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2014

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UNIVERSITY OF CALIFORNIA,
IRVINE

Novel Data Processing Techniques for High-Performance Brain-Computer Interface

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Biomedical Engineering

by

Po-Tang Wang

Dissertation Committee:
Professor Zoran Nenadic, D.Sc., Chair
Professor Frithjof Kruggel, M.D.
Professor James P. Brody, Ph.D.

2014
DEDICATION

To my parents and my brother...
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6.8 Average and best composite online performance score for SCI subjects for each experimental day as calculated using Equations. 6.2 and 6.3. The composite scores for random walk and the physical joystick are also shown for comparison. Note that Subject S3 did not achieve purposeful control on day 1 and was therefore unable to participate in online sessions on this day. Subject S1 did not participate after the first day.

6.9 Comparison of the present study to similar studies in the field.


6.11 Online performances: cross-correlation between BCI-RoGO walking and cues at specific lags, number of omissions and false alarms, and average duration of false alarm epochs.

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ACKNOWLEDGMENTS

I would like to thank my advisor Dr. Zoran Nenadic, co-Principal Investigator Dr. An H. Do, and my colleagues in the Center for Biomedical Signal Processing and Computation (CBMSPC) laboratory, Christine E. King and Colin M. McCrimmon, for all their contributions.

Studies and projects in this dissertation were funded by the Roman Reed Spinal Cord Injury Research Fund of California (RR 08-258 and RR 10-281), the National Science Foundation (Awards #1134575 and 1160200), the Long Beach Veterans Affairs Southern California Institute for Research and Education (SCIRED) Small Projects Grant, and the Spinal Cord Injury Fund.

Finally, I would like to acknowledge the publishers of our previous works for copyright permissions, BioMed Central Ltd., Institute of Physics and IOP Publishing, Elsevier Ltd., and Institute of Electrical and Electronics Engineers.
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ABSTRACT OF THE DISSERTATION

Novel Data Processing Techniques for High-Performance Brain-Computer Interface

By

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Doctor of Philosophy in Biomedical Engineering

University of California, Irvine, 2014

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Brain-computer interface (BCI) is a direct communication pathway that decodes brain signals directly into actions. It is intended for restoring the abilities to move and communicate for individuals who have become paralyzed. In electroencephalography (EEG)-based BCI, signals on the surface of the brain are analyzed and decoded in real-time into computer commands. However, the signals are weak and noisy. Current BCIs are thus limited in speed, accuracy, and number of useful applications.

By using novel data-driven, statistical machine learning algorithms, we developed a high-performance BCI framework that is intuitive, robust, and require short training time. Specifically, we developed a BCI-controlled spelling device and a BCI based on intuitive motor imageries.

The data-driven techniques eliminate traditional ad-hoc methods of selecting channels and frequencies. Instead, the dimension reduction (classwise principal component analysis) and discriminant feature extraction (approximate information discriminant analysis) algorithms work on all data to identify the most salient features. This means that BCI users are free to use intuitive mental imageries, such as the imagery of walking to control ambulation, thereby cutting down the training time from 3-4 weeks to 10-15 minutes.
6 able-bodied (AB) individuals participated in using the BCI-Speller and all achieved spelling speed at least 0.5 bits/s faster than 5 other studies found in the literature. The fastest subject was able to achieve 3 bits/s, almost 3 times faster than the next highest performing system.

For the Motor BCI, 8 AB and 6 subjects with paraplegia due to spinal cord injury (SCI) used BCI to control a virtual reality walking simulator. In 10-15 minutes training, almost all subjects were able to attain purposeful control and were able to complete a goal-oriented test with high scores. In addition, 1 SCI subject also used BCI to control a robotic gait orthosis to walk on a treadmill.

These achievements show that the data-driven approach is an important component of BCI. With further research, BCI may eventually become widely accepted in neurorehabilitation and in restoring independence to and lower the medical and societal costs of paralyzed individuals.
Chapter 1

Introduction

Brain-computer interface (BCI) is a direct communication pathway between a human brain and a computer device. It is often used for restoring functions for individuals who have lost some or all motor functions due to diseases or accidents. Particularly, individuals with amyotrophic lateral sclerosis (ALS), spinal cord injury (SCI), brain stem stroke, traumatic brain injury, and other neuromuscular diseases can benefit most from BCI [149, 11]. Depending on the severity of the injuries or medical conditions, the patients may have partial or total lost control to legs, arms, or even all muscle control. In these cases, BCIs can help the patients communicate with other people and help regain control of their disabled limbs.

In a BCI system, electrophysiological signals are recorded from the brain, analyzed in real-time, and translated to computer commands for various end-effectors such as a virtual keyboard [38], virtual reality environment [83], robotic arms [55, 134], functional electrical stimulation (FES) devices [97, 106]. A virtual keyboard, for instance, could enable a patient with end-stage ALS or severe tetraplegia to regain the ability to communicate. Also, a FES device could enable patients with paraplegia to regain the use of their legs. Essentially, the ability to reliably control a computer-attached device effectively affords these patients a
greater independence and a greater quality of life.

BCIs operate on the principle that a particular mental thought or physical movement elicits a particular brain activity pattern. These brain activities are picked up as electrical, magnetic, or other types of signals by sensors around the brain. To use BCI, the user forms a mental imagery or attempts to perform an action. Based on a set of pre-determined parameters, the brain signals are decoded to the corresponding commands, such as typing words on the computer screen or moving a robotic arm. The user receives the feedback (e.g. words appearing on screen or movement of robotic arm) and continues or adjusts their mental imagery or actions. Overall, these steps form a closed-loop flow of information between the user and the BCI-controlled device.

The problem with current BCI is the poor signal-to-noise (SNR) ratio of the brain signals, leading to a limited speed at which the user’s intentions can be reliably decoded. Electroencephalography (EEG), the most common non-invasive technique to acquire brain signals, suffers the problem of limited bandwidth and poor spatial resolution due to the tissue and bone layers acting as smearing filters, effectively blocking out any useful signals above 35 Hz frequency. Extensive user training or techniques are necessary to enhance the brain signals to make BCI practical as a prosthetic device. Some of these training involve using unintuitive mental imageries, such as moving a tongue and doing math to operate a computer mouse. Some may justify the lack of intuition by stating that BCI usage is a skill, since it merely replaces nerves and muscles. However, such training often require users to attend laboratory sessions for 2–3 weeks [149].

Here, we report on a new data-driven approach on BCI: By using data-driven statistical techniques to process brain signals, we propose that the BCI training time can be significantly shortened by shifting the burden of training from the user to the computer. Instead of the user conforming to arbitrary controls, such as modulating their brain wave frequencies [150], one can use natural motor imageries. As a result, the intuitiveness shortens the
time before a user can take effective control of the BCI. The proposed techniques also tailor specifically to each user, greatly improving the the speed and accuracy of BCI operation. In this dissertation, we report on the development of BCI systems that enable users to control a keyboard-like spelling device at up to 3 times the previously reported speeds, and to control a virtual walking simulator and a robotic walking orthosis with up to 100% accuracy, all with less than 15 minutes training time each. The BCI walking system is also a part of a more ambitious goal to restore able-body-like ambulation to individuals with paraplegia.
Chapter 2

Literature Review

2.1 Motivations

Many neurological disorders and injuries can disrupt the ability of a human brain to interact with the person’s surroundings. Spinal cord injury (SCI), brainstem stroke, traumatic brain injury, amyotrophic lateral sclerosis (ALS), and cerebral palsy are just a few examples that impair the neural pathways responsible for controlling the muscles. Studies reported that approximately 6.8 million and 273 thousand people in the U.S. are affected by stroke and SCI, respectively [2, 48]. Depending on the level of disability, affected individuals can become unable to walk, unable to move their arms, and even unable able to speak. The most severely affected may lose all voluntary control of muscles, including eye movements and respiration, resulting in a “locked-in” state, i.e. completely unable to move or communicate. Although modern life-support technology enables these affected individuals to live a long life, it has also resulted in prolonged personal, economical and societal burdens [149]. Each year, SCI alone costs the health care system $40.5 billion. Many people with SCI-related co-morbidities are also forced to rely on families and friends for caregiving. The value of such informal
caregiving is estimated to be $306 billion annually [9].

Since there are currently no restorative treatments for these affected individuals, technological approaches have been sought to substitute for the lost motor functions. Depending on the level of disability, different kinds of robotic and biomedical devices are used to restore independent mobility. For instance, robotic exoskeletons (Figure 2.1) [8], functional electrical stimulators (FES) [50], and spinal cord stimulators [52] can re-enable the ability to ambulate. However, these systems lack the able-body-like supraspinal control of ambulation, and therefore require manual (by hand) control. This means that when a user is engaged in ambulation using one of these devices, his/her hands are not available for other tasks. For example, while walking with a Parastep FES system [124] (Sigmedics, Fairborn, OH), the user is required to use a series of manual push buttons on a walker to ambulate (Fig. 2.1). In addition to being un-intuitive, these systems may be costly and cumbersome to use. Due to these issues, individuals with lower extremity paralysis are still limited to wheelchairs as the primary means of mobility.

There are also devices that attempt to restore the ability to communicate for individuals with tetraplegia or late-stage ALS. For example, eye gaze tracking systems have been developed to help these individuals answer yes/no questions, control speech synthesizers, and operate personal computers [77, 15, 79]. However, these systems monopolize the remaining motor functions of these individuals and are slow to use.

Ultimately, the underutilization of the affected parts of their body and extended reliance on wheelchairs typically lead to a wide variety of co-morbidities, such as muscular atrophy, metabolic derangements including diabetes [119], cardiovascular diseases [115], osteoporoses [153], and pressure ulcers [111], that significantly increase health-care costs.

BCI is a promising technology to improve the quality of life of paralyzed individuals, allowing them to maintain physical exercise, reduce the reliance on caretakers, regain independence
and social integration, and reduce the incidence of associated medical comorbidities.

2.2 Principles of Operation

2.2.1 Brief History

Electroencephalography (EEG) was discovered in the 1920s by Hans Berger when he recorded electrical signals from the brain (Figure 2.2) [10]. Since its discovery, EEG has been used mainly to evaluate neurological disorders such as seizures in the clinic and to investigate brain functions in the laboratory. Following the developments of biological amplifiers, electrodes, signal analyses techniques, new theories, and electrode placement standards in the
subsequent decades, ideas of using EEG as means to decipher the thoughts of a person began to surface [132, 149, 65]. In a pilot study at the University of California, Los Angeles in the 1970s, the feasibility of a BCI was carefully examined [140].

![First human EEG recorded by Hans Berger in the 1920s](image.png)

**Figure 2.2:** The first human EEG recorded by Hans Berger in the 1920s [10]. Top is the EEG, bottom is a reference 10 Hz timing signal.

### 2.2.2 How BCI Works

BCIs operate on the principle that there is a correlation between mental processes and measurable brain activities. These brain activities are picked up by sensors around the brain. EEG, for instance, would pick them up as time-varying electric signals. Figure 2.3 describes the flow of information between a user and the BCI. Generally, to use BCI in the “online mode”, the user performs a mental task (e.g. imagine moving a finger) or attempts to perform a physical movement (e.g. actually moving a finger). The changes in the brain activities are picked up by the sensors, sent to the computer, and decoded to computer commands based on a set of pre-determined parameters. These commands are sent to the end-effectors such as a computer screen or a robotic arm. The user receives the feedback (e.g. words appearing on screen or movement of robotic arm). Overall, these steps form a closed-loop flow of information between the user and the BCI-controlled device. On the other hand, “offline mode” refers to merely collecting brain signals and performing all the necessarily computations to estimate the performance if the user were to actually use the BCI for useful tasks. The user does not receive real-time feedback during this mode.

The following subsections elaborate on the different types of signal modalities, EEG signal acquisition, bioamplification, and BCI training and control paradigms.
Figure 2.3: Flowchart of a generic BCI in online mode (left) and offline training mode (right). Many BCIs require some forms of training to learn the user’s brain signals. During training mode, brain signals corresponding to known mental tasks are acquired, processed (e.g. band-pass filter, Fourier transform), and the algorithms learn the mapping between the brain signals and the mental task, including how to appropriately extract the important features from the brain signals to maximize decoder performance. Sometimes, experimenters need to manually adjust the BCI to improve decoder performance. The training parameters are saved to a database and are used again in online mode. In online mode, the BCI uses the training parameters to extract and decode brain signals into control commands for the output application, such as typing on screen, moving a cursor, or operating a robotic arm. The user observes the output as the feedback, forming a closed-loop flow of information.
2.2.3 Signal Modalities

Multiple methodologies are available for acquiring brain signals (Figure 2.4), including functional magnetic resonance imaging (fMRI), scalp electroencephalography (EEG, scalp EEG, surface EEG), electrocorticography (ECoG, intracranial EEG), cortically implanted microelectrode array (MEA), magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), and more. Considering that a practical BCI will be used in common places like a home, a shopping mall, or on the streets, size and cost of the equipment, concerns about aesthetics and infection risks must be considered. fMRI and MEG are unsuitable due to requirement of large and expensive equipment and shielded rooms. Invasive measurement techniques such as ECoG or implanted micro-electrodes offer superior signal fidelity than scalp EEG [85], but are currently not practical for BCI due to risks of surgery, infections, and tissue damage. fNIRS requires light emitters and detectors and cannot measure cortical activity more than 4 cm deep due to limitations in the emitter. Thus, most BCIs acquire brain activities via EEG.

2.2.4 Electroencephalography

EEG signals are generated by cortical nerve cell inhibitory and excitatory postsynaptic potentials (IPSP and EPSP). These potentials summate in the cortex and extend to the scalp surface where they are picked up by scalp-mounted electrodes [39]. Typically, these electrodes are arranged according to a standard. The 10-20 (and the 10-10) International Standards are commonly used in BCI (Fig. 2.6), where the head is divided into a horizontal grid from left ear to right ear and a vertical grid from nasion to inion, and electrodes are placed 10% and 20% apart on the grid. The 10-20 standard allows 21 electrodes, and the 10-10 standard allows 75 electrodes.

The EEG signals are picked up by metal electrodes, amplified using bioamplifiers, and then
Figure 2.4: Acquisition of brain signals using different modalities. Electroencephalography (EEG) measures electric signals on the scalp. Functional near-infrared spectroscopy (fNIRS) measures optical signals due to hemoglobin/deoxygenated-hemoglobin levels in the brain, which are tied to brain activities. Functional magnetic resonance imaging (fMRI), specifically the blood-oxygen-level-dependent (BOLD) method, also measures the hemoglobin/deoxygenated-hemoglobin levels. Magnetoencephalography (MEG) measures magnetic signals due to synchronized neuronal currents in the brain. Electroencephalography (ECoG) measures the electric signals under the dura mater of the brain. Microelectrode array (MEA) measures the neuronal spikes and local field potentials (electric signals) inside the cortex. See Figure 2.5 for the locations in/on the brain where EEG, ECoG, and MEA record. Image credits: fNIRS: Glenn Research Center, National Aeronautics and Space Administration. fMRI: Jan Ainali. MEG: National Institute of Mental Health, National Institute of Health. ECoG: Image source unknown. MEA: University of Utah.

Figure 2.5: Layers of the head and brain (side view) and some recording modalities. From top to bottom: Skin (scalp), bone (skull), dura mater, arachnoid, pia mater, and cerebral cortex. EEG records from above the skin. ECOG records from below the dura mater. MEA penetrates into the cortex.
Figure 2.6: EEG electrode placement and naming scheme of the 10-10 International Standard, or the 10-10 System. Each electrode is distanced 10% apart, where 100% is the distance between NZ and IZ (vertical) and between A1 and A2 (horizontal). NZ = Nasion. IZ = Inion. A1 = Left ear. A2 = Right ear. Fp = Frontal polar (forehead). The other electrode names are combinations of: A = Anterior, F = Frontal lobe, C = Central, P = Parietal lobe, O = Occipital lobe, T = Temporal lobe, Z = Zero (Middle), numbers 1-10 alternate between left and right sides with increasing distance from the middle. The 10-20 System is overlaid in green color with its own electrode names for the temporal lobe in smaller font.
digitized for storage and analysis on a computer. **Electrodes:** The electrodes are usually composed of either: gold (Au), chlorided silver (Ag/AgCl), tin, or stainless steel. Gold electrodes are very robust and provide excellent signals, but are not suitable for measuring very slow brain waves (<0.1 Hz). Chlorided silver electrodes also provide excellent signals, as well as providing the ability to accurately measure sub-0.1 Hz signals due to low electrochemical polarization and drift. Tin and steel electrodes have much lower signal quality than gold and silver electrodes. **Referencing:** EEG signals are commonly referenced to the A1 and A2 electrodes (linked-ear reference), to the AFz electrode, or to the Cz electrode. Choosing the correct referencing scheme enhances signal features that an experiment requires. **Amplifiers:** Bioamplifiers have 100 kΩ to $1 \times 10^{12}$ Ω input impedance. Since the EEG signals are already very weak (measured in μV) on the scalp, a higher input impedance allows for better signal quality and may permit higher frequency acquisition [68]. Some bioamplifiers also provide signal conditioning, such as pre-amplification (having first-stage amplifiers located on top of the electrodes) or active shielding (using signal mirroring to mitigate magnetic artifacts due to physical movements). These additional features enable BCI experiments that involve motions such as walking. Nevertheless, the resolution and reliability of detectable EEG is limited by the complex arrangement of cortical neurons and the non-linear distortions by the layers above the cortex, i.e. pia mater, arachnoid, dura mater, the skull, and the scalp. Even in the present day, EEG is limited to 1 cm resolution [43, 130].

### 2.2.5 BCI Training Paradigms

BCI training paradigms can be divided in three categories: Computer training, user training, and both. In the user training paradigm, the BCI computer is programmed to recognize a specific set of brain signals, and the user is left to figure out how to control their own brain signals to cause the appropriate response on the computer. Examples include controlling the $\mu$ (8-12 Hz) and $\beta$ (18-25 Hz) bands at specific electrode locations [150, 74, 92]. An
example of the $\mu$ wave can be seen in Figure 2.7. On the other hand, in the computer training paradigm, the computer is programmed to recognize patterns corresponding to a user’s intention, without requiring the user to unnaturally modulate any signals. Examples include kinesthetic motor imagery [31, 141] and (attempted) movement [106, 97, 13, 69, 71, 34, 30, 32]. Ultimately, since the user’s brain receives feedback and changes slowly during BCI usage, an ideal BCI uses both paradigms while maintaining the intuitiveness of the computer-training paradigm.

Figure 2.7: EEG $\mu$ rhythms as observed on our real-time EEG scope. The rhythms can be found between -10 and -9 s, as well as between -7 and -2 s, over the central (C), central-parietal (CP) and some frontal-central (FC) electrodes. Note the similarity between its wave shape when viewed upside-down and the Greek letter $\mu$. This rhythm, along with others, can be used by a BCI to determine a person’s intention of moving or staying still.
For computer-training paradigm, in order to develop the database of parameters to decode brain activities into commands, a consistent set of brain signals have to be discovered first, both in space and in time. Due to slight variation between persons, the database is optimal if created for the same BCI user on the same day. Through a procedure known as training, the user repeatedly performs a specified mental task or physical movement when prompted to, so that the computer learn to recognize the corresponding activity pattern and ignore unrelated brain activity. The repetition is necessary to build statistical power. The number of repetitions required varies depending on the mental task, the BCI algorithms, and the signal quality.

Finally, there are some intrinsic brain signal features that are universal among most people. BCIs using these signals may require less training and may work “out of the box.” Examples include steady-state visually evoked potential (SSVEP) [102], P300 potential [38], and occipital α-rhythm. With some training however, the BCI performance can still improve.

2.2.6 BCI Control Paradigms

The user control paradigms of a BCI can be divided into two types, cued and self-paced (Figure 2.8). In cued BCI, the computer generates a stimulus, such as a green dot on the screen or an audio tone, and waits for a brain-signal response from the user, typically in the form of an event-related potential (ERP) or evoked-response potential (ERP) (evoked-response requires no conscious effort). Cued BCI is easier to design, since it is reasonably certain that the presence or absence of the ERP will happen within a certain amount of time after the cue, usually less than one second. For examples, involuntary responses such as auditory evoked response [29], P300 potential [122], and SSVEP [5] have stereotypical waveforms and a fixed time window. On the other hand, self-paced BCI allows the user to control it in his/her own pace. The bio-signal of interest is generated voluntarily. The
computer continuously scans the measured signals for a match of known waveforms. Self-paced BCI paradigm is easier for the user because the user is in control of the speed of input. Through extensive training, users can manipulate their EEG to form path oriented control, such as movement trajectory [150]. However, it can be difficult to generate a consistent mental pattern over time without cues or extensive training, usually 20-70 thirty-minute sessions [150]. Also, voluntary ERP signals are more difficult to be detected in EEG than rhythmic signals. Rhythmic signals such as the $\mu$ and $\beta$ waves, modulated through movement or motor imagery, are readily detectable in EEG [91]; yet there is no reliable evidence of ERP representing starting or stopping of movement. Furthermore, certain EEG signals are only generated from cues. Signals such as P300 and P100 are only generated after receiving the appropriate visual or audio stimuli [122, 41]. A combination paradigm would be beneficial both to the user and to the computer. The computer can expect a cued response within the first second of a cue and can consider subsequent signals to be due to voluntary, self-paced thoughts from the user. This kind of BCI could harness ERP signals exclusive to stimulus-response and still allow the user to control the speed and process of input.

