategy presented here using EEG recordings [170]. The time required to learn how to decrease the power in the 7 Hz - 13 Hz band required 5 days using EEG compared to 15 minutes using ECoG. This reduction in time necessary for acquiring control over brain oscillations appears to be consistent with results from other research groups developing ECoG-based BMI technology [56]. In this implementation, it appears that the use of subdural electrode provides an advantage over surface recordings. We believe that the work presented here represents a simple alternative for BMI implementation to control two-dimensional movements.

There are important limitations to this study. First, this study was conducted with a single participant. The electrodes used for the implementation of the system described here were implanted over MI as part of an experimental treatment for the treatment of ET and Parkinson’s disease. The participant was the last of less than ten individuals who received this treatment. No further surgeries are planned and consequently, there will be no more individuals to conduct similar experiments until the effects of applying electrical stimulation MI is better understood. As a result, these experiments are very unique, and it may take several years before similar experiments can be performed again.
as at the present time it is not clinically justified to place ECoG electrodes over the MI area.

Further, the extremely small number of individuals undergoing this treatment also resulted in very limited available time windows in which it was possible to conduct studies. As a consequence, other limitations of this work include a small number of test conducted with different activation thresholds and activation time constants.

It is worth mentioning that the participant enjoyed the experience thoroughly. We cannot say the same thing for our previous BMI systems, where it was our impression that the users were either indifferent or were looking forward to the end of the experiments. In this particular case the patient had a lunch break in the middle of the session and returned on her own to continue to participate in the experiment. Although, this is a single case study, we believe that this observation is important and may suggest that patients are able to do this kind of task with ease.

Acknowledgments

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Conflict of Interest

The authors do not have any financial interest in any of the mentioned companies or products.
Chapter 7

Discussion and Conclusions

7.1 Summary

This document described a novel system for the identification of specific movements performed with the same limb using electrocorticographic signals recorded with four subdural electrodes. The two participants of the study were patients in the process of receiving a direct brain stimulation system for the treatment of tremor symptoms associated with Parkinson’s disease and essential tremor. ECoG signals and kinematics of an arm in motion were recorded simultaneously. The time-resolved spectral components of ECoG signals with the strongest correlations with each of the kinematics of arm movements were grouped in a histogram. These histograms were unique and consistent for each performed movement. Consequently they were used as features for classification using a nearest neighbour classifier with an accuracy of 89%.

The classification system was then coupled with a neuroprosthesis for grasping. This device allowed an individual with quadriplegia to lift and manipulate a series of objects via the electrical stimulation of his paretic hand muscles. To operate the neuroprosthesis, the user had to press one of three accessible buttons. Each button was used to facilitate one of the following functions: palmar grasp, lateral pinch, turning the neuroprosthe-
sion on or off. The activation of a button triggered the classification of an ECoG signal obtained previously, using subdural electrodes, from a different individual who had performed specific arm movements at the time of the recording. When the classification was correct (i.e., when the arm movement was identified correctly), the neuroprosthesis produced the movement corresponding to the button pressed. The system identified the arm movements with an accuracy of 94.5%.

Finally, two systems were described for the real-time asynchronous control of two-dimensional motion. Both BMIs were implemented as a switch which was activated whenever the power of the recorded neural signal fell beneath an experimentally defined threshold. The participants of these studies were able to change the power of the oscillatory rhythm in the 7 Hz - 13 Hz range through the imagination of hand movements. In one study an EEG signal was used to control a miniature remotely-controlled vehicle to any of three different targets. The user required three days to be able to modify the power in his EEG signals. In total, the participant of this study was able to reach 7 different targets in 11 minutes with an average time of 90.71 seconds to move between targets.

The second study showcased the control of a computer cursor using a single subdural electrode. The direction of the cursor had to be altered to reach moving targets placed randomly on the screen. In contrast to the three days required using EEG signals, the participant was able to gain control the cursor after only 15 minutes of exposure to the system.

7.2 Contributions of this work

The work presented here adds to the field of BMI in several ways. First, the ability to identify several movements performed with the same limb represents an important contribution. At the time of publication, most of the work conducted for the discrimina-
tion of movements from brain recordings involved motor tasks performed with different body parts. While this is adequate, identifying different movements performed with the same body part opens the possibility of controlling assistive devices for the facilitation of movement with a high degree of transparency. It may also increase the number of commands that can be generated with a BMI. This is of particular relevance given the high number of degrees of freedom that current neuroprosthetic systems offer as well as the proposed design changes on upper limb prosthesis currently proposed by the Revolutionizing Prosthetics Program of the Defence Advanced Research Projects Agency (DARPA). This new generation of upper limb prostheses intend to mimic the movement of a human hand as closely as possible. Indeed, the use of neural signals is being explored most extensively as one of the possibilities for the strategy to control this new generation of assistive technology.