2.3 Current BCIs

2.3.1 P300 Speller

One of the most well-known cue based BCI is the virtual keyboard speller based on the visual P300 ERP [149, 36], originally developed by Farwell and Donchin [38]. A P300 speller relies on the P300 evoked potential [131], or more precisely, a combination of the P3a and P3b potentials [129, 16]. It is a series of positive EEG deflections occurring around 300 ms post-stimulus in the parietal brain areas [110] related to attention (P3a) and improbable events (“oddball”) (P3b) [35]. Alphabet letters are arranged on a computer screen, and a user is
Figure 2.8: Two types of BCI control paradigms. Top: In a cued BCI, the computer generates a stimulus and decodes the brain response into an output. Example shown is the BCI-Speller (Chapter 5). Bottom: In a self-paced BCI, the user initiates a mental imagery, and it is decoded into an output. Example shown is the BCI-Avatar (Chapter 6).

asked to pay attention to the letter they intend to select. Groups of letters illuminate on screen in only two possible situations—the intended letter is either in the group of illuminated letters, or not in the group. Since there are more irrelevant letters than the intended letter, the intended letter is both the attention (P3a response) and the oddball (P3b response). If a P300 evoked potential is detected, the BCI computer knows that one of the illuminated letters is the user’s intention. The selection is narrowed down until one letter is finally selected. This system can thus be used to spell words and sentences to convey messages, which is potentially useful for individuals with locked-in syndrome with intact consciousness but no motor control [12, 126]. Furthermore, the on screen “keyboard” can be consisted of more than letters, such as pictures, icons, and arrows [125, 7, 108, 57].
2.3.2 Motor BCIs

Other widely-studied BCIs are based on activities in the motor cortex and other brain areas related to movements. These systems utilize a combination of frequency modulations (in the $\mu$ band (8-12 Hz) and $\beta$ band (18-25 Hz)) and spatial distributions to control 1 to 3 degrees of freedom, mainly in mouse cursor control [73, 150, 85, 74, 92, 59]. Users are trained to control their sensorimotor rhythm (SMR) to modulate these frequencies, so that they are eventually able to control the BCI. Other types of motor BCIs use machine learning algorithms to learn the user’s actual or imagined movements [106, 97, 13]. Users of this type of BCI train with intuitive motor imageries. For example in [97], the subject with tetraplegia trained on hand grasp to control a muscle stimulator for grasping on the same hand.
Chapter 3

Significance of Work

3.1 Medical contribution

The initial stage of the BCI-Gait system in this dissertation was applied to the SCI population to control simulated walking in a virtual reality environment, maintaining or restoring their skill of ambulation-related mental imagery. With additional research and future technological advancements such as lighter and more powerful computers, this may eventually allow SCI patients to achieve the much-sought-after able-body-like ambulation. Regaining this ability will greatly improve their quality of life and decrease medical complications and expenses. In addition, the experimental, scientific, and engineering methods in our research will provide the blueprint for future integration of BCI and prostheses. Specifically, this study assessed the improvements in BCI proficiency due to periodic BCI training, determined its optimal duration and frequency, and defined the user candidacy criteria needed for successful operation of the BCI-driven overground walking system.

The unique features of our BCI-Gait system will be instrumental to addressing scientific questions and facilitating new treatments. For example, prolonged use of BCI, coupled with
feedback that the user receives, as well as brain plasticity and adaptation mechanisms, may lead to the emergence of a “BCI motor cortex.” Such a dedicated cortical circuitry may improve BCI control over time and enable the storage and easy recall of newly learned motor behaviors [46]. Coupled with the intuitiveness of our BCI, these potential neuroplastic changes may be beneficial in the neurorehabilitation of stroke and incomplete SCI. With long-term use of the system, the surviving neural connections between cortical neurons and spinal motor pools can be strengthened through a Hebbian-like learning mechanism, thereby achieving better rehabilitation outcome. Finally, development and maintaining these cortical circuits may also prove useful in promoting synaptic re-integration in future cellular therapies, potentially speeding up rehabilitation for users with paraplegia [17].

3.2 Scientific contribution

Analysis of the collected data will delineate the general cortical areas involved in the control of gait. These areas could then be studied with higher resolution recording techniques, such as electrocorticogram, to reveal finer details. This will generate data of high scientific value that may also be applicable to future invasive BCI systems to provide a more permanent solution for lower extremity prosthesis.

The research findings may also lead to a shift in focus towards using data-driven approaches in the BCI research community to favor intuitive control paradigms, thereby shortening the time between subject recruitment and purposeful BCI results. Furthermore, the vastly improved speed of our BCI systems may encourage the community to look into new BCI techniques and applications and to expand BCI to non-medical applications.
Chapter 4

Designs and Methods

This chapter covers the mathematical framework, software implementations, and experimental procedures common in the studies presented in the next two chapters.

4.1 Overview

A BCI measures a user’s brain signals to decode their intentions, which are then converted to commands to the attached output device. To this end, the BCI computer must be trained to associate certain patterns of brain signals to their corresponding user intentions. Also, the user needs to be trained to operate the BCI. After the training procedure, the user can hopefully assume control of the output device via the BCI system. Since the BCI systems in our laboratory are focused on adapting the computer to the user, most users are able to achieve purposeful control after a minimal training procedure. Specifically, within a little more than one hour (see Table 4.1), a naive human subject is introduced to the concept of BCI and the mental task to be performed, undergoes in training procedure, and usually assumes purposeful online control. Note that most training procedures take 10 minutes, but
some BCI-naïve subjects have to repeat due to inconsistent mental imagery.

We believe that an intuitive BCI is useful in the restoration or rehabilitation of lost motor functions. We have therefore developed several practical BCI systems to this end. Although the function of each system differs, the underlying principle of operation remains the same, which is described in the first few subsections here. Finally, practical goal-oriented tasks were designed to assess the performances of these BCI systems.

### 4.2 Typical Experimental Day

#### 4.2.1 EEG Cap Mounting

A BCI experiment typically lasts 1-6 hours depending on the complexity of the protocol. Briefly, a subject dons an EEG cap, engages in an offline training procedure to train the BCI computer on their specific EEG patterns, and participates in a goal-oriented online evaluation to assess the effectiveness of the BCI. In the context of BCI, “online” means when the user is actually controlling the BCI and the attached output device with their brain signals, while “offline” means otherwise, e.g. training procedure, model generation, calibration, etc (Figure 2.3).

To begin, a human test subject is evaluated, consented, and briefed on the experimental
procedures. To comply with Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule, the Common Rule, and Institutional Review Board (IRB) policies, the subject is given a coded identifier to protect their privacy, and no part of their name is written down on any notes or in any computer files.

An EEG cap is mounted on the subject and is carefully centered. Conductive gels were injected into electrode sites on the cap via a syringe and a blunt needle to establish electrical contact. Scalp was abraded with the blunt needle on each electrode site to lower the contact impedance. Finally, EEG signals on all channels are visually inspected on the real-time scope (Figure 4.1) to ensure minimal noise and stability. This procedure takes 45-60 minutes with an experienced researcher.

4.2.2 Training Procedure

A training procedure immediately follows the EEG cap mounting, during which the subject performs two or more mental or physical tasks specific to the protocol over approximately 10-15 minutes. The common theme of all training protocols is repetition and consistency, which are crucial to building a prediction model. Consequently, subjects are asked to adjust themselves to a comfortable position before a training procedure and to remain in the same posture during the procedure. They are also asked to engage the same mental or physical activity during each repetition. To further facilitate consistency, the training procedure is conducted using computer cues (see Figure 6.2 for example) without intervention from the experimenters. The design of the computer cues is also important. During early stages of developing BCI-Avatar [142] (Chapter 6), we used videos of a person walking as cues. However, it became apparent that the visually-elicited brain signals of the subject watching the video as well as the mirror neuron signals [112] confounded with the subject’s own mental imagery. As a result, the cues are text-based without any animation.
Figure 4.1: The real-time EEG scope, custom written in MATLAB (MathWorks, Natick, MA) for the NeXus-32 bio-amplifiers (MindMedia, Roermond-Herten, The Netherlands). Shown here is the 2013 version of the scope software with wiper update style to minimize viewing fatigue (the traces appear to move less often). It also features a pop-up control panel to allow adjusting zoom and filter parameters. When the Record button (bottom right corner) is pressed, the system begins recording EEG. Behind the scenes, the EEG is always recorded on disk using the memory-mapped file technology whenever the scope is running. The Record button simply marks the start and end times and extracts the subset of EEG data for the experimenters. This setup allows recovery of data should the computer crash in the middle of an experiment. Later versions of this scope allow for the amplifiers to be unplugged for battery change as well as changing the channel names without restarting the interface. These improvements are important especially in a hospital setting, since any restarts generate interference with, for instance, medical EEG monitors.
4.2.3 Training Data Analysis

After the training procedure, the recorded data are analyzed using custom-written MATLAB (MathWorks, Natick, MA) programs in order to create a “prediction model” that enables the BCI to predict a subject’s intentions based on their EEG patterns. To ensure repeatability, all signal processing and analyses are done automatically using pre-written scripts. Any deviations are documented in the experiment notebook. The analysis procedure extracts important features that distinguish between the different mental/physical tasks (details in Section 4.3) and builds a prediction model based on these differences. The accuracy of the prediction model, i.e. offline performance, is estimated using stratified cross validation [72].

4.2.4 Online Calibration for Motor BCIs

Until the BCI is put in online mode (Figure 2.3-Left), the user receives no real-time feedback on their performance. The classification accuracy obtained from cross validation merely tells the subject how they and the BCI performed 10-15 minutes ago during training. Also, our Motor BCIs employ a binary state machine (BSM) with distinct state transition thresholds that require optimization. Furthermore, real-time human-BCI interaction can subtly change the subject’s mental strategies, especially when training and online experiences are dissimilar (e.g. different user interfaces). Therefore, a short 3-5-minute calibration stage that closely mimics the online mode is needed to both optimize the thresholds and to familiarize the subject.

To this end, the BCI is put in online mode (i.e. as described in the next section) using default parameters (Figure 4.4) but with output disabled, i.e. the BCI will not control any output devices at this time. An experimenter instructs the subject to perform the two tasks of idling and kinesthetic motor imagery (KMI) of, for e.g. walking, while noting down when these tasks occur (Figure 4.5-Blue). The BCI interface then generate histograms of all posterior
probabilities during idling and during KMI (see Figure 4.2 for example). The experimenter can then determine the BSM transition thresholds and decide whether the subject is ready for online control.

![Posterior Probability Histograms for Online Calibration](image)

Figure 4.2: A representative histogram during an online calibration session for BCI-Gait (Chapter 6). Every 250-500 ms, features ($f^*$) are extracted from brain signals and are decoded into posterior probabilities of walking, $P(W|f^*)$. Each pair of feature and probability also belongs to whether a subject is idling ($I$) or performing a walking KMI ($W$). The histograms show the frequencies of $P(W|f^* \in I)$ and $P(W|f^* \in W)$ (divided in 20 intervals), as well as the 3 quartiles. The quartiles provide a guideline on how the BSM thresholds should be chosen. Here, the subject had highly-consistent probabilities during idling, as indicated by the tight clusters around $P(W|f^* \in (0.00, 0.05))$. However, the walking KMI produced a more variable distribution of probabilities. Since $I$ and $W$ were easily separable, this subject was ready for online control.

### 4.2.5 Online Assessment

The online evaluation procedure assesses the subject’s performance operating the BCI in a high-level, goal-oriented task. The performance is also compared to a Monte Carlo random
walk to establish the level of significance (see Appendix E for implementation details). A random-walk test involves running thousands of the same repeated simulated online procedure with the BCI set to the chance-level offline performance. Note that EEG acquisition is not necessary when BCI is at chance level, i.e. the random walk can be done without the subject.

All of our Motor BCIs, such as BCI-Gait (Chapter 6), use a common, custom-written MATLAB graphical user interface (GUI) (Figure 4.5) to control the various output devices. This BCI features a binary state machine (BSM) (see Figure 4.3) to reduce volatility of decoding. The interface can be easily expanded for new BCI-controlled output devices or to accommodate new bio-amplifiers. Another GUI was also written (Figure 4.4) to assist the experimenter in correctly entering the optimized parameters into this BCI. The same interfaces also enable random walk simulations as well as replaying recorded sessions for research or troubleshooting purposes.

Figure 4.3: Illustration of a binary state machine (BSM) when applied to BCI-Gait (Chapter 6). The states “Idle” and “Walk” describe the state of the output device. For instance, at Idle, the virtual avatar does not move, whereas at Walk, the avatar walks. $P(W|f^*)$ is the averaged posterior probability of walking decoded from the extracted features of the brain signals (the step after “feature extraction” in Figure 2.3-Left). Since in this binary-classification, $P(I|f^*) + P(W|f^*) = 1$, only one needs to be considered. If the value $P(W|f^*)$ exceeds the threshold of walk, $T_W$, the BSM switches to the Walk state and makes the avatar walk. If $P(W|f^*)$ drops below the threshold of idle, $T_I$, the BSM switches to the Idle state and makes the avatar stop. If $P(W|f^*)$ is between $T_I$ and $T_W$, no state transition occurs, and the BSM and the avatar continue their current state.
Figure 4.4: A screenshot of the GUI to assist the experimenters to correctly and efficiently enter BCI parameters. Without this, an experimenter has to enter the 24 parameters manually each time. Thresholds are entered based on a short calibration session (e.g. Section 6.1.8). Dead times disallow switching states until the specified times have passed to prevent damaging output devices. Analysis duration specifies the window size of the power spectrum estimation. Posterior duration specifies the window size over which the posterior probabilities are averaged (using the averaging method in the box) to improve decoding stability. The output system menu is used to select the output device, such as virtual joystick (Section 6.1), emulated mouse (Section 6.4.5), functional electrical stimulation devices for overground walking (Section 7.1.3.1) and neurorehabilitation (Section 7.1.3.2), powered wheelchair, and more. The BCI is launched immediately when the “Execute” button is pressed.
Figure 4.5: A screenshot of the Real-Time BCI with Binary State Machine (RTBCIBSM) in action. The BCI runs a loop continuously. In each iteration, it acquires EEG signals, processes them, performs feature extraction, and decodes them into commands for the output device. All of these actions are performed within 125-250 ms, and a large amount of time in an iteration is occupied by the interfaces with the EEG acquisition driver and the output device. **Green box:** This small window is moved to the computer screen facing the subject, and displays the iteration number (top number), the instantaneous posterior probability (bottom left) and the averaged posterior probability (bottom right, also with a graphical bar display). The tiny green bars in the top half of the window indicate EEG power activities, which helps real time troubleshooting of failing electrodes. **Blue box:** A new window that enables the experimenter to adjust parameters in real time, such as speeding up/slowing down the BCI, changing state machine thresholds, temporarily disabling BCI-controlled output, and manually controlling the output device. The “Histogram Helper” facilitates performing a calibration session without needing to manually write down the iteration numbers. **Red box:** An optional Diagnostic Window that enables viewing real-time EEG signals (top), spectral powers in log scale (middle left), feature-space projections of training data as Gaussian curves and incoming EEG data as dotted lines (middle right), and classifier output and state machine states (bottom). Black line: Averaged posterior probabilities. Light gray line: Instantaneous posterior probability. Red/green dashed line: Stop/go thresholds. Blue dotted line: State that is sent to the output device. Finally, closing the blue or green box stops the BCI and saves the data.
4.2.6 End of Experiment

At the end of an experiment day, the EEG cap was removed, washed, and sterilized, and the subject was free to leave. Note that the duration of the experiment is strictly limited by the EEG cap. As the gel dries and solidifies, the electrodes become increasingly unreliable, causing random disconnections and amplified noises. At some point after 6 hours, the rate the signals deteriorate becomes unacceptable. Nevertheless, our experiment procedures usually only take about 2.5 hours for any motor BCIs and about 30 minutes for BCI-Speller.

The EEG cap and other electrodes are washed with a mild detergent and then submerged in a solution of 3.4% glutaraldehyde (Metricide Plus 30, Metrex Research Corp., Romulus, MI) for 10 hours to be sterilized. They are rinsed on the next day and then dried for the next experiment. Syringes and blunt needles are discarded off as biomedical waste.

4.3 Prediction Model Generation

The prediction model is the foundation of our BCI that enables data-driven subject-specific training of the BCI computer.

4.3.1 Trials extraction

The recorded data from the training procedure are divided into trials, which are short durations of EEG signals. The duration of each trial depends on the nature of the task and the representation of signals. For example, event based EEG signals are analyzed as time series and are typically less than 1 s long. On the other hand, if the interesting features are in the frequency domain, the duration of each trial can be variable. However, having more cycles, hence longer duration, improves the spectral power estimation. Note that increasing
the duration of a trial increases decoding stability but slows down the response time. Each trial has a class label corresponding to the mental/physical task. For example, if a trial was extracted from when the subject was imagining walking, it will be in the “imagined walking” class. The class labels from the training procedure are assumed to be the ground truth. Note that this assumes that the test subject was cooperative during the training procedure, as there is no overt signs on whether they performed the mental task as instructed.

4.3.2 Data pre-processing

EEG signals may not be immediately suitable for dimension reduction and feature extraction (in Section 4.3.3) and require processing first. Issues such as electrochemistry problems with deteriorating EEG electrodes, electrical interference, and tiny motion artifacts may not be apparent on EEG but subtly affects the data. Some subjects’ EEG, for unknown reasons, are also unsuitable until pre-processing steps are done. Here, we describe some common issues and our solutions.

4.3.2.1 Drifts

One of our EEG amplifiers (NeXus-32, MindMedia, Roermond-Herten, The Netherlands) is not rated for DC acquisition. The acquired signals drift slowly at the rate of about 0.001-0.01 Hz. Our solution is a Butterworth high-pass filter at 2 Hz. During online BCI, the same filter is applied to each incoming EEG segment with matching initial and final conditions. 2 Hz is chosen as the cutoff, since lower cutoff lengthens the time the online BCI requires to stabilize.
4.3.2.2 Class-dependent interference

Even though the feature extraction algorithm is expected to ignore features that are common in all classes, some interference and artifacts are only present during one class. For example, the presence of modulated electrical interference, e.g. 60-Hz power line noise that differs depending on the subject’s movement. There is not much that can be done to the data to fix this problem, except by band-stop filtering all subharmonics (30 Hz, 15 Hz, 7.5 Hz, ...). Unfortunately, this requires the training procedure to be repeated with different grounding configuration: Add/remove a grounding wrist-strap, change to battery powered amplifiers, or adding a plastic mat underneath the subject.

4.3.2.3 Electrical spikes

Rare and uncorrelated spikes in the EEG may overwhelm the BCI algorithms, since it is many orders of magnitude stronger than typical EEG. Causes may include brief disconnections from failing electrodes, physical impact with the EEG cap, and air bubbles in the electrode gel. We use the Iterative Artifact Rejection Algorithm (Appendix B) to discard trials containing those spikes.

4.3.2.4 Variance across frequencies

The noise in the power spectrum of stochastic processes is approximated by $1/f$, where $f$ is the frequency [66]. EEG, being the result of stochastic processes in the brain, exhibit the same behavior. The variance of low frequency bands such as $\mu$ (8-12 Hz) may be much higher than the variance of higher frequency bands such as $\beta$ (12-24 Hz) and $\gamma$ (>30 Hz). Since the principal component analysis used in dimension reduction (see the following subsection) aligns to the maximum variance, the disparity in variances alone may overwhelm
the algorithm. We implemented a “log power” switch in our BCI to take the logarithm of the spectral energy to reduce these variances. Logarithms are monotonic and preserves the relative strengths of power spectrum.

4.3.2.5 Variance across channels

Sometimes, groups of electrodes have much stronger signal amplitude than others, possibly due to uneven impedances. This effect results in uneven variance across channels, which can mislead the dimension reduction algorithm into using this artificial effect as principal axes, overshadowing other more important features. Our approach to mitigate this problem is to convert EEG amplitudes in each channel into standard scores (z-scores) or modified z scores (mz-scores) [1, 63], so that all channels have the same variance. A z-score is defined by:

$$z(t) = \frac{x(t) - \mu}{\sigma}$$

(4.1)

where $z$ is the z-score, $x$ is the original EEG amplitude, $\mu$ is the mean across time and $\sigma$ is the standard deviation. In the case of mz-score, $\mu$ is replaced by the median, and $\sigma$ is replaced by the robust standard deviation as approximated by the median absolute deviation (MAD),

$$\sigma \approx 1.4826 \text{ MAD}. \quad (4.2)$$

4.3.3 Dimension reduction

Trial data are analyzed in both electrode channels and time/frequencies simultaneously. Each trial is reshaped from its original matrix form of (channel, time) or (channel, frequency) to a CT×1 vector, where C is total number of channels and T is number of sampled time
points or frequency points (see Appendix F). Note that a training procedure produces a trial
data matrix of dimensions $CT \times n$, where $n$ is the number of trials. Since the data dimensions
$(C \times T)$ of each trial usually exceed the number of trials ($n$), a dimension reduction algorithm
is necessary to alleviate this small sample size problem [45]. To this end, principal component
analysis (PCA, Appendix G.1) or classwise PCA [23, 22] (CPCA, Appendix G.2) is used to
reduce the dimension of trial data. Briefly, PCA ranks the variance among the trial data
dimensions, using eigenvalues, from high to low as principal axes, with the first (orthonormal)
principal axis accounting for the most variance. To achieve dimension reduction, only the
first few principal axes are retained, and trial data are projected to the subspace spanned
by these principal axes:

$$ e = \Phi d $$

(4.3)

where $d$ is the trial data, $\Phi$ is the PCA transformation matrix formed by the retained
eigenvectors, and $e$ is the trial data projection on the reduced subspace. In our BCI, the
threshold to retain principal axes is set to the mean of the non-zero eigenvalues, i.e. keeping
only eigenvectors whose corresponding eigenvalues are above the mean.

Similarly to PCA, CPCA ranks the variances, but on a per-class basis, i.e. PCA is done on
trial data of each class. In addition, CPCA adds “between-class” covariances to each set of
per-class principal axes. As a result, there are as many CPCA transformation matrices as
there are classes:

$$ e_1 = \Phi_1 d $$

$$ \vdots $$

$$ e_C = \Phi_C d $$

(4.4)

where $\Phi_c$ and $e_c$ are the transformation matrix and reduced trial data from class $c$, respec-
tively, and $d$ is the training data trials from all classes. Note that the number of retained
principal axes do not have to be the same for all classes, and consequently $e_i$ and $e_j$, $i \neq j$ might not have the same dimensions. The main advantage of CPCA over PCA is the consideration of classes, as class labels are already a known information during training procedure. All of our two-class BCIs use CPCA as the first step to reduce trial data dimensions. In practice, this typically results in 20-50 dimensions in the reduced space.

4.3.4 Feature extraction

To further reduce dimensions in an effort to enhance class discrimination, a discriminant feature extraction (DFE) algorithm is used to reduce them to 1–3 dimensions. Figure 4.6 shows an example of training data projected onto a 2D feature space. We use approximate information discriminant analysis (AIDA) [99, 26] (see Appendix G.3) or Fisher’s linear discriminant analysis (LDA) [40] as feature extraction. The choice as well as the number of final dimensions is determined in an automated manner, detailed at the end of Section 4.3.6. Briefly, the DFE produces a transformation matrix $T$, similar to that of PCA, with the aim of reducing the dimensions of data. In addition, DFE maximizes class separability based on class means (LDA) or mutual information (AIDA). The transformation matrices $\Phi_e$ from CPCA and the corresponding $T$ from AIDA or LDA can be combined to form “feature extraction maps”, which indicate the areas of the brain at specific time or frequencies that encode the differences between the mental/physical tasks (see Figure 4.7 for example). Such maps can be insightful in revealing brain physiology during those tasks. The eventual choice of AIDA or LDA by the automated algorithm as well as the differences between the two feature extraction maps can also reveal the distribution of the data features.
Figure 4.6: Example of training data projection on a two-dimensional feature space, with two classes sufficiently described by their corresponding means and covariances. Note the overlap area, which contributes to classification error.

### 4.3.5 Classification

The Bayesian classifier is used to classify new trial data—to determine which class a new segment of EEG signals should belong, so that a BCI can predict the user’s intentions after the training procedure. To recap, the training data of different classes (mental/physical tasks) have been reduced from the original $C \times T$ dimensions to 1–3 dimensions in the feature subspace via dimension reduction and DFE:

$$f_c = T_c \Phi_c d$$  \hspace{1cm} (4.5)

where $d$ is the training data in original space and $f$ is the training data features in the low-dimensional subspace. If CPCA is used, there is one set of $(f, \Phi, T)$ for each class (otherwise $f_c$, $\Phi_c$, and $T_c$ are the same for all classes). The posterior probabilities are calculated using
Figure 4.7: Example of a one-dimensional feature extraction map (from P300 Speller, Chapter 5). X-axis: Time (s). Y-axis: Electrode locations. Time 0 = stimulus. Dark red and dark blue represent brain area and time where the class difference are most salient.
Bayes rule:

\[ P(c|f^*) = \frac{P(f^*|f \subset c)P(c)}{P(f^*)} \]  \hspace{1cm} (4.6)

where \( f^* \) is one trial of data features, \( f \subset c \) is the set of all training data features in class \( c \), \( P(f^*|f \subset c) \) is the likelihood of \( f^* \) belonging to class \( c \), \( P(c) \) is the prior probability of class \( c \), \( P(f^*) \) is the total probability, and \( P(c|f^*) \) is the posterior probability of class \( c \) when \( f^* \) is presented. The likelihood is calculated by assuming that each class is Gaussian-distributed with corresponding means \( \mu_c \) and covariances \( \Sigma_c \):

\[ P(f^*|f \subset c) = (2\pi)^{-\frac{d}{2}}|\Sigma|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(f^*-\mu_c)\Sigma^{-1}(f^*-\mu_c)\right) \]  \hspace{1cm} (4.7)

where \( d \) is the feature space dimension (usually 1–3D), \( \Sigma \) is the training data covariance, \( \mu_c \) is the mean of training data trials in class \( c \), and \((\cdot)'\) is the transpose. \( \Sigma \) is either pooled or per-class depending on whether linear or quadratic decision boundary is desired, respectively. For pooled covariance (linear),

\[ \Sigma = \sum_c P(c)\Sigma_c \]  \hspace{1cm} (4.8)

and for per-class covariance (quadratic),

\[ \Sigma = \Sigma_c = \text{cov}\{f, f \subset c\} \]  \hspace{1cm} (4.9)

Note that per-class covariance is more poorly estimated due to the reduced number of trials. However, it may still be beneficial to classification if the covariances of classes are very different. In our BCI, the choice is determined automatically, similar to the previous parameters. The prior probability is decided empirically based on the ratio of the frequency of each class in the training data. Finally, the total probability \( P(f^*) \) is the sum of all likelihoods over
all classes.

At this point, a decision can be made to classify any $f^*$ by choosing the class with the highest posterior probability using the maximum a-posteriori probability (MAP) rule:

$$c^* = \arg \max_c P(c|f^*)$$  \hspace{1cm} (4.10)

where $c^*$ is the optimal class of $f^*$. Note however, that CPCA generates one set of $(f^*, f, \mu_c, \Sigma)$ for every class, and hence there are as many sets of posterior probabilities as classes. Therefore, the decision rule needs to be modified to accommodate the use of CPCA during dimension reduction. To this end, we define the winning class to be the one with the highest posterior probability among all class-subspaces. If a tie occurs, the class with the highest mean posterior wins. Consequently, the posterior probabilities from Equation 4.6 when CPCA is involved have been modified to be the highest or mean (depending on the presence of a tie) posteriors over class-subspaces. Details of this implementation can be found in Appendices A and G.4. Finally, all transformation matrices and classifier parameters are saved and become the prediction model.

### 4.3.6 Cross validation

At this point, an EEG trial has been transformed to low-dimensional feature subspace and then classified into one of the mental/physical task labels. Cross validation is used to validate the classification performance. The goal of a cross validation is to predict the future classification (foresight) accuracy when the prediction model is presented with new trials. To this end, stratified 10-fold cross validation is performed [72]. Briefly, 10% of training data trials (10% from each class, hence “stratified”) are randomly selected and designated as “testing” while the remaining 90% of trials are used for prediction model generation. The model generation procedures are identical as described in this subsection, except with only
90% of training data. The “testing” trials are classified using the prediction model, and the classifier decisions are compared to the known training labels, i.e. truth. This step is repeated until all trials have been exhausted for “testing”. The outcome is then averaged and summarized in a confusion table, such as Table 4.2. Often, an overall “offline performance” probability is also desired, i.e. the probability of correctly decoding a new trial regardless of class. Such \( P(\text{correct}) \) is the total probability:

\[
P(\text{correct}) = \sum_c P(c)P(\text{decoded as } c \mid \text{presented with } c) \tag{4.11}
\]

Naturally, the chance level offline performance, i.e. the performance when guessing, is also the highest prior probability, since the classifier is expected to always choose the most likely class to maximize its performance when guessing. Hence, when priors are unequal, apparently high \( P(\text{correct}) \) from a training procedure may not be as impressive as when priors are equal.

The cross validation procedure is iterated on all free parameters to determine the best combination: AIDA vs. LDA, number of final dimensions, and quadratic vs. linear decision boundary. Although this increases the risk of overfitting (by using the same data to tweak the parameters and test them), we believe that the final data dimension is low enough to actually overfit. Besides, the model will be subjected to the ultimate test, online performance, when a subject is asked to operate the BCI to complete a goal-oriented task. Finally, the best combination of parameters and transformation matrices (from 100% of training) are saved to operate the online BCI for goal-oriented assessment.

Samples of the cross validation output can be found in Appendix H.1.
Table 4.2: An example two-class confusion matrix from a cross validation. $P(\hat{x}|y)$ is read as the probability of the prediction model decoding a trial as $x$ when the true label of the trial is $y$. The model is considered correct when it agrees with the truth, i.e. along the main diagonal in the table. This table is generalizable to higher number of classes.

<table>
<thead>
<tr>
<th>Decoded Class</th>
<th>Class a</th>
<th>Class b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth Class a</td>
<td>$P(\hat{a}</td>
<td>a)$</td>
</tr>
<tr>
<td>Class b</td>
<td>$P(\hat{b}</td>
<td>a)$</td>
</tr>
</tbody>
</table>

4.4 Information Transfer Rate Calculation

Information transfer rate (ITR) is one of the objective measures of online BCI performance when a comparison between dissimilar BCI systems is needed. There are two ways to calculate ITR: From empirical online performance, and from offline training data. The calculation from online performance depends on the application, but is essentially:

$$ITR = \frac{N}{T} \log_2 |A|$$  \hspace{1cm} (4.12)

where $N$ is the number of final decisions made during an online performance, $T$ is the total time taken, and $|A|$ is the number of choices at each decision. This empirical ITR calculation is well-defined in the context of cue-based BCI, such as the BCI-Speller (Section 5.1). On the other hand, ITR is not a common measure in self-paced BCIs due to arbitrarily defined goal-oriented assessments. There is currently no commonly accepted criterion available for evaluating self-paced BCI data [118].

To calculate ITR from offline training, elements of the confusion matrix (Table 4.2) and prior probabilities need to be obtained. Through the 10-fold cross validation procedure (see Section 4.3.6), the labels of test trials are decoded and compared to their true labels, and a confusion matrix is created (Table 4.2). The fractions of correct decodings form the main diagonal of the matrix. Conversely, misclassifications are in the off-diagonals. For a binary
channel with “yes” and “no” signals, e.g. a BCI with two classes, the confusion matrix is represented by the four elements: true positive–$P(\hat{y}|y)$, true negative–$P(\hat{n}|n)$, false positive (false alarm)–$P(\hat{y}|n)$, and false negative (omission)–$P(\hat{n}|y)$.

By the law of total probability, we have:

\begin{align*}
P(\hat{y}) &= P(\hat{y}|y)P(y) + P(\hat{y}|n)P(n) \\
P(\hat{n}) &= P(\hat{n}|y)P(y) + P(\hat{n}|n)P(n)
\end{align*}

(4.13)

where $P(y)$ and $P(n)$ are the respective prior probabilities, $P(\hat{y})$ and $P(\hat{n})$ are the unconditional probabilities of decoded trials. Note that the online priors can be estimated from expected usage pattern or from the class frequencies in the offline training data. If $\hat{y}$ and $\hat{n}$ are considered outputs of a binary communication channel, its unconditional entropy [18] is then given by:

\begin{align*}
H(out) &= -\sum_i P(\hat{c}_i) \log_2 P(\hat{c}_i) \\
&= -[P(\hat{y}) \log_2 P(\hat{y}) + P(\hat{n}) \log_2 P(\hat{n})]
\end{align*}

(4.14)

where each $c_i$ is a class label, i.e. $y$ or $n$. To complete the calculation of the mutual information, we estimate the conditional entropy, $H(out|in)$, in [18] as:

\begin{align*}
H(out|in) &= \sum_i H(out|in = c_i)P(c_i) \\
&= \sum_i \left(-\sum_j P(\hat{c}_j|c_i) \log_2 P(\hat{c}_j|c_i)\right) P(c_i) \\
&= -\left[ P(\hat{y}|y) \log_2 P(\hat{y}|y) + P(\hat{n}|y) \log_2 P(\hat{n}|y) \right] P(y) \\
&\quad -\left[ P(\hat{y}|n) \log_2 P(\hat{y}|n) + P(\hat{n}|n) \log_2 P(\hat{n}|n) \right] P(n)
\end{align*}

(4.15)
Thus, the mutual information:

\[ I(in, out) = H(out) - H(out|in) \] (4.16)

which measures the reduction of entropy in the output uncertainty by providing the input, can be calculated by subtracting Equation 4.15 from Equation 4.14.

The channel capacity is the theoretical maximum \( I(in, out) \), only limited by the channel design. When the communication is completely error-free, e.g. \( P(\hat{y}|y) = 1.0 \) and \( P(\hat{n}|n) = 1.0 \) in the binary case, \( I(in, out) \) is only limited by the prior probabilities. For a symmetric binary channel (both priors are equal to 0.5), the capacity is \( \log_2 2 = 1.0 \) bits per trial. However, physiological constraints in a BCI often reduce the symmetry and thus reduce the channel capacity. For instance, if the prior ratio is 1:6 such as the case of our BCI-Speller (Chapter 5), \( P(n) = 0.8571 \) and \( H(out) = 0.592 \). Essentially, no BCI system with a 1:6 prior ratio can achieve higher than 0.592 bits/trial. To compensate for the slow down due to uneven priors, the number of trials per second is increased so that the effective communication rate is higher, but this is also subject to physiological limits.

Finally, combining the bits per trial and trials per second, ITR can be calculated:

\[ ITR = \frac{I(in, out)}{T} \] (4.17)

where \( T \) is the inter-trial interval (ITI, the time between the starts of consecutive trials), and \( I(in, out) \) is the mutual information, i.e. “bits per trial”. The trade-offs between raw speed (trials per second) and accuracy (bits per trial) in the presence of physiological constraints must be carefully considered when designing a BCI.
Chapter 5

BCI-Speller for Restoring Communication

The BCI-Speller uses a combination of the P300 (P3b) attentional oddball paradigm [38, 131, 128, 42] and N200 (N2c) visual search paradigm [87, 42] to operate a virtual on-screen keyboard. To use such keyboard, a user is instructed to pay visual and mental attention to a desired letter on screen. Their intentions to select that letter can be decoded by detecting the presence of the N200-P300 potentials (from the occipital and parietal cortices) that coincide with the illumination of letters. It was hypothesized in [38] that such a system could achieve information transfer rates (ITRs) as high as 0.2 bits/s (2.3 characters/min). While subsequent developments such as [75, 138] have managed to optimize the original system and improved the speeds, they are still well below the speeds of communication devices that rely on residual movements, such as an eye gaze system [62].

In this study, we report on the development of a novel EEG-based BCI communication system, where subjects with little to no prior BCI experience were able to accurately spell words and sentences after 6-10 minutes of training, and achieve error-free speeds in excess
of 3 bits/s in a real-time typing test.

## 5.1 Methods for the BCI-Speller

### 5.1.1 Experimental Overview

This study was approved by the University of California, Irvine Institutional Review Board. 6 able-bodied individuals (demographics data in Table 5.1) with normal or corrected vision and no neurological impairments gave informed consent to participate.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Gender</th>
<th>Age</th>
<th>Prior BCI experience</th>
<th>Native English speaker</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>F</td>
<td>23</td>
<td>3 hours</td>
<td>Yes</td>
</tr>
<tr>
<td>B</td>
<td>M</td>
<td>40</td>
<td>10 hours</td>
<td>No</td>
</tr>
<tr>
<td>C</td>
<td>M</td>
<td>29</td>
<td>1 hour</td>
<td>Yes</td>
</tr>
<tr>
<td>D</td>
<td>M</td>
<td>22</td>
<td>Naïve</td>
<td>Yes</td>
</tr>
<tr>
<td>E</td>
<td>M</td>
<td>24</td>
<td>Naïve</td>
<td>Yes</td>
</tr>
<tr>
<td>F</td>
<td>F</td>
<td>56</td>
<td>10 hours</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Each participant completed three experimental sessions performed on 3 different days over the course of 1-3 weeks. Within each daily session, a subject performed BCI spelling experiments at three different interface speeds (see Table 5.2). For each speed, a short training procedure was performed, followed by 1-3 online spelling sessions. Detailed descriptions of these procedures is given in Sections 5.1.3 and 5.1.5.

<table>
<thead>
<tr>
<th>Day</th>
<th>Interface speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>slow medium fast</td>
</tr>
<tr>
<td>2</td>
<td>medium fast</td>
</tr>
<tr>
<td>3</td>
<td>fast slow</td>
</tr>
</tbody>
</table>

Online sessions were performed in a free spelling mode [12], and the subjects were asked
to correctly spell the following benchmark sentence: THE QUICK BROWN FOX JUMPS OVER THE LAZY DOG*. This sentence contains 44 characters, including spaces and the symbol * at the end, which serves to exit the interface. It is also an English-language pangram, i.e. each letter of the English alphabet appears at least once in the sentence. In the case of a typing error, the subjects used backspace to delete erroneously selected characters, and then proceeded with the correct sequence of letters. A session was not considered complete until the entire sentence was spelled correctly. All subjects were able to accomplish the task, i.e. type the benchmark sentence that is free of errors and exit the interface (see Section 5.2 for results). Also, the subjects had no trouble memorizing the sentence and were able to track their spelling progress on the computer screen. The total daily involvement per subject, including both preparation and experimental procedure, was 2–3 hours.

5.1.2 Data Acquisition

Each subject was seated in a chair approximately 0.8-1.0 meter from a 19-inch computer monitor (Figure 5.1) that displayed a 6×7 matrix of characters (Figure 5.2). EEG was recorded using a 19-channel EEG cap (Compumedics USA, Charlotte, NC) with sintered Ag-AgCl electrodes arranged according to the 10-20 International Standard (see Figure 5.5 for electrode locations). Conductive gel (Compumedics USA, Charlotte, NC) was applied to a subset of 8 electrodes at the following locations: C3, Cz, C4, P3, Pz, P4, O1, O2. Ear clip electrodes, A1 and A2, were linked together and used as a reference electrode. However, if the ear-to-ear (A1–A2) impedance (at 30 Hz) was greater than 10 kΩ, only the ear with the lower impedance (to other EEG electrodes) was used as the reference. The impedances between each of the 8 electrodes and the reference electrode were reduced to <5 kΩ by scalp abrasion. The signals were acquired using eight single-channel EEG amplifiers (MP150 and EEG100C, Biopac Systems, Goleta, CA) at 200 Hz sample rate, 5000x gain, and 1–35 Hz bandpass.
Data acquisition and analysis were performed using custom-made MATLAB programs.

Figure 5.1: Experimental setup. A subject dons an EEG cap with an ear-clip reference (A1) and sits 0.8-1.0 m from a 19-in computer monitor.

### 5.1.3 Training Procedure

A training session started by instructing the subject to pay attention to a specific character from the matrix for 30 seconds. Within this time frame, 42 characters were illuminated randomly in 7 groups of 6 in a block randomized fashion, i.e. already illuminated characters would not be illuminated again until all 42 characters were illuminated exactly once each. The randomization algorithm was based on the frequency of characters as they appear in the English language (details can be found in Appendix D). Note that as only one group
Figure 5.2: A screenshot showing the matrix of characters during online performance. The illuminated characters are bold-faced and highlighted in pink. The typing prompt (yellow) shows the spelling progress. Note that during training procedure, the same screen and flashing pattern are displayed except the typing prompt.
of illuminated characters contains the target character, i.e. “oddball” character, the ratio of odd to non-oddball stimuli in the training session is 1:6. At the end of one cycle, the illumination sequence was re-randomized for the next cycle. The cycles continued for a total of 30 seconds. The speed of illumination was controlled by the inter-trial-interval (ITI) time with a duty cycle of 60% (see Figure 5.3). After training for 30 seconds on one character, the subject was then asked to pay attention to a different character, and the same procedure was repeated for a total of 10 training characters. The choices of the 10 training characters were based on their locations on screen - centers, corners, and edges. Note, however, that there should be no difference in the EEG responses due to different characters, since they are all oddball responses. Finally, the whole training session lasted \( \sim \)6.5 minutes (5 minutes training and \( \sim \)1.5 minutes for breaks between each character).

Figure 5.3: The timing diagram of experimental protocol. Each trial consists of illumination of characters (logical high in the boxcar trace) for \( t_{on} = 0.60 \) ITI long and followed by no illumination, for a total duration of ITI. Unilluminated characters remain in faint green color on screen. At the beginning of each illumination, EEG signals were recorded for 400 ms. Note that the first 100 ms \( (t_1, \text{shaded}) \) is discarded as it contains no pertinent information for the corresponding trial. The remaining signals \( (t_2) \) were analyzed. At higher interface speeds, this mode of acquisition results in overlapping EEG signals between trials.

In response to each illumination, \( t_a = 400 \) ms of EEG data were acquired and stored for prediction model generation. Throughout this study, a single 400-ms data segment is referred to as a trial. The total number of trials depended on the choice of ITI time. In particular, the slow, medium, and fast interface speeds (see Table 5.2) corresponded to ITI times of 400,
240, and 160 ms, respectively. Note that for medium and fast speeds, the adjacent trials partially overlapped (as illustrated in Figure 5.3).

Since P300 is a time-domain event related potential, no frequency domain processing was done. A basic electrical overvoltage filter removed all trials whose voltage swing exceeded 170 \( \mu \text{V} \) (before amplification) to remove unintended motion artifacts. Note that ocular artifacts were not removed and were treated as noise by the signal processing algorithm (see next section).

5.1.4 Prediction Model Generation and Validation

Within each trial, the first \( t_d = 100 \) ms of data was presumed to contain no useful information due to the lag in visual information processing [135], and so the trials were effectively truncated to 300 ms long. Therefore, individual trials from the training procedure, represented by \( 8 \times 60 \) matrices (8 channels, 0.300\( \times \)200 samples), were reshaped into 480-dimensional (480D) vectors. To facilitate subsequent classification of new trials into oddball and non-oddball classes, the dimension of data was reduced using CPCA [22, 23] and AIDA [26]. Further justification for using CPCA and AIDA can be found in Appendix C.