This work also contributes to the field by describing a BMI using subdural electrodes. At the time of publication, Chapter 3 was one of approximately ten peer reviewed articles describing the use of ECoG signals for BMI development. To day, the majority of reports in the BMI field describe systems that are implemented using surface (EEG) recordings likely due to their availability and non-invasive nature. However, EEG signals are very susceptible to interference, provide limited spatial resolution and their acquisition requires the placement of electrodes which ability to record degrades quickly. There are also several reports describing the use of single neuron and or neuronal ensemble activity for the implementation of BMI systems. These recordings are obtained using intracortical microelectrodes and are considered to be highly invasive. ECoG signals, such as the ones used in the work described here, are considered to be an intermediate technology: they are more resilient to interference, they do not require the repetitive placement of sensors and they are considered minimally invasive as they are placed on the surface of the cerebral cortex, rather than penetrating it. Also, the system is robust and once installed there is no need to consistently verify the contact viability as is the case with
single neuron recordings. Furthermore, the system does not damage neural tissue; unpublished experiments conducted in our laboratory suggest that penetrating electrodes cause the damage to the tissue that can be reflected in altered body functions such as balance. While it is still not clear what is the best signal for BMI implementation, it is hoped that the material presented here helps answer this question in the future.

Another important contribution of the material presented here was the integration of BMI technology with a novel strategy for single switch asynchronous control. This resulted in a novel implementation in which a switch-like BMI was used as a control signal for a complex task.

All of the systems created during the development of this project were characterized by simple feature extraction procedures as well as classification and detection approaches. Further, in every case, the systems can be setup, calibrated and tested in only a few hours. While it was not a primary goal of this project, it appears that the severe scheduling environment under which most of this work was conducted, facilitated the creation of highly portable and configurable systems.

The participant in the study reported in Chapter 6 learned to control the computer cursor after only 15 minutes. While similar decreases in training time have been reported for ECoG-based systems, it is important to mention that the individual found the system intuitive; the operation of the BMI never appeared to be an obstacle to achieve the primary goal of the task (directed cursor control). In fact, the participant appeared relaxed and seemed to enjoy using the system, which differs significantly from any other experience we have had in the development of BMI technology.

The direction of the computer cursor was not constrained by any function that maps the brain activities into specific behaviours (e.g., movement directions) of the system. Instead, the implemented system allowed the use of a neural signal without any additional processing to control the device. It appears that this lack of restrictions imposed by a mathematical function to which the user must comply, results in a system that is more
intuitive and easier to use. It also suggests that this approach would minimize or eliminate
the calibration process involving the creation of novel mapping functions to deal with
changing neural responses, as it is currently the case with single neuron and neuronal
ensemble-based BMI systems.

7.3 Limitations of the study

There are several limitations to the work presented in this thesis. First, the number of
participants of the studies here was very small. This was due to the fact that only a few
individuals undergo implantation of subdural electrodes over the motor cortex per year.
Further, not every individual who receives this treatment is willing or able to participate
as the studies are conducted a few days after the surgical implantation of the sensors.

Third, the study for which these electrodes were originally implanted was also exper-
imental in nature. As patients did not show overwhelmingly positive results the study
was discontinued, which in turn resulted in a temporary cessation of ECoG electrode
implantations in MI area of the cortex at the Toronto Western Hospital. For this reason,
we were unable to continue with this work and test our ideas and BMI systems with a
larger patient population.

Another limitation of the work presented here is that the identified arm movements
in Chapters 3 and 4 were real. This is not ideal given that the target population of
this technology will have limited or no ability to move voluntarily, or even missing limbs
with which to perform the motion. Furthermore, the feature extraction process makes
use of the correlation between ECoG activity and a kinematic recording. However, this
represents a starting point for the development of this technology.

Another important area of improvement for the work concerning the two-dimensional
motion control in Chapters 5 and 6 is the fact that the temporal parameters of the
control strategy were not optimized for the individual. These parameters include: 1) the
“latency time” during which it was not possible to activate the BMI, 2) the amount of
time during which the user was required to maintain a reduced power level in the 7 Hz -
13 Hz range, and 3) a selection of frequency ranges over which the user may have more
immediate control.

The studies conducted as part of this work were all proof in principles in nature. We
wanted to show that very different types of BMI systems can be developed and used
from those presently available. Our main concern was on providing different alternative
strategies an not the optimization and improvement of efficacy of the developed systems.
There is much room for improvement for the BMI strategies presented here. We hope
this will provide a platform for the formation of future researchers in the field of BMI.

7.4 Lessons learned

7.4.1 Identification of arm movements using ECoG recordings

The participants of this study showed a lot of initial interest. It is likely that taking part
on these experiments provided a distraction from their hospital stay. However, they all
became uninterested in the experiments very quickly given the repetitive nature of the
task.

A particularly challenging aspect for the completion of this project was the limited
number of experimental subjects. This was worsened by the fact that access to the par-
ticipants was usually limited to a few hours including experimental setup time. Despite
the limited availability of experimental individuals, the amount of collected data was
overwhelming. It is now clear that access to powerful computation equipment is required
for a detailed analysis of ECoG signals.
Chapter 7. Discussion and Conclusions

7.4.2 ECoG Neuroprosthetic control

While there have been other examples integrating BMI technology and neuroprostheses, these studies often focused just on the creation of BMI systems with commercially available orthotic or prosthetic systems. We are the only group that was able to create both technologies internally. One of the most valuable lessons learned consisted in the practical experience in integrating neuroprosthetic and BMI systems.

We have now come to understand that it will probably take a very long time before an ECoG-based BMI system can be used by a person that does not require implantation of subdural electrodes. It is likely that the difficulty of finding experimental subjects will be much greater than the one faced when obtaining the ECoG recordings.

7.4.3 Asynchronous BMI implementation

A surprising finding concerning the work conducted on the asynchronous control of two-dimensional trajectories using ECoG signals was the short time, 15 minutes, that the user required to operate the BMI reliably. Initially, motor imagery of the hand was suggested to the participant as a strategy to induce changes in this frequency band. A special interface (not described in Chapter 6) with a graphical display of the power in the 7 Hz-13 Hz frequency range was presented to the participant who was asked to reduce or increase the power in this frequency band for ten minutes. The subject reported not to achieve any level of control over the brain oscillations. Given the small time window allowed for our experiments, a decision was then made to present the participant with the two-dimensional control task. After only five minutes of operation, the user was able to elicit changes in the direction of the cursor voluntarily and was able to reach targets appearing on the screen. The participant was asked how she was switching the direction of the cursor in motion (activating the BMI). She reported that she had stopped using motor imagery of the hand and instead just concentrated on “making the cursor move”.
7.4.4 General experiences gained

After the completion of this research, it has become evident that conducting research in a clinical environment often poses challenges that exceed those found in a dedicated research facility. In the case of this particular work, these difficulties included a complete dependency on the status of the patients (i.e., their willingness and/or ability to participate), and availability of staff to supervise or assist in the conduction of the experimental procedures. While these problems are not of a technical nature, they have a significant impact on the plausibility of BMI experimentation within a hospital setting.

The difficulty of performing BMI experiments is also increased if the research is conducted off-site. This was the case for most of the work presented in this document. To conduct our research, it was first necessary to implement an experimental setup that was portable, fast to setup, easy to troubleshoot and easy to interface with other recording equipment. In total, four different versions of this setup were created.

It has also become evident that BMI research and development requires a team of individuals with different abilities given the multiple aspects on which successful experimentation depends on. The work presented here required extensive work on the areas of hardware and software development, instrumentation, neuroscience, signal processing, and automatic classification. Without input from individuals representing each one of these disciplines, this work would not have reached completion.

7.5 Future directions

Future work should focus on identifying intended movements. This would represent eliminating the correlation between the kinematic and spectral ECoG components. The development of BMI that can be operated with the intention of performing specific movement could likely be performed with the data already obtained from the work conducted here. This would be achieved by focusing on the activity prior to the onset of move-
ment [37]. Such work would represent a significant improvement over the work presented here as it would provide the opportunity to explore the control of neuroprosthetic devices by individuals with spinal cord injuries.

An important next step in the integration of BMI and neuroprosthetic systems is to ensure that the identified movements (whether real or intended) match the movements facilitated by the neuroprosthesis. This will result in a novel assistive device in which the mental state adopted by the user is highly related with the functional outcome.

While the asynchronous control strategy proved useful in the implementation of a BMI system, its efficiency may be improved significantly by optimizing: a) the frequency band(s) that that the subjects use to activate the BMI, b) the threshold under which the power must be maintained to operate the BMI, c) the amount of time during which this power level must be sustained, and d) the latency time during which it is not possible to operate the BMI once triggered. Significant improvements may also result from the use of different feature extraction techniques and by combining the control strategy with predictive systems that may be used to increase the speed at which the BMI converges to the desired action.

Additionally, careful thought will be required to implement the asynchronous control strategy in the context of three-dimensional motion control, likely required for the control of prosthetic limbs or neuroprosthetic devices. While the control strategy is ideal for navigation in two dimensions, three-dimensional control will pose a significant challenge to ensure that rejection of a particular behaviour (e.g., a specific trajectory) does not imply rejection of a secondary one that is actually desired.

There is also a great opportunity to compare BMI systems implemented using intracranial and surface electrodes. Exploration of differences in BMI performance should be conducted to provide additional information on advantages and/or disadvantages of each one of these systems. Areas of comparison may include usability considerations (e.g., training time required and ease of operation) and communication throughput.
Finally, it appears that the implementation of BMI technology using subdural signals offers some advantages over the use of both EEG and single neuron (and neuronal ensemble) recordings. And while subdural electrodes have a good track record of reliability and safety for human use, it is still unknown what the long-term stability, reliability, and safety of subdural recordings is. For this reason, future work should include an assessment of the long-term viability of an ECoG based BMI system.
Bibliography


vice: a neurophysiological approach to communication in total motor paralysis.,”


[34] G. E. Birch, Z. Bozorgzadeh, and S. G. Mason, “Initial on-line evaluations of the lf-asd brain-computer interface with able-bodied and spinal-cord subjects using imag-