Similar to the previously described dimension reduction, feature extraction, Bayes rule, and validation techniques (see Sections 4.3.3, 4.3.4, 4.3.5, 4.3.6), 1D features were extracted from the training-procedure data and were classified using Bayes rule (Equation 4.6). Unlike the BCI-Gait project, this study uses event related potentials with clearly defined timing boundaries. Therefore, no online calibration procedure is necessary, and a state machine is also not required for online performance. To recapitulate, optimal CPCA and AIDA transformations were computed from the EEG trials from a training session, and the EEG

49
trials were projected to the 1D feature subspaces using these transformations:

\[
\begin{align*}
    f_o &= T_o \Phi_o d \\
    f_e &= T_e \Phi_e d
\end{align*}
\]  

(5.1)

where \(d\) is the collection of trials \((480 \times n)\) with \(n\) trials, \(\{\Phi_o, T_o, f_o\}\) and \(\{\Phi_e, T_e, f_e\}\) are the corresponding CPCA transformation matrix, AIDA transformation matrix, and trial features, for odd and “even” (non-odd) balls, respectively. Then, as a new EEG trial became available during a real-time online session or during cross validation, it was transformed in the same manner. After transforming the trial into feature, Bayes rule with linear decision boundary was used to calculate the posterior probabilities, \(P(o | f^*)\) and \(P(e | f^*)\). However, an odds threshold was used, instead of a simple MAP rule, to classify:

\[
\frac{P(o | f^*)}{P(e | f^*)} > \theta \\
\]

(5.2)

where \(P(o | f^*)\) and \(P(e | f^*)\) are the posterior probabilities of odd and non-oddball classes given the observed feature \(f^*\), respectively, and \(\theta\) is the odds threshold. This decision rule is read as: “classify \(f^*\) as oddball if \(P(o | f^*)/P(e | f^*) > \theta\), and vice versa.” In general, the threshold \(\theta\) represents the ratio of the costs associated with false alarm and omission errors, i.e. \(\theta = \lambda_{\text{FA}}/\lambda_{\text{OM}}\), in which case the classifier is known to minimize the total risk function [37, 100]. The thresholds differed only in the online operation (see next section). Note that during cross validation, the threshold was assumed to be the same as that of “Stage 1” of online operation, i.e. \(\theta = 1\), since the training and online Stage 1 shared the same character presentation pattern.
5.1.5 Online Operation

During online sessions, the BCI computer illuminated the characters in two stages: In Stage 1, the computer illuminated characters in 7 groups of 6 in the same randomization manner as done in training sessions. An EEG trial corresponding to each illumination (see Figure 5.3) was processed in real time and classified according to Equation 5.2, with $\theta = 1$. As long as the trials were classified as non-oddball, the interface kept cycling, re-randomizing before a new cycle. Once an oddball trial was detected, the BCI computer transitioned to Stage 2, where individual characters from the selected group were illuminated one at a time. On average, the more frequently used characters in the English language were illuminated earlier in Stage 1, thus facilitating faster transition to Stage 2.

Similar to Stage 1, the order in which characters were illuminated in Stage 2 was based on the character’s relative frequencies (Appendix D). An EEG trial corresponding to an illumination was also classified similarly, but with threshold $\theta = 0.5$. Once an illuminated character was selected here, the interface further highlighted the character in a solid green box and paused for 3.0 seconds to let the subject know of the decision. In addition, the selected character appeared on the typing prompt (see Figure 5.2), so that the subject can track their typing progress. The BCI computer then transitioned to Stage 1, and the whole process was repeated. An exception to this transition occurred when the BCI computer found a sufficiently small number ($\leq 5$) of dictionary completions to the partially spelled word. In this case, instead of going back to Stage 1, the possible completion characters were illuminated individually in a random order. For example, if the subject has spelled “LAZ” so far, the BCI computer would cycle among “I” (for LAZILY), ‘Y” (for LAZY), and the usual control characters (backspace, forward space, and exit). Repeated failure (over 3 cycles) to select a character in this dictionary completion stage resulted in the stage timing out and the BCI computer returning to Stage 1. Note that in this dictionary completion stage, the odds threshold $\theta = 0.5$, similar to Stage 2. This choice of threshold reflects our empirical
finding that P300 weakens when characters are illuminated individually.

In addition to the aforementioned single-trial selection method, the interface also kept track of the highest letter count (HLC). More specifically, this method integrates the evidence, $P(o|f^*)$ of individual characters, and the character with the highest integrated probability for over 10 consecutive trials is immediately classified as oddball and selected, thus bypassing Stage 2. This mechanism is useful when the evidence based on single trial is not strong enough to make a character selection. When a character is selected and entered to the typing prompt (whether by single-trial or HLC), the counters and integrated probabilities are reset.

Each subject performed 1–3 online sessions for each interface speed. Their session times were recorded. Note that they were required to correctly spell the entire benchmark sentence (corrections were facilitated by the backspace character), and that the BCI computer did not know the correct sentence. Should subjects exit the spelling interface without the correct sentence, they were asked to repeat the whole session.

### 5.1.6 ITR Calculation

The BCI-Speller system can be modeled as a binary communication channel (see Figure 5.4), whose inputs (left side) are user intentions: $o$ for selecting the highlighted character–oddball, $e$ for not selecting the highlighted character–non-oddball, respectively, and whose outputs (right side) are the decoded intentions: $\hat{o}$ for selecting the character and $\hat{e}$ for not selecting the character. The transition probabilities between inputs and outputs govern the chances of correctly or incorrectly decoding each type of intentions, and can be estimated from the confusion matrix from training-procedure data (see Section 4.3.6).

The amount of information per transmission (decoding) is given by the mutual information
Figure 5.4: BCI communication system as an asymmetric noisy communication channel.

between inputs and outputs, i.e.

\[ I(in; out) = H(out) - H(out|in) \]  \hspace{1cm} (5.3)

See Section 4.4 for details on mutual information and ITR. Briefly, ITR=\(\frac{I(in,out)}{T}\), where \(T\) is the inter-trial interval.

For online performances, the total time \(T\) to correctly type the benchmark sentence (44 characters) was recorded by the BCI computer. This time included the 3 sec pause after each selection that allowed subjects to be notified of their selection. This was true regardless of whether a correct or incorrect selection was made. In addition, the subjects were required to correct the incorrect selections by backspacing. While in this case, the selection of the backspace character represents an intended action, backspaces were not counted as correct selections since their purpose is to merely rectify previously committed error(s). As stringent as these requirements are, we believe that they set a standard for the definition of ITR that is completely immune to bit rate manipulations. More formally, practical, error-free ITR is defined as:

\[ ITR = \frac{N_c}{T} \log_2 |\mathcal{A}| \]  \hspace{1cm} (5.4)

where \(N_c\) is the number of correctly spelled characters in the benchmark sentence (\(N_c = 44\)), \(T\) is the total time taken to spell the sentence, and \(|\mathcal{A}|\) is the size of the alphabet (\(|\mathcal{A}| = 42\)).
5.2 Results for the BCI-Speller

The data from each training procedure were used for offline estimation of feature extraction and classification parameters. Event-related potential (ERP) analysis (obtained by averaging oddball and non-oddball trials), consistently revealed that subjects utilized both N200, mostly visible on the occipital lobe \( \sim 190 \) ms post-stimulus (see Fig. 5.5), and P300 which was present on all channels \( \sim 285-300 \) ms post-stimulus. This is consistent with findings reported by other groups, e.g. [75, 121]. In addition, a prominent positive potential seen in the fronto-parietal areas (most notably at Cz, C4, and Pz electrodes) approximately 190 ms post-stimulus may be an anterior-P200 response, which is related to various cognitive processes such as visual priming and search [44, 87].

The offline performances estimated through 10-fold CV and expressed as the probability of correct classification are presented in Table 5.3. Classification rates as high as 97.4% were achieved, and all subjects performed significantly above the 85.71% threshold, determined to be the chance-level performance of the Bayesian classifier (see Section 4.4). The number of trials varied depending on the ITI: 750 trials (ITI=400 ms), 1250 trials (ITI=240 ms), and 1870 trials (ITI=160 ms). To rule out the effect of the sample size on the achieved classifier performances, the feature extraction and classifier training procedures were repeated in the case of ITI=250 ms and ITI=160 ms by randomly sub-selecting 750 trials while preserving the 1:6 oddball-to-non-oddball ratio. The classification rates were not significantly different than those using all available trials, so the differences in the offline performances observed across ITIs are likely caused by other factors, such as the dependence of the P300 amplitude on ITI time [49]. Finally, the offline ITRs were calculated using mutual information (Eqn. 4.16). Based on these performances, all subjects were expected to have purposeful control of the BCI in the online mode (see below).

In the online sessions, the performance of each subject was determined by the total time
Figure 5.5: Event-related potentials of oddball (red) and non-oddball (blue) trials for Subject B, collected at the slow interface speed. The error bars represent the standard error of mean. Each panel is 18 $\mu$V $\times$ 300 ms, with the grid lines corresponding to 200 and 300 ms post-stimulus.
Table 5.3: Offline performances of subjects as assessed through 10-fold CV. Rows show mean performance (top), best performance (middle), and ITR of best performance (bottom).

<table>
<thead>
<tr>
<th>Subject</th>
<th>ITI (ms)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>400</td>
<td>240</td>
<td>160</td>
</tr>
<tr>
<td>A</td>
<td>95.7±1.5%</td>
<td>94.1±1.1%</td>
<td>93.4±1.6%</td>
</tr>
<tr>
<td></td>
<td>97.0%</td>
<td>94.9%</td>
<td>94.4%</td>
</tr>
<tr>
<td></td>
<td>0.403*</td>
<td>0.308</td>
<td>0.293</td>
</tr>
<tr>
<td>B</td>
<td>95.2±1.9%</td>
<td>93.9±2.5%</td>
<td>94.3±2.9%</td>
</tr>
<tr>
<td></td>
<td>97.4%</td>
<td>96.2%</td>
<td>96.6%</td>
</tr>
<tr>
<td></td>
<td>0.427**</td>
<td>0.365</td>
<td>0.385</td>
</tr>
<tr>
<td>C</td>
<td>93.9±2.5%</td>
<td>93.7±2.8%</td>
<td>93.5±1.9%</td>
</tr>
<tr>
<td></td>
<td>96.6%</td>
<td>96.9%</td>
<td>95.5%</td>
</tr>
<tr>
<td></td>
<td>0.385</td>
<td>0.397*</td>
<td>0.335</td>
</tr>
<tr>
<td>D</td>
<td>91.2±0.8%</td>
<td>90.5±0.2%</td>
<td>91.1±1.0%</td>
</tr>
<tr>
<td></td>
<td>92.1%</td>
<td>90.7%</td>
<td>92.2%</td>
</tr>
<tr>
<td></td>
<td>0.196</td>
<td>0.150</td>
<td>0.202*</td>
</tr>
<tr>
<td>E</td>
<td>91.2±1.5%</td>
<td>92.8±2.2%</td>
<td>90.5±2.3%</td>
</tr>
<tr>
<td></td>
<td>92.3%</td>
<td>95.1%</td>
<td>92.4%</td>
</tr>
<tr>
<td></td>
<td>0.211</td>
<td>0.325*</td>
<td>0.221</td>
</tr>
<tr>
<td>F</td>
<td>94.2±0.9%</td>
<td>93.3±0.9%</td>
<td>93.8±0.3%</td>
</tr>
<tr>
<td></td>
<td>95.3%</td>
<td>94.2%</td>
<td>94.0%</td>
</tr>
<tr>
<td></td>
<td>0.327*</td>
<td>0.279</td>
<td>0.273</td>
</tr>
</tbody>
</table>

* marks personal best and ** overall best.
taken to correctly type the 44-character sentence (see Table 5.4). All subjects achieved their best results at the high interface speed and were able to complete the task within a 3.45–4.51 min time window. The subjects’ average performances also demonstrate that they preferred the high interface speed (note that Subject A performed \( n = 5 \) online sessions for the 400 ms speed, while all other averages were based on \( n = 6 \) sessions). This was true despite the highest offline ITRs being achieved at the slow interface speed (cf. Table 5.3), and it indicates that the speed-accuracy trade off is well exploited using an ITI=160 ms. In addition, the practical, error-free ITRs were calculated using (4.12), and they reached values as high as 1.146 bit/sec. This bit rate corresponds to correctly typing 12.75 character/min. It should be noted that out of the 207.1 sec to complete the sentence, only 78.1 sec were spent on letter selection while 129 sec were spent on post-selection pauses. A similar breakdown applies to other subjects, where post-selection time constituted more than 60% of the total time.

Table 5.4: Online performances (in sec, includes the 3 sec pause after letter selection) across subjects and days. Mean performance (top row), best performance and day at which it was achieved (bottom row), and information transfer rates of the best online session (last column) are given.

<table>
<thead>
<tr>
<th>Subject</th>
<th>ITI (ms)</th>
<th>ITR (bit/sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>400</td>
<td>240</td>
</tr>
<tr>
<td>A</td>
<td>324.6±28.1</td>
<td>328.5±37.0</td>
</tr>
<tr>
<td></td>
<td>302.9 (3)</td>
<td>289.4 (2)</td>
</tr>
<tr>
<td>B</td>
<td>337.9±27.7</td>
<td>304.1±48.1</td>
</tr>
<tr>
<td></td>
<td>299.8 (3)</td>
<td>248.9 (3)</td>
</tr>
<tr>
<td>C</td>
<td>395.8±67.3</td>
<td>305.4±44.8</td>
</tr>
<tr>
<td></td>
<td>301.8 (3)</td>
<td>254.6 (3)</td>
</tr>
<tr>
<td>D</td>
<td>495.4±61.3</td>
<td>380.7±77.0</td>
</tr>
<tr>
<td></td>
<td>447.0 (1)</td>
<td>275.0 (1)</td>
</tr>
<tr>
<td>E</td>
<td>558.3±104.4</td>
<td>397.6±83.2</td>
</tr>
<tr>
<td></td>
<td>471.9 (1)</td>
<td>323.5 (2)</td>
</tr>
<tr>
<td>F</td>
<td>465.4±118.3</td>
<td>346.2±53.4</td>
</tr>
<tr>
<td></td>
<td>354.7 (3)</td>
<td>263.4 (3)</td>
</tr>
</tbody>
</table>

* marks personal best and ** overall best.
Before comparing the sustained, error-free ITRs achieved in this study to those of other EEG-based BCI systems, we make the following observations: (i) reported ITRs often exclude or simply ignore post-selection time (3 sec in the present study) from calculations [67, 93, 123], and (ii) reported ITRs are rarely, if ever, calculated in an error-free fashion, i.e. the subjects are not required to correct spelling errors before proceeding. Table 5.5 shows a comparison of

Table 5.5: Comparison of the best achieved information transfer rates for several EEG-based BCI studies. Note that ITRs here exclude paused and wait times. Comparisons with other studies assume optimal conditions.

<table>
<thead>
<tr>
<th>Study</th>
<th>ITR (bits/trial)</th>
<th>Trial Frequency (trials/sec)</th>
<th>ITR (bits/sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>present</td>
<td>A 0.363</td>
<td>5.81</td>
<td>2.109</td>
</tr>
<tr>
<td></td>
<td>B 0.514</td>
<td>5.82</td>
<td>2.992</td>
</tr>
<tr>
<td></td>
<td>C 0.522</td>
<td>5.82</td>
<td>3.038</td>
</tr>
<tr>
<td></td>
<td>D 0.422</td>
<td>5.82</td>
<td>2.455</td>
</tr>
<tr>
<td></td>
<td>E 0.302</td>
<td>5.85</td>
<td>1.766</td>
</tr>
<tr>
<td></td>
<td>F 0.415</td>
<td>5.86</td>
<td>2.434</td>
</tr>
<tr>
<td>[75]</td>
<td>0.039</td>
<td>5.71</td>
<td>0.224</td>
</tr>
<tr>
<td>[127]</td>
<td>0.144</td>
<td>5.82</td>
<td>0.836</td>
</tr>
<tr>
<td>[138]</td>
<td>0.129</td>
<td>8</td>
<td>1.028</td>
</tr>
<tr>
<td>[150]</td>
<td>2.373</td>
<td>0.526</td>
<td>1.249</td>
</tr>
<tr>
<td>[51]</td>
<td>0.859</td>
<td>0.463</td>
<td>0.398</td>
</tr>
</tbody>
</table>

the peak character selection ITRs achieved in the present study to those derived from other EEG-based BCI studies. The present-study ITRs were obtained from (4.12) by subtracting the total post-selection time from the personal best times reported in Table 5.4. While these rates were nominally achieved at ITI=160 ms (or 6.25 trial/sec), the values reported in the middle column are somewhat lower due to real-time processing demands. For the study in [75], the performance of the best subject (Subject A) was determined based on 11 illumination sequences (the study uses 15 sequences, but a 0% error rate appears to be achieved after 11 sequences). This corresponds to correctly spelling at a rate of 23.1 sec (11 × 2.1) per character, which given a 36-character matrix and according to (4.12), yields an ITR of 0.224 bit/sec. Also, this study used an ITI=175 ms, which is equivalent to 5.71
trial/sec. The same BCI system was used in [127] with an additional natural language processing algorithm, which resulted in the best subject (Subject 1) achieving the highest error-free bit rate after only 3 illumination sequences. Similar to [75], this corresponds to correctly spelling at a rate of 6.2 sec (3 × 2.06) per character. Given the same 36-character matrix and according to (4.12), this subject’s result yields an ITR of 0.836 bit/sec. Since an ITI similar to that of [75] was used in this study (~172 ms), an equivalent trial frequency and ITR in bits/trial of 5.82 trials/sec and 0.144 bit/trial, respectively, can easily be calculated.

Bit rates as high as 61.70 bit/min were reported in [138] (Subject 14), from which the value in Table 5.5 immediately follows. The illumination frequency of 8 trials/sec readily follows from an ITI=125 ms used in the study. The study in [150] was not concerned with a BCI spelling task, rather it reported on BCI-controlled cursor movements to a series of 8 screen targets. The best performance (Subject D) corresponded to accuracy of 92%, which when symmetric channel is assumed (see Section 4.4), yields 2.373 bit/trial. With the average duration of a trial being 1.9 sec, the ITR of 1.249 bit/trial follows readily. Finally, the study in [51] determined the speed and accuracy of two different flashing paradigms: single letter display and row-column display of flashing characters in a 6 × 6 matrix. It was determined that the single letter display paradigm was able to achieve higher communication speeds, spelling approximately 1 letter every 13 sec with a 95% accuracy across all 5 participants. Thus, with this typing speed, subjects were able to spell a 42-character sentence in 546 sec, which corresponds to a 0.398 bit/sec ITR using equation (4.12) while assuming error-free performances and ignoring post-selection notification times.
5.3 Discussion for the BCI-Speller

5.3.1 Performance

The results dispel the common assumption regarding ITRs achievable by EEG-based BCIs [150, 117]. In particular, our system allows characters to be selected in an error-free fashion with ITRs in excess of 3 bit/sec (cf. Table 5.5), which is three times higher than the best bit rates achieved with similar EEG spelling systems [138], and nearly three times higher than those achieved with 2-D cursor control [150].

The superior performance of our system can be attributed to several factors. Firstly, it is a truly single-trial system, i.e. it reliably classifies oddball and non-oddball stimuli after a single illumination. Other systems, such as those based on the original Farwell-Donchin paradigm [38], require repeated (up to 20) presentations of an oddball stimulus before a selection is made [75, 138]. Similar requirements are imposed in the so-called checkerboard paradigm [138]. Also, the ability to classify oddball and non-oddball stimuli on a single-trial basis with rates as high as 97.4% (see Table 5.3) is facilitated by a combination of techniques [22, 24, 21] briefly described in Sections 4.3.3 and 4.3.4. The most distinct feature of this method is that it can efficiently handle high-dimensional (480-D in the present study) spatio-temporal data without resorting to heuristic strategies such as subsampling EEG signals [75, 122] or constructing a feature set by addition/deletion of individual attributes [75, 138, 122]. This method has also been used to successfully classify other types of neurophysiologic data such as electrocorticograms (ECoG) [25], and in other types of BCI applications, such as asynchronous control of a virtual reality avatar [141, 71], hand orthosis [69], and functional electrical stimulator [30]. Secondly, biasing the illumination order of characters according to their frequencies (see Appendix D) significantly reduces the time the subject spends waiting for the desired character to get illuminated. For example, based on 100,000 Monte Carlo trials, we estimated that the 12 most frequent characters (see Fig. D.9)
are on average illuminated within the first two groups. For comparison, if the characters had been grouped in a uniformly random fashion, both frequent (e.g. E) and infrequent (e.g. Z) characters would have been on average found in the fourth group. Thus, the above sampling procedure exploits the relatively low entropy of the English language [18], which in turn facilitates faster character selection. Similarly, the partial word completion feature prompts users to first select those letters that represent dictionary-defined completions, thereby bypassing stage 1 and yielding significant time savings.

5.3.2 Information Transfer Rates

The discrepancy in per-trial ITRs between the offline (Table 5.3) and online performances (Table 5.5) can be explained by two factors. Firstly, the effect of feedback and subsequent user-interface interaction (e.g. excitement, frustration), specific to online sessions, cannot be accounted for with offline data. Secondly, the 1:6 oddball-to-non-oddball ratio observed in the training procedure may be significantly higher in the online procedure. Since the order of character illumination depends on their frequencies, the desired characters are likely to be illuminated early in the cycle (see Appendix D), and users are likely to select them before all 7 groups are illuminated, thereby disturbing the 1:6 ratio. To underscore this point, offline ITRs corresponding to a high interface speed (see Table 5.3) were recalculated according to the mutual information formula (Eqn. 4.16) with the assumed 1:3 oddball-to-non-oddball ratio, and values between 0.274 and 0.524 bit/trial were obtained, which are remarkably close to the ITRs achieved online (see Table 5.5). Therefore, the mutual information formula provides a reasonably accurate estimate of ITRs achievable online.

Based on the above, it follows that the formula [109]:

$$I(\text{in, out}) = \log_2 C + p_c \log_2 p_c + p_c \log_2 \left( \frac{p_c}{C - 1} \right)$$  (5.5)
frequently used to express ITRs in BCI studies [149, 98, 148], is not correct for BCIs based on the oddball paradigm. First note that for a two-class system ($C = 2$), the expression (5.5) reduces to $I(\text{in}, \text{out}) = 1 + p_c \log_2 p_c + p_\varepsilon \log_2 p_\varepsilon$, which represents the capacity (the maximum achievable ITR) of a binary symmetric channel [18]. To achieve this upper limit, in addition to being symmetric, the BCI communication channel must maintain equal prior probabilities of oddball and non-oddball trials, i.e. $p(o) = p(e)$. This, however, contradicts the very definition of the oddball paradigm, where by design we must have $p(o) \ll p(e)$. Similarly, for a chance level performance, we have $p_c = p(e)$ and $p_\varepsilon = p(o)$ (see Section 4.4), and so it follows from (5.5) (assuming the standard $p(o)$ to $p(e)$ ratio) that $I(\text{in}, \text{out}) = 0.408$ bit/trial, which presents an obvious contradiction. On the other hand, subjects with performances $p_c \leq p(e)$ are not able to spell, since $I(\text{in}, \text{out}) = 0$. For successful online spelling, offline performances need to be much higher than the chance level $p(e)$.

For an asymmetric communication channel (Section 4.4), the probabilities $p_\varepsilon$ and $p_c$ cannot be unequivocally linked to the mutual information, i.e. the confusion matrix probabilities must be used explicitly. If these are not available, a lower bound based on the Fano inequality [18] may be used

$$I(\text{in}, \text{out}) \geq H(\text{in}) + p_c \log_2 p_c + p_\varepsilon \log_2 (p_\varepsilon) \quad (5.6)$$

where $H(\text{in}) = -[p(o) \log_2 p(o) + p(e) \log_2 p(e)]$ (similar to (4.14)). Likewise, an upper bound on the mutual information may be derived from the Hellman-Raviv inequality [99, 54].

5.3.3 Improvements

While it has achieved unprecedented, error-free, online typing rates, our BCI-speller has not been optimized. For example, as the users underwent multiple experiments, they became familiar with the character layout, and felt that further reduction of post-selection pause (e.g.
from 3 to 2 sec) would not compromise the spelling accuracy. This step alone would have reduced the total spelling times (see Table 5.4) by at least 43 sec, and increased the practical, error-free ITRs by at least 25%. Furthermore, addition of a full word completion feature similar to current text-messaging systems on cellular phones could further significantly increase the practical bit rates. Implementation of these improvements is straightforward, although some user training may be required.

Fine tuning of ITI and increasing the number of channels, especially over the parietal lobe [75], could conceivably improve the ITRs even further. Also, optimization of luminance [133], background/foreground color, and character size and spacing [116], may lead to further improvements.

5.3.4 Conclusion

By exploiting basic concepts from pattern recognition theory and information theory, our EEG-based BCI communication system allows for error-free selection of characters with sustained, online bit rates that are several-fold higher than those that have been achieved with similar BCI systems. More importantly, these results disprove the common assumption that ITRs of EEG-based BCI systems are limited to $\sim$1 bit/sec [149, 117]. Since the parameters of the present system have not been optimized, we hypothesize that further substantial improvements of both character-selection and practical ITRs can be achieved. Many of these improvements are straightforward, while others may require some user training. These results may have significant implications on the viability and adoption of EEG-based BCIs in both clinical and non-clinical applications. They also offer compelling evidence for further development of state-of-the-art statistical signal processing and pattern recognition methods aimed at the single-trial processing and analysis of high-dimensional EEG data.
5.3.5 Future Work

Our BCI-Speller was tested on able-bodied subjects, whereas the intended users of this system are individuals with tetraplegia and locked-in syndrome. Other researchers have conducted similar studies, albeit with slower BCIs, on individuals with SCI [107], ALS [122, 125, 57, 107], multiple sclerosis [57, 107], traumatic brain injury [57], locked-in stroke [107], and others [57, 107]. Specifically, these people may suffer compromised cerebral cortex, potentially affecting the performance of BCI. Further testing is necessary to ensure that our system works on individuals with these conditions.
Chapter 6

BCI-Gait for Restoring Ambulation

The BCI-Gait is a long-term project aimed to restore able-body-like ambulation to individuals with paralysis due to spinal cord injury (SCI) by allowing them to control lower extremity walking prostheses directly with their brain. Incremental experimental protocols were developed to test the feasibility of this idea. Specifically, the project is divided into three steps: 1. Ambulation of a virtual reality avatar (BCI-Avatar [141]), 2. walking in a robotic gait orthosis on a treadmill (BCI-RoGO [34]), 3. and finally BCI-Parastep, free overground walking through functional electrical stimulation (FES). The last step is still ongoing as of year 2014. Also, despite the conclusion of the formal study in year 2012, Step 1 is still performed as a training platform for Steps 2 and 3.

6.1 Methods for the Avatar Experiments

To determine the feasibility of future BCI-lower extremity prosthesis systems for ambulation, we interfaced the BCI to a virtual reality environment (VRE) [141]. This VRE simulator provides a similar, albeit virtual, experience to the operation of a real prosthesis, without
Table 6.1: List of participants with demographic data and prior BCI experience relevant to the task. SCI status scored according to American Spinal Injury Association (ASIA) Impairment Scale.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Gender</th>
<th>Age</th>
<th>BCI experience</th>
<th>SCI status</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>M</td>
<td>40</td>
<td>~1 hr</td>
<td>-</td>
</tr>
<tr>
<td>A2</td>
<td>M</td>
<td>29</td>
<td>~1 hr</td>
<td>-</td>
</tr>
<tr>
<td>A3</td>
<td>F</td>
<td>23</td>
<td>~1 hr</td>
<td>-</td>
</tr>
<tr>
<td>A4</td>
<td>F</td>
<td>57</td>
<td>0 hr</td>
<td>-</td>
</tr>
<tr>
<td>A5</td>
<td>F</td>
<td>24</td>
<td>0 hr</td>
<td>-</td>
</tr>
<tr>
<td>A6</td>
<td>M</td>
<td>21</td>
<td>0 hr</td>
<td>-</td>
</tr>
<tr>
<td>A7</td>
<td>M</td>
<td>25</td>
<td>0 hr</td>
<td>-</td>
</tr>
<tr>
<td>A8</td>
<td>M</td>
<td>32</td>
<td>0 hr</td>
<td>-</td>
</tr>
<tr>
<td>S1</td>
<td>F</td>
<td>27</td>
<td>0 hr</td>
<td>T8 ASIA B, 11 yr post injury</td>
</tr>
<tr>
<td>S2</td>
<td>M</td>
<td>34</td>
<td>0 hr</td>
<td>T11, ASIA A, 8 yr. post injury</td>
</tr>
<tr>
<td>S3</td>
<td>M</td>
<td>46</td>
<td>0 hr</td>
<td>T1, ASIA B, 4 yr. post injury</td>
</tr>
<tr>
<td>S4</td>
<td>M</td>
<td>43</td>
<td>0 hr</td>
<td>C5, Syringomyelia, 14 yr. post onset</td>
</tr>
<tr>
<td>S5</td>
<td>M</td>
<td>59</td>
<td>0 hr</td>
<td>T1, ASIA B, 2 yr. post injury</td>
</tr>
<tr>
<td>S6</td>
<td>M</td>
<td>21</td>
<td>0 hr</td>
<td>T11, ASIA B, 1 yr. post injury</td>
</tr>
</tbody>
</table>

the associated physical risks [83]. In addition, the use of VRE in the context of BCI has been shown to reduce the decoding error [105]. The ability to rapidly achieve purposeful control of an avatar within the VRE represents a necessary step towards successful integration of EEG-based BCI systems and physical prostheses. It also implies the feasibility of envisioned BCI lower extremity prosthesis systems. Finally, it may in the future act as the first step in training SCI users to operate such prosthesis systems once they become available.

6.1.1 Experimental Overview

This study protocol was approved by the University of California, Irvine Institutional Review Board. 8 able-bodied subjects and 6 subjects with paraplegia due to SCI (see Table 6.1 for demographics) used kinesthetic motor imagery (KMI) of walking to operate the ambulation of the avatar within the VRE.
In the training procedure, they underwent alternating epochs of walking KMI and idling while their EEG data were collected. Subsequently, a computer algorithm used this training data to extract salient EEG signal features and train an EEG classifier. The training procedure was followed by an online BCI evaluation, where subjects utilized the same KMIIs to control the linear ambulation of an avatar within the VRE. To assess the attainment of purposeful control, subjects’ performances were recorded over several online sessions and compared to random walk Monte Carlo simulations.

6.1.2 EEG Data Acquisition

Each subject was seated in a chair approximately one meter from a computer monitor that displayed either textual cues (during training sessions) or the VRE (during online sessions). EEG was recorded using a 63-channel EEG cap (Medi Factory, Heerlen, The Netherlands) with Ag-AgCl electrodes arranged according to the 10-10 International Standard (see Figure 6.1). Conductive gel (Compumedics USA, Charlotte, NC) was applied to all electrodes and the 30-Hz impedances between each electrode and the reference electrode were maintained at <10 KΩ by abrading the scalp with a blunt needle. Two NeXus-32 EEG systems (MindMedia, Roermond-Herten, The Netherlands) were linked together and used to amplify and digitize (sampling rate: 256 Hz, resolution: 22 bits, built-in anti-aliasing filter: 27% of sampling rate) the EEG signals. Signals were streamed in real-time to a computer and subsequently re-referenced in a common average mode. Data acquisition and analysis were performed using custom-made MATLAB programs.

6.1.3 Training Procedure

To facilitate intuitive control of the BCI, subject-specific EEG decoding models were generated to differentiate between EEG underlying idling and walking KMI. In addition to being
Figure 6.1: Electrode arrangement on our EEG cap, abiding by the 10-10 (Extended 10-20) International Standard. Figure shown top-down view of a head with the nose pointing up. Each electrode is 10% arc length apart from the next, where a semicircle of the head is considered 100% arc length. The letters are derived from the names of the brain lobes and cortices. The numbers start low from the center (Z = center) and increase. Odd numbers are on the left, and even numbers are on the right. M = Mastoid electrodes. GR = Signal reference.
more intuitive than visual motor imagery, KMI is known to provide better separability of EEG for BCI applications [101]. To this end, subjects were instructed by textual cues to generate consistent and continuous walking KMI (i.e. imagine themselves walking) and idling KMI (i.e. relax), while their EEG data were recorded (see Figure 6.2). Specifically, subjects can imagine walking in different manners, such as marching or walking in large steps, and in different environments such as in water or on snow. The textual cues alternated every 30 s for a total of 10 min. At the same time, the EEG data were labeled as either walking or idling by a corresponding computer signal recorded by an auxiliary data acquisition system (MP150, Biopac Systems, Goleta, CA). The labeling and EEG signals were synchronized by sending a common pulse train (5 volts boxcar signal, 2000 ms cycle time, 50 ms pulse width) to both the MP150 and NeXus-32 data acquisition systems. Electromyogram (EMG) activity was not recorded to monitor for minor limb movements, since increased EMGs are often observed during KMI [64, 147, 80, 28]. Instead, the subjects were instructed to refrain from moving during the training procedure, which was enforced by observing the procedure and discarding the entire session if it was considered contaminated by movements.

### 6.1.4 Trial Extraction

The training EEG data were analyzed offline to generate a subject-specific prediction model, i.e. each subject has their own model. First, the EEG and labeling signals were aligned using the common synchronization pulse train. In addition, EEG channels with excessive EMG activity were excluded from further analysis using an iterative artifact rejection algorithm (see Appendix B). The pre-processed continuous 10-min EEG record was then split into 30-s long segments of idling and walking states based on the labeling signal. Due to uncertainties in timing between the computer cue and the subject’s reaction, the first 8 s of each segment were removed from analysis. Each remaining 22-s segment was then divided into five 4-s non-overlapping trials for a total of 100 trials. The labeled EEG trials were then Fast Fourier
Figure 6.2: A subject with SCI participating in the BCI-Avatar training procedure. 1. The right monitor displays the training cues—IDLE or WALK and a small counter on the number of repetitions remaining. The training cues also generate a computer signal to inform the computer on which cue the subject is receiving. 2. Upon receiving the cues, the subject performs a KMI of walking or idling, or simply attempts to walk or idle. 3. His brain signals are acquired and amplified by the NeXus-32 bio-amplifier. 4. The computer signal is reacquired by the MP150, allowing the computer to associate the subject’s EEG signals with the appropriate label (IDLE or WALK). 5. The left monitor displays the EEG traces and other information. Here, only 24 channels (those in Figure 7.3) are acquired, since the specific experiment (BCI-Parastep, Section 7.1.3.1) requires wireless EEG transmission. The monitor is also angled away from the subject to minimize distraction. Note that adhesive tape is used to prevent the heavy cables from pulling the EEG cap.
Transformed (FFT), and their power spectral densities were integrated in 2-Hz bins (see Appendix G.5 for implementation) that were centred at 1, 3, . . . , 39 Hz, yielding 20 power spectral values per channel.

### 6.1.5 Prediction Model Generation and Validation

The high dimensionality (>1000 dimensions) of a trial, exceeding the number of trials (50 trials per class), necessitates the use of dimension reduction. Therefore, CPCA and either AIDA or LDA are implemented. The combination of these methods yields a piecewise linear feature extraction mapping that approximately maximizes the mutual information between the features and class labels [99]. This resulted in the extraction of typically one-dimensional (1D) spatio-spectral features (see Equation 4.5). The classification and cross validation procedures are identical to those described in Section 4.3.

During trial extraction, the full range of frequency bins were used (1, 3, . . . , 39 Hz). Then, the lower bound of the frequency range was increased in 2-Hz steps, and the model generation and validation procedures were repeated until the classifier performance stopped improving. This defined the optimal lower frequency bound, FL. Once FL was found, the optimal higher frequency bound, FH, was found in a similar manner. The parameters of the prediction model, including the optimal frequency range, the feature extraction maps, and the classifier parameters, were then saved for real-time online evaluation procedure.

### 6.1.6 Virtual Reality Environment

The VRE was constructed using Garry’s Mod™ simulated physics environment (Valve Corporation, Bellevue, WA), and consisted of a flat grassland with 10 non-player characters.

---

1Final dimensions of 1D, 2D, and 3D are tested automatically, but 1D has always been chosen by the algorithm in all BCI-Gait experiments.
(NPCs) standing in a straight line. The course length was \( \sim 120 \) body lengths \( \sim 210 \) m, assuming a body length of 1.75 m) along the user’s avatar’s linear path (see Figure 6.3). This design is intended to facilitate a goal-oriented online test in which the subjects utilized walking KMI and idling to walk the avatar forward and stop by each NPC, similar to [83]. Further details of the online evaluation are described in Section 6.1.9.

To interface the BCI software and VRE, a virtual joystick program (Parallel Port Joystick [139]) was used. To this end, a C++ dynamic-link library was developed to relay BCI commands to move/stop the avatar via the virtual joystick. Finally, a custom-made C# program performed optical character recognition on the position readouts from the VRE’s display (see Figure 6.3) in order to automatically track the subject’s online BCI performance.

### 6.1.7 Online Signal Analysis

During any online operation (calibration or performance, described in the next two sections), 0.75-s segments of EEG data were streamed in real time to be analyzed. Since the experiments for able-bodied and SCI subjects were conducted on different computers (we upgraded our computer between the two), the acquisition rates were adjusted. For the experiments with able-bodied subjects, refresh cycle was 0.5 s, i.e. the BCI acquired and processed data every 0.5 s. On the other hand, the refresh cycle was 0.25 s for the experiments with SCI subjects. Note that nearby segments overlapped with each other. The EEG data segments were then processed for trial extraction, as described in the previous section. Briefly, the artifact channels identified in the training data were removed, and the EEG segments were converted to spectral data (over the optimized frequency range). The spectral data were then processed by the feature extraction matrices (see Equation 4.5), resulting in low dimensional spatio-spectral features. The features were classified according to Equation 4.6 and Appendix A, producing posterior probabilities of idling and walking. Note that the MAP
Figure 6.3: The VRE with the BCI-controlled avatar in 3rd person over-the-shoulder view. A subject can command the avatar to move forward or stop by using BCI. Shown next to the avatar is an NPC and a traffic cone. The position/speed readouts are shown in the top right corner.
rule (Equation 4.10) was not directly used to decide on the class label of the EEG segment.

6.1.8 Online Calibration

Prior to online BCI operation, a short calibration procedure was performed to determine state transition rules suitable for self-paced online BCI operation. This is necessary because unlike offline analysis (when generating the prediction model) that is based on well-segmented and labeled EEG trials, online data segments may lie at class transitions. This would cause the MAP rule (Equation 4.10) to create an excessively noisy state transition sequence, which may frustrate the user during online BCI operation. Furthermore, the calibration procedure, in addition to cross validation, verifies the quality of the prediction model by providing new data.

The real-time, self-paced BCI operation is modeled as a binary state machine (see Figure 6.4), where state transitions are triggered by comparing the posterior probabilities to suitably chosen thresholds, $T_{I}$ and $T_{W}$. The system transitions from the idling to walking state when $\bar{P}(W|f^*) > T_{W}$, where $\bar{P}(W|f^*)$ is the posterior probability of the walking class given the observed feature, $f^*$, averaged over the most recent 1.5 s of walking class posterior probabilities (note that averaging may further smooth the state transitions at the expense of responsiveness). Conversely, the system transitions from the walking to idling state whenever $\bar{P}(W|f^*) < T_{I}$. When $T_{I} < \bar{P}(W|f^*) < T_{W}$, the system remains in the present state. Unlike the MAP rule that essentially uses $T_{I} = T_{W} = 0.5$, this scheme provides a switch-like control that reduces the subject’s mental workload.

To determine the optimal $T_{I}$ and $T_{W}$, the BCI-Gait system was loaded with the prediction model from training data and set to run in the online mode without the VRE. Subjects were verbally prompted to alternate between 20–30-s epochs of idling and walking KMI for a total of 4 min. During each mental state, the averaged posterior probabilities $\bar{P}(W|f^*)$
were calculated, and their histograms were plotted (see Figure 6.5 for example). Based on these histograms, the thresholds were initially chosen as: $T_W = \text{median}\{P(W|f^* \in W)\}$ and $T_I = \text{median}\{P(W|f^* \in I)\}$, where $P(W|f^* \in W)$ and $P(W|f^* \in I)$ represent the posterior probabilities of walking given that the subject was instructed to engage in walking KMI and idling, respectively. A short online test was then performed and based on the subject’s feedback, these thresholds were further adjusted to help optimize the performance.

6.1.9 Online Performance and Assessment

To assess the online BCI performance, subjects used walking KMI and idling to move the avatar within two body lengths of each NPC and stand still for at least 2 s. Similar to the training procedure, the subjects were instructed to refrain from moving and were asked to repeat the task if movements were detected. Each subject repeated this task over 5 total sessions within a single day. The experiment (including training procedure and prediction model generation) was repeated for each SCI subject for a total of 5 days on a weekly basis. Two performance measures were recorded during each session: the time taken to complete the course and the stop scores. Subjects received one point for continuously idling the avatar within the designated stop for at least 2 s; therefore, the maximum stop score was 10 points.
Figure 6.5: An example of the calibration histograms. X-axis: Probability. Y-axis: Number of occurrences. Note the highly concentrated cluster for $P(W|f^* \in W)$. 
In addition, only a fraction of the point was awarded for dwelling between 0.5 and 2.0 s:

\[ S = \begin{cases} 
0, & t_{\text{stop}} < 0.50 \text{s} \\
1, & t_{\text{stop}} \geq 2.00 \text{s} \\
(t_{\text{stop}} - 0.50 \text{s})/1.50, & 0.50 \text{s} < t_{\text{stop}} < 2.00 \text{s}
\end{cases} \]  

(6.1)

where \( S \) is the stop score, and \( t_{\text{stop}} \) is the contiguous time stopped at a NPC. Note that subjects were not penalized for dwelling longer than 2 s, however, this will inevitably increase the completion time and therefore lower the overall performance. A 20-min time limit was enforced, beyond which the online session was interrupted and the number of successful stops achieved thus far was recorded. Ideally, it should take on average 18 s to walk from one NPC to the next without stopping, with the total course completion time of 202 s (182 s for walking and 20 s for idling).

**Control Experiments:** The completion time and stop score were compared to those achieved by random walk to determine whether purposeful control was achieved. Random walk performances were simulated by sampling the posterior probabilities uniformly between 0 and 1 and applying the state transition rules using the same subject-specific thresholds \( T_I \) and \( T_W \). The random walk simulator was also allotted the 20-min time limit, and the stop score was calculated in the same manner as above. To facilitate statistical testing, 1000 Monte Carlo runs of the random walk simulation were performed. The subjects’ performances were then compared to those of the Monte Carlo simulation, and empirical p-values were calculated. An additional control experiment consisted of an able-bodied subject manually performing the same task with a physical joystick.

**Statistical Tests:** The 2D probability density function (PDF), with completion times and stop scores as variables, of each subject’s simulated random walk was estimated using the Parzen window method [37, 14]. Through each subject’s observed performance point (completion
time and stop score), a constant-value PDF contour was drawn. The volume under the PDF outside the contour was then found by numerical integration, effectively defining the p-value (the null hypothesis being that the subjects’ performances are no different from random walk). Purposeful control was defined as the ability to complete the task within 20 min with performances significantly different from random walk in a multivariate analysis.

**Composite Scores:** Due to the inherent trade-off between completion time (speed) and stop score (accuracy), it is difficult to objectively determine whether an online session was better than another. A subject may choose to expend little effort to stop at every NPC to finish the course faster, or vice versa. Therefore, to achieve a meaningful comparison of performances across sessions and subjects, the two performances measures were normalized:

\[
\begin{align*}
    c_s &= \frac{s}{s_{\text{max}}} \\
    c_t &= \frac{t_{\text{max}} - t}{t_{\text{max}} - t_{\text{min}}}
\end{align*}
\]  

(6.2)

where \( s \) is the subject’s stop score, \( s_{\text{max}} = 10 \) is the maximum stop score, \( t \) is the subject’s completion time, \( t_{\text{max}} = 1200 \) sec is the maximum allowed time, and \( t_{\text{min}} = 202 \) sec is the minimum time required, as determined by the course design, to complete the course while achieving 10 successful stops. Note that the values of \( c_s \) and \( c_t \) range from 0 to 1, with 1 being an ideal performance. To express performance as a single number, a composite score is defined as the geometric mean of the two normalized performance measures, i.e.:

\[
c = \sqrt{c_sc_t}
\]

(6.3)

Note that the use of geometric mean favors a performance that is balanced in both the stop score and completion time over a performance that sacrifices one measure over the other (see Figure 6.6). For an extreme example, finishing the course in a short time while failing to make any stops leads to zero composite score. Also note that the normalization of \( c_s \) and \( c_t \),
and in turn, $c$, ensures that the units of time and stop score do not affect the comparison between different sessions or subjects, and that the trade-offs between accuracy and speed can be meaningfully compared.
6.2 Results for the Avatar Experiments

6.2.1 Offline Performance

The study was conducted separately over able-bodied (AB) and SCI populations. The subjects underwent training data collection, and subject-specific EEG prediction models were generated. Cross-validation of these models resulted in offline classification accuracies ranging from 60% to 95% (Table 6.2 for AB, Table 6.3 for SCI), with p-values < 0.002 for all but 3 sessions (these 3 had p-values < 0.02). The null hypothesis is defined as having a chance level classification accuracy of 50%. AB subjects averaged 75.1% classification rate, and SCI subjects averaged 80.2% classification rate. These averages were not significantly different (p=0.13) to each other.

Further analysis of the subject-specific feature extraction maps demonstrated that the most informative features for classification in AB subjects were the EEG powers in the 4-18 Hz frequency range over the lateral central/centro-parietal areas (see Figure 6.7 for example). However, no consistency was found among the SCI subjects. Their maps suggested that they employed different brain areas while performing this task. For example, Subjects S1 and S3 used mostly the Cz area (Figures 6.8 and 6.9), whereas Subject S6 used areas C3 and C4 (Figure 6.10). Furthermore, they employed different brain areas on different days. For example, the employed brain areas for Subject S6 progressively shifted in the posterior direction. Nevertheless, the salient brain areas were mostly confined to the $\mu$ (8-12 Hz) and low $\beta$ (12-16 Hz) bands.
Table 6.2: Offline performances represented as classification accuracies estimated with 10 runs of stratified 10-fold CV. The classification accuracy is defined as the probability of correctly classifying a trial given the feature, $f^*$, i.e. $P(\text{correct} \mid f^*) = P(I \mid f^* \in I)P(I) + P(W \mid f^* \in W)P(W)$, where $P(I \mid f^* \in I)$ and $P(W \mid f^* \in W)$ are defined in Section 6.1.5, and $P(I)$ and $P(W)$ are the prior probabilities of idling and walking classes, respectively. The number of retained channels (RC) after artefact rejection and the optimal frequency range corresponding to each subject’s offline performance are also included. *32-channel EEG montage was used due to technical difficulties.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$P(\text{correct} \mid f^*)$</th>
<th>p-value</th>
<th>RC</th>
<th>Freq. band</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>88.3 ± 0.7%</td>
<td>1.27 x 10^{-16}</td>
<td>54</td>
<td>6-20 Hz</td>
</tr>
<tr>
<td>A2</td>
<td>86.6 ± 0.8%</td>
<td>6.56 x 10^{-15}</td>
<td>54</td>
<td>8-24 Hz</td>
</tr>
<tr>
<td>A3</td>
<td>76.0 ± 1.3%</td>
<td>9.05 x 10^{-8}</td>
<td>54</td>
<td>6-20 Hz</td>
</tr>
<tr>
<td>A4</td>
<td>80.9 ± 1.2%</td>
<td>1.35 x 10^{-10}</td>
<td>32</td>
<td>4-40 Hz</td>
</tr>
<tr>
<td>A5</td>
<td>67.4 ± 2.2%</td>
<td>2.04 x 10^{-4}</td>
<td>54</td>
<td>8-40 Hz</td>
</tr>
<tr>
<td>A6</td>
<td>72.5 ± 1.6%</td>
<td>2.35 x 10^{-6}</td>
<td>42</td>
<td>4-18 Hz</td>
</tr>
<tr>
<td>A7</td>
<td>64.3 ± 1.1%</td>
<td>1.76 x 10^{-3}</td>
<td>50</td>
<td>6-40 Hz</td>
</tr>
<tr>
<td>A8</td>
<td>64.5 ± 1.8%</td>
<td>1.80 x 10^{-3}</td>
<td>25</td>
<td>4-40 Hz</td>
</tr>
<tr>
<td>S1</td>
<td>94.5 ± 0.8%</td>
<td>6.26 x 10^{-23}</td>
<td>53</td>
<td>8-40 Hz</td>
</tr>
<tr>
<td>A1-8</td>
<td>75.1 ± 9.5%</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>All</td>
<td>77.2 ± 11.0%</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Figure 6.7: Spatio-spectral feature extraction maps in the 12-14 Hz bin for Subject A2. Dark colors (red and blue) represent the areas that were responsible for encoding the differences between idling and walking KMI. Since the feature extraction method is piecewise linear, there are two maps: the map on the left (right) corresponds to the subspace adapted to the idle (walking) class, respectively.
Table 6.3: Offline performances represented as classification accuracies estimated using 10 runs of stratified 10-fold CV. The classification accuracy is defined as the probability of correctly classifying a trial given the feature, $f^*$, i.e. $P(\text{correct} | f^*) = P(I | f^* \in I)P(I) + P(W | f^* \in W)P(W)$, where $P(I | f^* \in I)$ and $P(W | f^* \in W)$ are defined as in Section 6.1.5, and $P(I)$ and $P(W)$ are the prior probabilities of idling and walking class, respectively. †32-channel EEG montage was used due to technical difficulties.

| Subject | Day | $P(\text{correct} | f^*)$ | p-value | RC | Freq. band |
|---------|-----|--------------------------|---------|----|------------|
| S2      | 1   | 71.9 ± 2.2%              | 6.29 × 10^{-6} | 54 | 6-40 Hz    |
|         | 2   | 89.4 ± 1.2%              | 1.53 × 10^{-17} | 54 | 6-40 Hz    |
|         | 3   | 83.9 ± 2.0%              | 1.30 × 10^{-12} | 54 | 8-40 Hz    |
|         | 4   | 84.0 ± 1.9%              | 1.30 × 10^{-12} | 54 | 8-40 Hz    |
|         | 5   | 82.2 ± 1.7%              | 6.55 × 10^{-12} | 54 | 8-40 Hz    |
| Avg.    |     | 82.3 ± 6.4%              | 1.26 × 10^{-6}  |    |            |
| S3      | 1   | 62.2 ± 1.8%              | 6.00 × 10^{-3}  | 53 | 4-40 Hz    |
|         | 2   | 62.0 ± 1.8%              | 1.05 × 10^{-2}  | 53 | 4-40 Hz    |
|         | 3   | 60.5 ± 2.0%              | 1.76 × 10^{-2}  | 53 | 6-40 Hz    |
|         | 4   | 91.6 ± 1.7%              | 1.60 × 10^{-19} | 54 | 4-40 Hz    |
|         | 5   | 82.5 ± 1.6%              | 6.55 × 10^{-12} | 25†| 6-20 Hz    |
| Avg.    |     | 71.8 ± 14.3%             | 6.82 × 10^{-3}  |    |            |
| S4      | 1   | 90.3 ± 1.3%              | 1.66 × 10^{-18} | 53 | 4-40 Hz    |
|         | 2   | 83.9 ± 1.1%              | 1.30 × 10^{-12} | 54 | 4-40 Hz    |
|         | 3   | 72.8 ± 2.9%              | 2.35 × 10^{-6}  | 53 | 6-40 Hz    |
|         | 4   | 81.0 ± 2.1%              | 1.35 × 10^{-10} | 46 | 28-40 Hz   |
|         | 5   | 83.3 ± 1.2%              | 1.30 × 10^{-12} | 32†| 4-12 Hz    |
| Avg.    |     | 82.3 ± 6.3%              | 4.69 × 10^{-7}  |    |            |
| S5      | 1   | 74.7 ± 1.7%              | 2.82 × 10^{-7}  | 53 | 4-32 Hz    |
|         | 2   | 92.3 ± 1.6%              | 1.36 × 10^{-20} | 53 | 4-40 Hz    |
|         | 3   | 81.5 ± 1.3%              | 3.07 × 10^{-11} | 32†| 6-40 Hz    |
|         | 4   | 80.5 ± 2.0%              | 1.35 × 10^{-10} | 32†| 8-40 Hz    |
|         | 5   | 83.5 ± 2.2%              | 1.30 × 10^{-12} | 46 | 8-40 Hz    |
| Avg.    |     | 82.5 ± 6.4%              | 5.64 × 10^{-8}  |    |            |
| S6      | 1   | 82.7 ± 1.3%              | 6.55 × 10^{-12} | 32†| 4-40 Hz    |
|         | 2   | 86.3 ± 1.3%              | 6.56 × 10^{-15} | 32†| 4-40 Hz    |
|         | 3   | 78.9 ± 1.4%              | 2.17 × 10^{-9}  | 32†| 10-40 Hz   |
|         | 4   | 82.2 ± 1.5%              | 6.55 × 10^{-12} | 32†| 4-40 Hz    |
|         | 5   | 81.0 ± 1.3%              | 1.35 × 10^{-10} | 32†| 4-40 Hz    |
| Avg.    |     | 82.2 ± 2.7%              | 4.30 × 10^{-10} |    |            |
6.2.2 Online Calibration

After the short calibration procedure, the distributions of the averaged posterior probabilities, $\bar{P}(W|f^*)$, were estimated as histograms. Note that in an ideal situation, $\bar{P}(W|f^* \in W) = 1$ and $\bar{P}(W|f^* \in I) = 0$, but as long as these values are separable, accurate decoding of idling and walking should be achievable. The state transition thresholds, $T_I$ and $T_W$ were then determined using these histograms, and their values are presented in Tables 6.4 (AB) and 6.5 (SCI). The values of $T_I$ and $T_W$ ranged from 0.07 to 0.70 and 0.09 to 0.91, respectively. Despite the wide range, all individual pairs of $T_I$ and $T_W$ were separable. In addition, the chosen $T_W$ were found to linearly correlate with the offline performances in Tables 6.2 and 6.3 ($\rho=0.40$, $p=5.2 \times 10^{-8}$, $n=169$). However, the correlation was much weaker for $T_I$ ($\rho=0.18$, $p=0.017$). Finally, it was found that the offline performances also correlate with the separability of $T_I$ and $T_W$ (i.e. $T_W - T_I$) with $\rho=0.28$ and $p=1.9 \times 10^{-4}$.
Figure 6.9: Selected feature extraction maps of Subject S3 across days, showing chronological changes in the brain areas that were important for decoding.
Figure 6.10: Selected feature extraction maps of Subject S6 across days, showing chronological changes in the brain areas that were important for decoding.
Table 6.4: The chosen values of thresholds $T_I$ and $T_W$.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$T_I$</th>
<th>$T_W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>0.53</td>
<td>0.91</td>
</tr>
<tr>
<td>A2</td>
<td>0.24</td>
<td>0.64</td>
</tr>
<tr>
<td>A3</td>
<td>0.19</td>
<td>0.56</td>
</tr>
<tr>
<td>A4</td>
<td>0.43</td>
<td>0.58</td>
</tr>
<tr>
<td>A5</td>
<td>0.55</td>
<td>0.57</td>
</tr>
<tr>
<td>A6</td>
<td>0.53</td>
<td>0.61</td>
</tr>
<tr>
<td>A7</td>
<td>0.41</td>
<td>0.43</td>
</tr>
<tr>
<td>A8</td>
<td>0.19</td>
<td>0.45</td>
</tr>
<tr>
<td>S1</td>
<td>0.32</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Table 6.5: The chosen values of thresholds $T_I$ and $T_W$.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Day</th>
<th>$T_I$</th>
<th>$T_W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>S2</td>
<td>1</td>
<td>0.37</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.42</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.45</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.22</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.35</td>
<td>0.44</td>
</tr>
<tr>
<td>S3</td>
<td>1</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.42</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.60</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.60</td>
<td>0.66</td>
</tr>
<tr>
<td>S4</td>
<td>1</td>
<td>0.20</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.57</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.26</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.70</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.40</td>
<td>0.90</td>
</tr>
<tr>
<td>S5</td>
<td>1</td>
<td>0.62</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.61</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.38</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.40</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.58</td>
<td>0.65</td>
</tr>
<tr>
<td>S6</td>
<td>1</td>
<td>0.30</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.40</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.30</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.40</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.30</td>
<td>0.85</td>
</tr>
</tbody>
</table>
6.2.3 Online Performance

The online performances of all subjects operating the BCI-controlled walking simulator were evaluated by comparing the completion times and the stop score to those of the simulated random walk. Representative comparisons in the form of PDF contours are shown in Figures 6.11 and 6.12. Overall, in 39 out of 41 sessions with able-bodied subjects and 123 out of 128 sessions with SCI subjects, the subjects achieved performances that were significantly different (i.e. “outside of the contours”) from those of random walk (p<0.01). In addition, the average completion times and successful stops are summarized in Tables 6.6 and 6.7. Note that the completion time consists of a fixed walking time (182 s) and a variable amount of idling time.

As previously mentioned, based on the definition in Section 6.1.9, purposeful BCI control of the avatar was achieved by all subjects in 162 out of 169 online sessions. The performance breakdown according to individual measures is as follows. Subjects A1, S1, S4, S5, and S6 achieved purposeful control with superior performance in both measures. Subjects A4, A5, A6, and S3 achieved purposeful control with superior performance in completion time only. On the other hand, Subjects A2, A3, A7 and A8 achieved purposeful control with superior performance in the stop score, although they required more time to complete the task. However, it is crucial that these individual performance measures be interpreted in the context of each other in order to be meaningful, and these points will be further elaborated upon in Section 6.3. Finally, to demonstrate the performance level achievable by manual control, an able-bodied subject performed the task with a physical joystick. The manual joystick performance was significantly different and superior to the BCI performances in terms of completion times (p=0.002) but was not different in terms of the number of successful stops (p=0.072).

To illustrate the level of control achievable by this BCI system, Figure 6.13 shows a repre-
Figure 6.11: Online performances for representative able-bodied subjects and one SCI subject. Each cross is an online session (next to p-values). A perfect session would land at the top left corner. The PDF contour represents the random walk’s simulated online performances. Crosses outside the contour indicate significant purposeful control.

Legend:
- Blue: p < 0.01
- Green: p < 0.05
- Red: NS
Figure 6.12: Online performances for SCI subjects on their best days. All performances were significant. Composite scores in parentheses. All subjects here received more stop scores and most are faster than the random walk.
Figure 6.13: Time-space course of representative online sessions for Subjects A8 (left) and S4 (right). The pink areas mark the ten designated stopping zones. Orange segments mark false starts. Red segments mark false stops. In order to finish the course, a subject is required to walk the avatar out of the last stopping zone. The minimum possible time to achieve perfect stop score is 202 s.

A representative time-space course of an online session for Subject A8. In this session, the subject completed the course with maximum stop score and completion times as little as 23 s over the minimum possible time. In addition, he had only two false starts (walking more than necessary within a stop zone). Over 5 online sessions, this subject averaged 0.4 false starts and 2.6 false stops. By factoring in the duration of false starts and stops, as well as the completion time, these correspond to error rates of 0.42% and 3.34%, respectively. The same figure also shows Subject S4 achieving equally impressive performances and low amount of false transitions. One of the subjects also participated in a live demonstration (see Figure 6.14).

The composite scores were calculated to compare performances over experiment days and are summarized in Table 6.8. In general, the performances improved significantly over time; the average on day 1 was 77.8% and the average on day 5 was 85.7% (p=0.0302). For comparison, the composite score of the joystick task is also shown. On their best days, Subjects S4, S5, and S6 achieved performances similar to those of the hand-controlled joystick, reaching nearly perfect performances (100%).
Figure 6.14: A subject with SCI participated in this live demonstration of operating the BCI-controlled ambulation of the virtual reality avatar. The subject was able to converse with visitors while maintaining control of the BCI. Filmed at Meet the Scientists Forum, Reeve-Irvine Research Center, University of California, Irvine in March, 2010.
Table 6.6: Average online performances of the able-bodied subjects compared to those of random walk (denoted by RW in the immediate row). Sessions are also broken down by number of purposeful and non-purposeful performances, i.e. \((p<0.01, p\geq 0.01)\)

<table>
<thead>
<tr>
<th>Subject</th>
<th>Completion Time mean±std (sec)</th>
<th>Stop Score mean±std</th>
<th>Session breakdown</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>320±48</td>
<td>9.1±0.6</td>
<td>(5, 0)</td>
</tr>
<tr>
<td>A1-RW</td>
<td>&gt;1200</td>
<td>0.2±0.4</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>267±11</td>
<td>7.8±1.1</td>
<td>(5, 0)</td>
</tr>
<tr>
<td>A2-RW</td>
<td>224±18</td>
<td>1.5±1.1</td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>292±19</td>
<td>8.0±1.1</td>
<td>(5, 0)</td>
</tr>
<tr>
<td>A3-RW</td>
<td>219±10</td>
<td>2.5±1.4</td>
<td></td>
</tr>
<tr>
<td>A4</td>
<td>292±21</td>
<td>9.0±1.4</td>
<td>(4, 1)</td>
</tr>
<tr>
<td>A4-RW</td>
<td>383±27</td>
<td>9.2±0.8</td>
<td></td>
</tr>
<tr>
<td>A5</td>
<td>325±54</td>
<td>8.1±0.9</td>
<td>(5, 0)</td>
</tr>
<tr>
<td>A5-RW</td>
<td>603±39</td>
<td>9.9±0.2</td>
<td></td>
</tr>
<tr>
<td>A6</td>
<td>318±27</td>
<td>8.1±1.1</td>
<td>(6, 0)</td>
</tr>
<tr>
<td>A6-RW</td>
<td>699±53</td>
<td>9.9±0.2</td>
<td></td>
</tr>
<tr>
<td>A7</td>
<td>292±24</td>
<td>7.7±1.2</td>
<td>(4, 1)</td>
</tr>
<tr>
<td>A7-RW</td>
<td>252±10</td>
<td>5.6±1.2</td>
<td></td>
</tr>
<tr>
<td>A8</td>
<td>229±14</td>
<td>9.3±0.6</td>
<td>(5, 0)</td>
</tr>
<tr>
<td>A8-RW</td>
<td>194±2</td>
<td>0.4±0.5</td>
<td></td>
</tr>
<tr>
<td>All AB subjects</td>
<td>292±41</td>
<td>8.4±1.1</td>
<td>(39, 2)</td>
</tr>
<tr>
<td>Joystick</td>
<td>205±4</td>
<td>9.4±0.9</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.7: Average online performances, including completion time and stop score for SCI subjects, upon achieving purposeful control, which was on day 2 for Subject S3, and on day 1 for all other subjects. Also presented are the average online performances of each subject’s best experimental day. Performances of random walk are shown for comparison. Sessions are also broken down by number of purposeful and non-purposeful performances, i.e. \( p<0.01 \), \( p\geq0.01 \). \( \dagger \)Subject S1 did not participate after the first day.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Completion Time</th>
<th>Stop Score</th>
<th>Session</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean±std (sec)</td>
<td>mean±std</td>
<td>Breakdown</td>
</tr>
<tr>
<td>S1 n=4( \dagger )</td>
<td>411±37</td>
<td>9.3±1.0</td>
<td>(4, 0)</td>
</tr>
<tr>
<td>Random Walk</td>
<td>&gt;1200</td>
<td>4.5±1.6</td>
<td></td>
</tr>
<tr>
<td>S2 n=29</td>
<td>275±45</td>
<td>6.2±1.8</td>
<td>(26, 3)</td>
</tr>
<tr>
<td>Best: Day 5</td>
<td>298±77</td>
<td>6.8±2.3</td>
<td></td>
</tr>
<tr>
<td>Random Walk</td>
<td>258±12</td>
<td>6.9±1.3</td>
<td></td>
</tr>
<tr>
<td>S3 n=25</td>
<td>271±66</td>
<td>5.7±2.3</td>
<td>(24, 1)</td>
</tr>
<tr>
<td>Best: Day 5</td>
<td>293±26</td>
<td>8.1±1.2</td>
<td></td>
</tr>
<tr>
<td>Random Walk</td>
<td>1050±85</td>
<td>10.0±0.2</td>
<td></td>
</tr>
<tr>
<td>S4 n=24</td>
<td>277±65</td>
<td>9.4±1.3</td>
<td>(24, 0)</td>
</tr>
<tr>
<td>Best: Day 4</td>
<td>231±8</td>
<td>10.0±0.0</td>
<td></td>
</tr>
<tr>
<td>Random Walk</td>
<td>&gt;1200</td>
<td>0.1±0.3</td>
<td></td>
</tr>
<tr>
<td>S5 n=19</td>
<td>289±43</td>
<td>8.3±1.8</td>
<td>(18, 1)</td>
</tr>
<tr>
<td>Best: Day 1</td>
<td>264±12</td>
<td>8.9±0.3</td>
<td></td>
</tr>
<tr>
<td>Random Walk</td>
<td>&gt;1200</td>
<td>4.3±0.7</td>
<td></td>
</tr>
<tr>
<td>S6 n=27</td>
<td>258±31</td>
<td>7.7±2.1</td>
<td>(27, 0)</td>
</tr>
<tr>
<td>Best: Day 4</td>
<td>260±17</td>
<td>10.0±0.0</td>
<td></td>
</tr>
<tr>
<td>Random Walk</td>
<td>&gt;1200</td>
<td>5.1±1.4</td>
<td></td>
</tr>
<tr>
<td>All SCI subjects</td>
<td>277±56</td>
<td>7.4±2.3</td>
<td>(123, 5)</td>
</tr>
<tr>
<td>Physical joystick</td>
<td>205±4</td>
<td>9.4±1.0</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.8: Average and best composite online performance score for SCI subjects for each experimental day as calculated using Equations 6.2 and 6.3. The composite scores for random walk and the physical joystick are also shown for comparison. Note that Subject S3 did not achieve purposeful control on day 1 and was therefore unable to participate in online sessions on this day. Subject S1 did not participate after the first day.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 3</th>
<th>Day 4</th>
<th>Day 5</th>
<th>Composite Score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S2</td>
<td>66.2±3.1</td>
<td>76.8±9.1</td>
<td>75.0±11.3</td>
<td>74.4±11.6</td>
<td>76.9±11.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Best 69.7</td>
<td>90</td>
<td>85.6</td>
<td>80.5</td>
<td>89.9</td>
<td></td>
</tr>
<tr>
<td>S3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>69.9±11.2</td>
<td>69.3±13.5</td>
<td>59.9±12.3</td>
<td>85.4±5.4</td>
<td>85.4±5.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Best 86.8</td>
<td>89.3</td>
<td>68.9</td>
<td>90.4</td>
<td>90.4</td>
<td></td>
</tr>
<tr>
<td>S4</td>
<td>86.4±3.2</td>
<td>87.5±14.2</td>
<td>93.0±5.6</td>
<td>98.4±0.4</td>
<td>97.3±2.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Best 89.9</td>
<td>95.2</td>
<td>98.5</td>
<td>99</td>
<td>98.6</td>
<td></td>
</tr>
<tr>
<td>S5</td>
<td>91.5±1.7</td>
<td>90.1±5.3</td>
<td>89.7±4.1</td>
<td>79.4±16.3</td>
<td>80.7±2.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Best 93.2</td>
<td>95.5</td>
<td>93.1</td>
<td>96.1</td>
<td>82.3</td>
<td></td>
</tr>
<tr>
<td>S6</td>
<td>66.4±9.0</td>
<td>80.7±5.1</td>
<td>93.5±3.5</td>
<td>96.9±0.9</td>
<td>88.7±6.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Best 76.7</td>
<td>86.8</td>
<td>97.3</td>
<td>98.2</td>
<td>98.3</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>77.8±13.0</td>
<td>79.8±11.5</td>
<td>81.7±13.9</td>
<td>80.7±17.7</td>
<td>85.7±10.2</td>
<td></td>
</tr>
<tr>
<td>Joystick</td>
<td>96.5±3.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
6.3 Discussion

The experiment reports on a successful implementation of a self-paced BCI-controlled virtual walking simulator in which able-bodied and SCI subjects acquired intuitive, purposeful BCI control of the avatar’s ambulation after only 10-minute training session. The rapid training and acquisition of purposeful control were facilitated by the use of the novel data-driven machine learning technique to generate subject-specific decoding models, which allow the subjects to use intuitive control strategy, significantly reducing the training time. The decoding models were validated offline (cross-validation) first and then during online BCI operation. These results indicate that this system fulfills the requirements of an ideal BCI-controlled lower extremity prosthesis (robustness, intuitiveness, rapid training), and it may be feasible to implement such a system in the near future.

With the exception of our preliminary work [142], this study represents the first demonstration of integrating an EEG-based BCI with a VR walking simulator. A comparison between this study and related BCI-VRE studies [105, 83] is given in Table 6.9. Note that the present approach utilizes KMI of walking/idling as a control strategy, which intuitively matches the task. On the other hand, the study in [83], and especially the one in [105], were less intuitive. Furthermore, the present approach requires significantly shorter training time before the subjects are able to gain online BCI control. With the present approach, both BCI-naïve and BCI-experienced subjects were able to achieve purposeful online BCI control within minutes as opposed to months required in the other studies. In addition, this system has been tested in a substantially larger population of subjects, suggesting that it may generalizable. Finally, a direct comparison of the results between the present study and related BCI-VRE studies is not possible due to variations in experimental designs.
### Table 6.9: Comparison of the present study to similar studies in the field.

<table>
<thead>
<tr>
<th>Study</th>
<th>Mental Strategy</th>
<th>Training Time</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Present</td>
<td>KMI of walking/idling</td>
<td>10 min</td>
<td>8 AB, 6 SCI</td>
</tr>
<tr>
<td>Wang et al. [142]</td>
<td>KMI of walking/idling</td>
<td>12 min</td>
<td>3 AB</td>
</tr>
<tr>
<td>Pfurtscheller et al. [105]</td>
<td>KMI of foot/hand movement</td>
<td>3–5 mo</td>
<td>3 AB</td>
</tr>
<tr>
<td>Leeb et al. [83]</td>
<td>KMI of foot movement/idling</td>
<td>4 mo</td>
<td>1 SCI</td>
</tr>
</tbody>
</table>

#### 6.3.1 Offline performance

It follows from Tables 6.2 and 6.3 that idling and walking states could be decoded from EEG signals with high accuracy. With only 10 minutes of data during a training session, the data-driven machine learning algorithm could generate subject-specific EEG decoding models. These models achieved offline classification accuracies between 60.5% ($p=0.02$) and 94.5% ($p=6.26 \times 10^{-23}$) with an average of 78.3%, where random chance is 50%. This was true even for SCI subjects who were BCI-naïve.

The EEG decoding models also yielded feature extraction maps (e.g. Figures 6.7, 6.8, 6.9, 6.10) that could be used to uncover the brain areas and frequency bands that differentiate the mental states of idling and walking. In the able-bodied subjects, the EEG features responsible for encoding the differences between the two states were the powers in the $\mu$ and $\beta$ EEG bands from the lateral central and lateral centro-parietal electrodes. The activity measured by these electrodes is most likely localized to the lateral sensorimotor cortex, which is typically associated with hand and arm movements. On the other hand, the discriminating EEG features varied across SCI subjects and also evolved over experimental days. For example, the most informative features for Subject S1 were the EEG powers in the $\mu$ and $\beta$ bands over the mid-central electrodes, indicating activity from medial sensorimotor cortex, where the leg and foot cortical representation areas are classically located. Furthermore, EEG features from the other SCI subjects resided on mid-frontal, central-lateral, and other areas. The differences in the brain areas and EEG frequencies across SCI subjects may be
due to variations in cortical reorganization following SCI, resulting in significant changes in motor cortical representation areas for lower extremity motor imagery [19, 114, 4, 58]. The differences in imageries employed by each subject (e.g. the KMI of walking instructions may have been interpreted differently by each subject) may also have been a factor. Nevertheless, many of the SCI subjects showed activation of mid-frontal areas, which likely overlay the pre-motor cortex and supplementary motor area, as well as the pre-frontal cortex. Their activation during walking KMI is consistent with functional imaging findings, such as those in [78]. Similar to able-bodied subjects, another common pattern was the presence of activity near bilateral, lateral central-parietal electrodes, which likely represents the arm sensorimotor areas, which is hypothesized to originate from arm swing imagery. Unlike simple motor imageries often used in BCI studies, such as fist clenching [90, 104] or foot tapping [104], walking KMI emulates a highly complex set of upper and lower extremity movements for which there may not be a universal motor imagery strategy. It is also possible that due to the extremely small sample size (only 100 training EEG trials), the relative contribution of other potential brain representation areas (e.g. lower extremity motor areas) was masked by a more dominant arm swing imagery in these maps. Finally, the evolution of the feature extraction maps over the 5 experimental days may be indicative of a neuro-plasticity process associated with practice and learning [146, 103].

The data-driven machine learning methodology was able to produce subject-specific decoding models that accommodate for the neurophysiological variations across subjects. This is especially important for BCI users with SCI due to potential post-injury cortical reorganization–No single decoding model could fit all SCI subjects. By accommodating specific models for each subject, the user training time necessary to acquire purposeful BCI control in this study was significantly shorter than those of other BCI studies where users must learn a completely new cognitive skill to modulate pre-selected EEG features, such as the \( \mu \)-rhythm over lateral central areas [150]. This further underscores the importance of a data-driven EEG decoding model to allow rapid acquisition of online BCI control. On the other hand,
its lack of specificity may mean that the optimal spatio-spectral features identified by this model are not exclusively associated with walking, but also with non-ambulatory leg or foot movements. Hence, additional studies are necessary to better pinpoint the source and nature of neurophysiological signals underlying both walking KMI and attempted walking in this population. Given the limited signal-to-noise ratio and resolution of EEG, this feat may require the use of invasive recording modalities. Nevertheless, the data-driven approach carries a significant potential value in the future practical implementation of BCI-prostheses. Regardless of recording modalities, the approach may drastically reduce the training time needed to attain purposeful and useful control of self-paced BCIs from a timescale of weeks to months to one of minutes to days. This in turn may significantly reduce the cost of training users to operate future BCI-prostheses.

6.3.2 Online calibration

The state transition thresholds determined in the BCI-Avatar online calibration session (Tables 6.4 and 6.5) demonstrated that the transitions from idling to walking states (and vice versa) were highly separable. Despite the limited sample size, the values of $T_W$ appeared to exhibit a positive correlation trend with the offline performances. This further validates the proposed decoding methodology and its translation from offline to online operation. Note that the threshold values also affected the performance of simulated random walk (Tables 6.6 and 6.7). In instances where the values of $T_W$ were high (e.g. Subjects A1, S1, S4, S5, and S6), the random walk simulator had difficulty moving the avatar and consequently could not finish the task within the 20-min time limit. On the other hand, the low values of $T_I$ (e.g. Subjects A1, A2, A3, and A8) resulted in the random walk simulator having difficulty stopping the avatar and therefore yielded low successful stop scores. Finally, when the two thresholds were close to each other and around the chance level (e.g. Subjects A4, A5 and A6), the random walk simulator “inched” the avatar forward, thereby achieving
high successful stop scores at the expense of longer completion times. In summary, these observations are consistent with the ideal conditions where $T_W$ and $T_I$ approach the values of 1 and 0, respectively. They also underscore a trade-off between the completion times and successful stop scores inherent in the design of the online task.

### 6.3.3 Online performance

The subjects’ BCI-Avatar online performance measures averaged to 292 s (AB) and 277 s (SCI) for completion time, and 8.4 (AB) and 7.4 (SCI) for number of successful stops, with Subjects A1, A8, S1, and S4 achieving the highest number of successful stops. It is also encouraging to note that SCI Subject S4 achieved a perfect 10.0 number of successful stops for 5 contiguous sessions in one of the experimental days. Furthermore, subjects demonstrated purposeful BCI control in 96% of all online sessions.

Among the SCI subjects, Subjects S1 and S4 achieved successful stops similar to those obtained using a hand-controlled joystick. Even though no subjects achieved the completion speed of hand control, it is encouraging that the average composite scores increased significantly over the course of the study. Furthermore, composite scores of Subjects S4 and S6 approached 100% towards the end of the study. Therefore, not only was online control significantly different from random walk, but it was also meaningful. Given this trend, additional training and practice may help SCI subjects further improve performance, possibly to the point of approaching that of hand-controlled joystick.

While there is a positive correlation between the offline classification accuracy and online performance measures (see Section 6.2), only 21% of the offline classification variance can be accounted for by the completion times and number of successful stops. This indicates that offline and online performances are only moderately coupled, which may have several underlying causes. First, the high variability of online performances (see Figs. 6.11, 6.12 and
Tables 6.6, 6.7) may cause a poor linear regression fit. Second, a linear regression may not be the best model to link offline and online performances. Finally, the presence of outliers may cause the parameters of the linear regression model to be chosen suboptimally.

As an example of the above discrepancy, the best AB subject, A8, had an offline performance of only 65% and yet was able to achieve the level of online control that nearly matched that of a hand-controlled joystick. This discrepancy may be caused by physiological and behavioral factors. First, it may be hypothesized that a relatively low offline performance reflects the subject’s inconsistency in generating KMI and/or occasional lapse in attention. Since offline training is done without feedback, the subject may not be aware of these issues. Ultimately, this may lead to a decoding model that is suboptimal and hence yields a low offline performance. When online, the feedback is always present, allowing the subject to hone their mental strategy and presumably utilize KMI that is most consistent with the model. The subject’s ability to adapt and achieve good performance during online BCI operation may also indicate that the decoding model retained useful KMI features despite being suboptimal.

Among the SCI subjects, Subjects S1 and S4 achieved successful stops similar to those obtained using a hand-controlled joystick. Even though no subjects achieved the completion speed of hand control, Subject S4 was only 26 s slower than the joystick on his best day, despite being a naïve BCI user. It is also encouraging that the average composite scores increased significantly over the course of the study. Specifically, composite scores of Subjects S4 and S6 approached 100% towards the end of the study. Therefore, not only was online control significantly different from random walk, but it was also meaningful. Given this trend, additional training and practice may help SCI subjects further improve performance, possibly to the point of approaching that of hand-controlled joystick. Should this goal be achieved, it could further justify the pursuit of BCI-controlled lower extremity prostheses, whose performances would approach those of hand-controlled prostheses while emulating
able-bodied like control.

6.4 Methods for the RoGO Experiment

The Robotic Gait Orthosis (RoGO) experiment ([34]) was devised to test the continued feasibility of the BCI-Gait system during upright assisted walking. The use of the RoGO does not require extensive strength training and physiotherapy as required by an actual FES-based walking prosthesis, since the subject’s body weight is supported by the equipment, and their legs and feet are moved entirely by motors. The RoGO enables safe testing and familiarization of upright assisted walking without expensive and time-consuming therapy sessions. Therefore, it is an important milestone before an actual FES-based prosthesis.

6.4.1 Experimental Overview

To facilitate the development of a BCI-controlled RoGO, EEG data were recorded from subjects engaged in alternating epochs of walking and standing kinesthetic motor imagery (KMI), similar to the procedure outlined in Section 6.1.3. These data were analyzed to generate an EEG prediction model for online BCI operation. A commercial RoGO system (suspended over a treadmill), was interfaced with the BCI computer to allow for computerized control. In an online test, subjects were tasked to ambulate using the BCI-RoGO system when prompted by computerized cues. Cross-correlation analysis of BCI-RoGO walking epochs and computerized cues was conducted to assess the performance of this system.
6.4.2 Data Acquisition and Training Procedure

This study was approved by the Institutional Review Boards at the Long Beach Veterans Affairs Medical Center and the University of California, Irvine. The same NeXus-32 bioamplifier system, setup, and training procedure as described in Section 6.1.2 were used with one exception: Instead of being seated in a chair, subjects were suspended into a treadmill-equipped RoGO (Lokomat, Hocoma, Volketswil, Switzerland) using partial weight unloading (see Figure 6.15). Note that unlike overground orthoses, this system facilitates safe and easy testing suitable for early development of BCI-prostheses for ambulation. Finally, during this training procedure, subjects were instructed to stand still with arms at the sides.

The NeXus-32 bioamplifiers are actively shielded, which should provide immunity against motion artifacts and electromagnetic interference. Their battery power source also prevents signal contamination from a ground loop. Therefore, no artifacts should be present in EEG recordings when the RoGO was in the walking state (in online performance). Nevertheless, EEG signals were carefully inspected during test runs and found to be free of artifacts.

6.4.3 EMG and Leg Movement Measurement

For able-body (AB) subjects, EMG was measured to rule out BCI control by voluntary leg movements, i.e. forcing the BCI and RoGO to move by actually moving. To this end, baseline lower extremity EMG were measured under 3 conditions: Active walking (subject voluntarily walks while the RoGO servos are turned off); Cooperative walking (subject walks synergistically with the RoGO); and Passive walking (the subject is fully relaxed while the RoGO makes walking movements). Three pairs of surface EMG electrodes were placed over the left quadriceps, tibialis anterior, and gastrocnemius (Figure 6.15), and signals were acquired with a bioamplifier (MP150 and EMG100C, Biopac, Goleta, CA) in the 0.1 Hz to 1000 Hz band (sample rate = 4000 Hz). In addition, a gyroscope (Wii Motion Plus,
Figure 6.15: The experimental setup showing the subject suspended in the RoGO, while donning an EEG cap, surface EMG electrodes, and a gyroscope on the left leg. A monitor (not shown), placed in front of the subject at eye-level, presented instructional cues. The EMG and gyroscope were not used during training data acquisition.
Nintendo, Kyoto, Japan) with a custom wristwatch-like enclosure was strapped to the distal left lower leg (proximal to the ankle), and was used to measure leg movements (Figure 6.15) [6]. Approximately 85% body-weight unloading was necessary for proper RoGO operation, and the walking velocity was set at 2 km/hr. Note that the baseline recording is not part of the training procedure, and is skipped entirely for subjects with paraplegia.

6.4.4 Offline Procedures

The training procedure, trial extraction, and prediction model generation and validation are identical to those described in Sections 6.1.3, 6.1.4, and 6.1.5, respectively, with the exception that subjects stood in the RoGO with partial weight unloading.

6.4.5 BCI-RoGO Integration

The medical center in which the experiment was conducted prohibited software installation on the RoGO. Therefore, the RoGO computer was interfaced with the BCI using only mouse emulation with a pair of microcontrollers. Microcontroller #1 relayed commands from the BCI computer to microcontroller #2 via an Inter-Integrated Circuit (I²C) connection. Microcontroller #2 then acted as a slave device programmed with a mouse emulation firmware [61] to automatically manipulate the RoGO’s user interface. Dead times have been added into the microcontroller software to prevent switching between idling and walking states before the RoGO was physically able to switch. This setup enabled the BCI computer to directly control the RoGO idling and walking functions.
6.4.6 Online Performance and Assessment

6.4.6.1 Online Data Acquisition

During online operation, 0.75-s segments of EEG data were streamed in real time to be analyzed. Also, the BCI refresh rate was 0.25 s. Therefore, there was an overlap of 0.50 s in the analyzed data. The remainder of the signal analysis is consistent with Section 6.1.7. The online calibration procedure is also identical to that described in Section 6.1.8. Similarly, the RoGO was inactive during the calibration procedure.

6.4.6.2 Online Performance

In an online performance, while mounted in the RoGO, subjects used idling and walking KMI (for AB) or attempted walking (for paraplegic) to elicit 5 alternating 1-min epochs of BCI-RoGO idling/walking, as directed by textual cues on the monitor. Ideally, during walking KMI (idling), the BCI decodes the imagery as intention to walk (idle) and switches the RoGO to walking (idling) state, respectively. Subjects were instructed to make no voluntary movements of any body parts and to keep arms still at the side. For AB subjects, left leg EMG and physical movements were measured as described in Section 6.4.3. The online performance was repeated for a total of 5 sessions.

6.4.6.3 Assessment

Online performance was assessed with the following metrics: 1. Cross correlation between the cues and BCI-RoGO walking, 2. Omissions (OM)—failure to activate BCI-RoGO walking when “Walk” cue was presented, and 3. False Alarms (FA)—unintended activation during “Idle” cue. 4. Significance of performance compared to random walk.
6.4.6.4 Control (AB Subjects)

Analysis of EMG and leg movement data was performed to ascertain that RoGO operation was entirely BCI controlled and not as a result of 1. physically forcing the RoGO to start or stop walking, or 2. physically maintaining the walking state. First, to demonstrate that movements were not used to initiate BCI-RoGO walking, gyroscope and rectified EMG data were compared to the BCI decoded walking states in each session. Ideally, the BCI should always switch to “walking” state before the increased EMG activity and leg movements are observed. Then, to establish that voluntary movements were not used to maintain BCI-RoGO walking, EMG during these epochs were compared to the baselines (see Section 6.4.3). To this end, EMG data were segmented by individual steps based on the leg movement pattern [6]. The PSD of these EMG segments were averaged over steps and were compared to those of the baseline walking conditions. Ideally, the EMG power during BCI-RoGO walking should be similar to that of passive walking and should differ from those of active and cooperative walking.

6.5 Results for the RoGO Experiment

Two subjects (one AB and one with paraplegia due to SCI) were recruited for this study (Table 6.10). All subjects successfully underwent the training EEG procedure. The offline analysis resulted in a model classification accuracy of 94.8±0.8% and 77.8±2.0% for Subjects 1 and 2, respectively (chance: 50%). The EEG feature extraction maps are shown in Figure 6.16. After the calibration procedure, a histogram of posterior probabilities was plotted (Figure 6.18). Based on this histogram and a familiarization trial, the respective values of $T_I$ and $T_W$ were set at 0.04 and 0.65 for Subject 1, and 0.50 and 0.90 for Subject 2.

The performances from the 5 online sessions are summarized in Table 6.11. The average
Table 6.10: Demographic data of the RoGO subjects. ASIA = American Spinal Injury Association.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Age</th>
<th>Gender</th>
<th>Prior BCI Experience</th>
<th>SCI Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42</td>
<td>Male</td>
<td>~5 hours</td>
<td>N/A</td>
</tr>
<tr>
<td>2</td>
<td>25</td>
<td>Male</td>
<td>~3 hours</td>
<td>T6 ASIA B</td>
</tr>
</tbody>
</table>

Figure 6.16: The one-dimensional CPCA-AIDA feature extraction maps for both subjects. Since feature extraction is piecewise linear, there is one map for each of the 2 classes. Brain areas with values close to +1 or -1 are most salient for distinguishing between idling and walking classes at this frequency. The most salient features were in the 8-10 Hz bin for Subject 1 and the 10-12 Hz bin for Subject 2.
cross-correlation between instructional cues and the subjects’ BCI-RoGO walking epochs was $0.812 \pm 0.048$. For control, the maximum cross-correlation between the instructional cues and simulated BCI operation using 100,000 Monte Carlo random walk runs were 0.438 and 0.498 for Subjects 1 and 2, respectively. This indicates that all cross-correlations in Table 6.11 were significant with an empirical p-value $< 10^{-5}$. Also, there were no omissions for either subject. The false alarm rate averaged 0.8 across all sessions and both subjects. While the duration of these false alarm epochs averaged 7.42 $\pm$ 2.85 s, much of this time can be attributed to the RoGO’s locked-in startup sequence ($\sim 5$ s). In addition, each subject managed to achieve 2 sessions with no false alarms. Figure 6.17 shows a snapshot of the SCI subject operating the BCI-RoGO. Full videos of representative online sessions for the able bodied subject (Subject 1) and for the subject with SCI (Subject 2) are available: youtu.be/W97Z8fEAQ7g, and youtu.be/HXNCw0mGjG8.

For Subject 1, EMG and gyroscope measurements indicated that no movement occurred before the initiation of BCI-decoded “walking” states (Figure 6.19). When compared to the baselines, the EMG during online BCI-RoGO walking in all 3 muscle groups were statistically different from those of active or cooperative walking conditions ($p<10^{-13}$), and were not different from those of passive walking ($p=0.37$). These results confirm that the BCI-RoGO system was entirely controlled via BCI. Note that passive walking is known to generate EMG activity [88], hence a similar level of activity during BCI-RoGO (Figure 6.20) walking is expected.

6.6 Discussion

The results of this study demonstrate that BCI-controlled lower extremity prostheses for walking are feasible. Both subjects gained purposeful and highly accurate control of the BCI-RoGO system on their first attempt. It is particularly notable that the subject with
Figure 6.17: Subject with paraplegia due to SCI operated BCI-RoGO. In this snapshot, he was cued to walk by the computer screen, generated kinesthetic motor imagery of walking by attempting to walk. The computer analyzed and decoded his brain signals into the “walk” command for the robotic orthosis. The orthosis and the treadmill turned to the walking mode. Note that the BCI software was unaware of the on-screen cues, and the “walk” command was decided solely from the subject’s brain signals. Filmed at Long Beach Veterans Affairs Medical Center.
Figure 6.18: Histogram of averaged posterior probabilities, $\bar{P}(W|f^*)$, for the RoGO experiment.
Table 6.11: Online performances: cross-correlation between BCI-RoGO walking and cues at specific lags, number of omissions and false alarms, and average duration of false alarm epochs.

<table>
<thead>
<tr>
<th>Session</th>
<th>Cross-corr. (lag in s)</th>
<th>Omissions</th>
<th>False Alarms (avg. duration in s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.771 (10.25)</td>
<td>0</td>
<td>1 (12.00)</td>
</tr>
<tr>
<td>2</td>
<td>0.741 (4.50)</td>
<td>0</td>
<td>2 (5.50±0.00)</td>
</tr>
<tr>
<td>3</td>
<td>0.804 (3.50)</td>
<td>0</td>
<td>1 (5.30)</td>
</tr>
<tr>
<td>4</td>
<td>0.861 (4.50)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0.870 (12.00)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Avg.</td>
<td>0.809±0.056 (6.95±3.89)</td>
<td>0</td>
<td>0.8 (7.08±3.28)</td>
</tr>
<tr>
<td>Subject 2</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>1</td>
<td>0.781 (6.25)</td>
<td>0</td>
<td>1 (8.80)</td>
</tr>
<tr>
<td>2</td>
<td>0.878 (6.75)</td>
<td>0</td>
<td>0</td>
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<tr>
<td>3</td>
<td>0.782 (6.25)</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
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<td>0</td>
<td>1 (5.50)</td>
</tr>
<tr>
<td>5</td>
<td>0.785 (5.75)</td>
<td>0</td>
<td>2 (8.40±4.10)</td>
</tr>
<tr>
<td>Avg.</td>
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<td>0</td>
<td>0.8 (7.76±2.80)</td>
</tr>
<tr>
<td>Overall Avg.</td>
<td>0.812±0.048 (7.40±3.56)</td>
<td>0</td>
<td>0.8 (7.42±2.85)</td>
</tr>
</tbody>
</table>

Figure 6.19: Results from a representative online session, showing epochs of idling and BCI-RoGO walking determined from the gyroscope trace (green blocks). Red trace: decoded BCI states, Blue trace: instructional cues. Thick block: walking, Thin block: idling. Corresponding EMG (gold: quadriceps; teal: tibialis anterior; purple: gastrocnemius) are also shown. Note that EMG was not measured for Subject 2.
Figure 6.20: Representative EMG PSD of the quadriceps, demonstrating that EMG during BCI-RoGO walking are different ($p<10^{-13}$) from baseline active or cooperative walking conditions, and are not different ($p=0.37$) to passive walking.

paraplegia due to SCI (Subject 2) was able to accomplish this with minimal prior BCI experience and after only a brief 10 min training data acquisition session. To the best of our knowledge, this represents the first-ever demonstration of a person with paraplegia due to SCI re-gaining brain-driven basic ambulation and completing a goal-oriented walking task.

The EEG prediction models for both subjects had high offline classification accuracies. For Subject 1, despite standing while suspended in the RoGO, the EEG prediction model’s classification accuracy was higher than that from the same training procedure when performed in the seated condition (Subject 1 in [142] and Subject in Table 6.2). Also, the salient brain areas underlying walking KMI (Figure 6.16) were consistent with those previously reported. These areas likely overlie the pre-frontal cortex, supplementary motor (SMA), and arm motor representation areas. Activation of the pre-frontal cortex and SMA during walking KMI has been described in functional imaging studies (e.g. [78]). Similarly, involvement of bilateral
arm areas during walking KMI may be associated with arm swing imagery (see Figure 6.7 for example). Finally, this EEG prediction model was further validated by generating separable posterior probability distributions (Fig. 6.18) and facilitating highly accurate online BCI-RoGO control.

The average online cross-correlation between the computer cues and the BCI response ($\rho=0.812$, see Table 6.11) was higher than those achieved with lower (0.67) and upper (0.78) extremity BCI-prostheses [30, 69], despite EEG being acquired under more hostile (ambulatory) conditions. Furthermore, not only did the SCI subject (Subject 2) attain immediate BCI-RoGO control, but he also had a higher average online performance than the AB subject. This implies that future BCI-prostheses for restoring overground walking after SCI may be feasible. Additionally, both subjects’ online BCI-RoGO operations were purposeful with a 100% response rate (no omissions). Although Subject 1 had no false alarms by the end of the experiment, Subject 2 still experienced false alarms in the final session. Although few in numbers and brief in duration, false alarms carry the risk of bodily harm in future BCI-prostheses for overground walking, and this problem must be addressed with additional safeguards. These could be minimized using a longer posterior probability window and longer practice in a controlled environment. Table 6.11) also shows that the maximum correlation is attained at an average lag of 7.4 s. Most of this lag can be attributed to the RoGO’s locked-in power-down sequence ($\sim 5$ s). Minor sources of delay include a combination of user response time and the 2-s long posterior probability averaging window (see *****). This delay can potentially be minimized with additional user training in a controlled environment. Also, reducing the averaging window may eliminate some of the delay, but this would be at the expense of increasing the false alarm and omission rates.

With no more than $\sim 5$ hr of relevant BCI experience (operating the BCI-Avatar as described in Section 6.1 and [142, 141, 71]) Both subjects attained highly accurate online control of the BCI-RoGO system. This was achieved immediately on their first attempt after a series of
short procedures (10 min training data collection, 5 min calibration, 5 min familiarization), and the performance generally improved through the course of the 5 online sessions. This indicates that a data-driven prediction model as well as prior virtual reality training (in BCI-Avatar) may have facilitated this rapid acquisition of BCI control. In addition, the BCI operation was achieved using an intuitive control strategy, i.e. walking KMI to induce walking and idling imagery to stand still. This is in contrast to requiring subjects to undergo months of training in order to acquire a completely new skill of modulating pre-selected EEG signal features as frequently done in operant conditioning BCI studies (see Sections 2.2.5 and 2.3.2 for examples). However, it remains unclear whether applying an EEG decoding model generated from idling/walking KMI will be robust enough against EEG perturbations caused by other simultaneous cognitive and behavioral processes common during ambulation (e.g. talking, head turning). Anecdotally, no disruption of BCI operation was observed in this study and related previous BCI studies [141, 71] when the subjects engaged in brief conversations or hand and arm gestures during the familiarization session. Formalized testing of this hypothesis would require additional studies to be performed.

Based on the above observations, this data-driven BCI approach may be necessary for future intuitive and practical BCI-controlled lower extremity prostheses for people with SCI. This approach would enable subjects with SCI to use intuitive BCI control strategies such as walking KMI or attempted walking. Similar to Subject 2 in this study, this can potentially be accomplished with minimal user training and supervision from the experiment operator. Finally, this approach may enhance the appeal and practicality of future BCI-controlled lower extremity prostheses for ambulation by reducing the time burden and associated costs.

In conclusion, these results provide preliminary evidence that restoring brain-controlled ambulation after SCI may be possible. However, future work is necessary to test this system in a population of subjects with SCI. Since SCI users are able to operate the BCI-Avatar, it is expected that they can readily transfer their skills to the BCI-RoGO system like the two sub-
jects here. If successful, such a system may justify the future development of BCI-controlled lower extremity prostheses for free overground walking. This includes addressing issues such as additional degrees of freedom (turning, speed, ability to sit down and stand up), as well as appropriate solutions for long-term signal acquisition (e.g., electrocorticography). It can also be applied to incomplete motor SCI, where it could add Hebbian-like learning to gait rehabilitation to improve neurological outcomes beyond those of standard physiotherapy.

6.7 Conclusion and Future Work

6.7.1 Conclusion

The Avatar and RoGO experiments show that SCI subjects can purposefully operate a self-paced BCI-Avatar system, and likely the robotic orthosis system, in real time, and that the current data-driven BCI design approach is able to overcome the potential problems associated with variations in neurophysiology due to cortical reorganization after SCI, learning and plasticity processes, and differences in KMI strategies. Furthermore, the system satisfies the requirements of an ideal BCI-lower extremity prosthesis, namely: intuitiveness, robustness, and short training time. The operation of the system is intuitive as it enabled subjects to use walking KMI to control ambulation. The system is robust in that the data-driven decoding methodology successfully accommodated for person-to-person and day-to-day variations in the neurophysiological underpinnings of idling and walking KMI behaviors. In addition, SCI subjects were able to maintain purposeful online control over the course of several weeks, further underscoring the system’s robustness over time. Finally, the system required only a short training time, as BCI control was generally attained after only a 10-min training data collection procedure followed by a shorter calibration and familiarization session on the 1st experimental day (for 5 out of the 6 SCI subjects).
In summary, the high level of control achieved by SCI subjects over the course of the study indicates that BCI-controlled lower extremity prostheses for gait rehabilitation or restoration after SCI may be feasible. The BCI-Avatar system may also serve as a low-cost training platform for BCI-controlled lower extremity prostheses once they become widely available. In the mean time, this training platform may help SCI individuals remember the imagery of ambulation, shortening the relearning time.

6.7.2 Future Work

The success of Avatar and RoGO experiments with subjects with SCI suggests that restoring BCI-controlled ambulation after SCI may be feasible. To formally test this concept, integration of our BCI system with a physical ambulation prosthesis, such as a functional electrical stimulation (FES) system (e.g. Parastep, Sigmedics, Fairborn, OH) is necessary. If such a system is successfully tested in a small SCI population, clinical trials to develop a commercial BCI-prosthesis would be warranted. Finally, these research efforts may ultimately lead to the development of a permanent BCI prosthesis for ambulation; for example, the integration of an electrocorticography (ECoG)-based BCI system with an implanted or needle-based FES system for ambulation. This type of system would eliminate the need for any preparation or mounting of EEG, while potentially achieving better performances.
Chapter 7

Conclusions and Future Work

7.1 Conclusions

This dissertation set out to develop a high-performance, intuitive brain-computer interface (BCI) with short training time, which is necessary for better adoption outside laboratory settings. BCI is a promising technology that can potentially restore functional independence to and lower the medical and societal costs of individuals with paralysis. Over 40 years since the first research on BCI [140], low-cost, non-invasive BCI has been perceived to be slow due to the limited brain signals available on the scalp of the head. The research literature has even stated an upper speed limit of 1 bit/s [149, 117], too slow to be of practical use for all but the most severely disabled individuals. With this speed, it will take just under 11 minutes to send a text message (140 letters and spaces). This assumes that the user has not made any mistakes in the first place. As a challenge to improve the speed, this dissertation was set out to apply novel data processing techniques to create a high-performance BCI system (Chapter 4). Such data-driven machine-learning techniques were successfully applied to develop a P300 Speller from scratch that attained at least three times the speed of the next
highest performing system, without using much of the pre-existing methods (Chapter 5). The success of this cue based BCI paved the way for a more ambitious goal: To cure paralysis. We set out to apply the same data processing techniques on building the BCI-Gait system, even through no other BCI research has been published on restoring able-body-like ambulation. The BCI-Gait Project is a three step plan (Chapter 6) to 1) develop a platform to train users with paraplegia in a comfortable virtual environment, 2) allow the users to test BCI control while suspended on a treadmill, and finally 3) connect the BCI to muscle stimulators on the users’ legs, allowing them to actually walk on their own. Once again, we decided to start with a completely data-driven approach like we did in the BCI-Speller. This approach was successful, with almost all subjects able to control their BCI on the first day. After conducting experiments with 8 able-bodied subjects and 7 with paraplegia due to spinal cord injury (SCI), the first two steps have come to a successful conclusion. Although the last step is still ongoing, we have good results with one SCI subject so far.

7.1.1 Feature Extraction Algorithms

7.1.1.1 Heat Maps

The dimension reduction and feature extraction techniques are themselves intuitive. Their transformation matrix can be readily converted back to a “heat map” of the brain, which can reveal the brain areas that separate the different mental tasks (classes), such as the difference between idling and kinesthetic motor imagery (KMI) of walking. Higher dimensional heat maps (when the final dimension is set to more than 1-D) may also reveal the importance ranking of electrodes and frequencies. This heat map may also allow us to detect anomalies during experiment. For examples, 1) if an electromagnetic interference (EMI) were to cause sub-harmonic waves to appear on EEG on during one mental task, the frequency-based feature extraction heat maps will display obvious, sharp bands at those interference frequen-
cies. 2) if the user were to zone out during only one mental task, $\alpha$ waves will dominate the occipital-parietal region. 3) if the user has involuntary facial electromyogram (EMG) activities, they will show up on the heat map. To elaborate, the three examples here all describe when the noise is not common mode—when noise signals (e.g. EMI, $\alpha$-waves, EMG) are stronger or weaker during only one mental task. To a data-driven classifier algorithm, the noise signal is a valid and useful feature to help separate the mental tasks. However, it does not come from the correct brain areas ($\alpha$ waves do not originate from the motor cortex), or even from the brain at all (EMI and EEG), and it detracts the importance of the legitimate features. If these noise signals were accepted as valid BCI features, the user will not be able to induce the same noise signals when they move to a noise-free room or have relaxed their facial muscles, and the BCI will fail to operate. Hence, the ability to generate such heat maps is crucial in ensuring the quality and validity of the BCI experiments. In this regard, we decided on a subset of 32 electrodes (Figure 7.3) that are least affected by EMG artifacts for future Motor BCIs. Finally, the heat maps can be compared across days or weeks to study the effect of brain plasticity and user training (e.g. Section 6.3).

### 7.1.1.2 Dimension and Multi-class

The feature extraction technique is also less restrictive than some of the other algorithms. Unlike Fisher’s LDA or support vector machine (SVM), AIDA is not restricted to the number of final dimensions or the number of classes, respectively. This is a helpful bonus in developing future multi-class BCI systems, as this already-implemented technique can provide immediate technical and biological insights to the collected data.

The benefits of CPCA, a supervised PCA, may also be more apparent in multi-class decoding. It may be less likely for multiple classes to be all separable on the first principal axis using traditional, unsupervised PCA. However, each CPCA subspace may individually contain separable pairs of classes due to the piecewise trait of the technique.
7.1.2 Offline Optimization Algorithm

The offline analysis algorithm, including the automated search method to identify the best combination of feature extraction parameters, is a valuable addition to our BCI toolbox. Since there is “no free lunch” in machine learning, i.e. there is no single combination of machine learning algorithms (feature extraction, classification, etc.) that is always better for any input data [151], choosing sub-optimal parameters is inevitable without some ways to easily and quickly test all of them. During cross validation, our algorithm tests each feature extraction and classification parameters. This enables personalized BCI parameters not just on the training data, but also on the classifier meta-data.

The choice of AIDA or LDA by the automated cross-validation algorithm may also reveal the nature of the EEG data. For instance, brain signals during BCI-Speller (time-domain) and BCI-Foot-Stroke [89] (frequency-domain) tend to be extracted best by AIDA. On the other hand, there are many instances in BCI-Gait where LDA was chosen as the best feature extraction algorithm. We have not understood the cause of this preference. One possible explanation is that gait is a systemic process in the central nervous system involving choreographed movements of several limbs and torso, while the others are less involved. From the point of view of classifier design, this warrants additional investigation.

7.1.3 Practical Applications and Implications

7.1.3.1 Overground Walking

The third step of the BCI-Gait Project (Chapter 6) is to interface the BCI with functional electrical stimulation (FES)-based walking prosthesis (Parastep I, Sigmedics Inc., Fairborn, OH). Parastep is a Food and Drug Administration (FDA)-approved microcomputer-controlled FES for overground walking. The FES electrodes are applied to the bilateral
quadriceps, tibialis anteriors, and gluteus medius/maximus muscles to allow standing up, stepping, and maintaining posture, respectively. King et al [70] reports successful control by a subject with paraplegia due to SCI (male, age 26, T6, ASIA B) on the Parastep to walk across a 12-ft corridor while stopping at 3 designated positions (similar in concept to the stops in Section 6.1.9). Briefly, the SCI subject has undergone 17 weeks (one day per week) of physical therapy to regain muscle strength while participating in the BCI-Avatar training (see Section 6.1). After adequate muscle strength and BCI mastery have been attained (see Figure 7.1), the subject was equipped with an EEG cap, FES electrodes on his legs, a walker, a body weight support harness, and other physical sensors (see Figure 7.2). EEG signals were recorded and sent wirelessly via Bluetooth to a nearby BCI computer for decoding. The computer then wirelessly controls the FES prosthesis to walk or stop walking. As a result, this subject was able to walk 12 feet across a long corridor 7.4. Unfortunately, the gluteal muscle electrodes could not be used due to electrical interference with EEG. The subject had to support his posture with arms, generating some unwanted false activations while using the BCI.

7.1.3.2 Neurorehabilitation

The successful demonstrations of our BCI systems may also have significant implications on the viability and adoption of BCIs in physical rehabilitation applications. For example, one of the ongoing BCI projects in this lab is the neurorehabilitation of foot drop due to stroke using BCI-controlled FES [89]. The methodology is similar to the testing on able-bodied subjects in [32] (see Figure 7.5) and uses the same software interface as the BCI-Gait (Chapter 6). Briefly, chronic stroke survivors with foot drop problems were recruited into a 12-session therapy (3 times per week). They were asked to perform repeated foot dorsiflexion (i.e. tapping their feet) on the side impaired by stroke, similar to the training procedure in Section 6.1.3. Instead of imagined walking, the subjects here actually attempted to tap their
Figure 7.1: EEG decoding model performance in percent correct classification in the BCI-Parastep experiment [70]. The subject’s offline BCI performance reached stability around the 7th day to above 90% classification accuracy and continued to nearly 100% around the 11th day. The stable feature extraction image using our method (Section 4.3) is shown in the inset.

feet. Once the BCI computer was trained with the brain patterns of foot tapping vs. idling, the subjects performed the same foot tapping, while their feet were stimulated by the BCI-controlled FES to assist in dorsiflexion whenever the attempted foot tapping was decoded by the computer. The hope is to couple the activation of post-stroke cerebral cortex via the BCI with the activation of the motor neurons via the antidromic electrical stimulation on the peripheral neuromuscular system, thus strengthening the connections between them. Although still in safety trials, many stroke survivors using this BCI have shown positive improvements (see Figure 7.6).

7.1.3.3 Implanted BCI

Simplicity in the decoding algorithm may even lead to “BCI-on-a-chip” designs, simple enough to be implemented on a hand-held computer such as a tablet [81]. Our laboratory
Figure 7.2: Setup of the BCI-Parastep goal-oriented online walking task [70]. The subject, accompanied by an experimenter and a physical therapist, was strapped into the Zero G body weight support system (Aretech LLC, Ashburn, VA) for partial weight unloading and fall prevention, donned an EEG cap, and mounted with FES electrodes and gyroscope sensors on each leg. A laser distance meter was also mounted on the Zero G trolley. The subject would use the walker and BCI-controlled FES to perform the walking test. Note that during this test, EEG signals, gyroscope and laser signals, and the FES control signals are all sent via Bluetooth wireless. To conserve bandwidth, only 24 EEG channels are recorded (Figure 7.3-Right).
Figure 7.3: Left: The 32-channel configuration for EEG signal acquisition via optical fiber cables. This configuration is the result of the “hat band” channels (the outer two rings of electrodes) being consistently rejected by the artifact rejection algorithm (Appendix B) and during inspections of the feature extraction heat maps as having excessive EMG artifacts. Right: The 24-channel configuration for Bluetooth-wireless acquisition of EEG signals. In these configurations, only the highlighted channels are gelled and used. These configurations cover electrodes that commonly encode for kinesthetic motor imagery of ambulation, as seen in these heat maps: Figures 6.7, 6.8, 6.9, 6.10, and 7.1. Both configurations require only one NeXus-32 bio-amplifier unit, allowing two different experiments to be conducted simultaneously.
Figure 7.4: Sensor records of the 23rd day of the BCI-Parastep experiment [70] with 0.909 correlation coefficient between verbal cue and BCI states and only 1 false positive (FA). The test consists of a subject with paraplegia walking linearly across 12 ft (3.66 m) and stopping at each of the 3 pairs of cones, spaced 6 ft apart, for 10-20 s. Verbal cues were given by an experimenter to the subject to start or stop walking. BCI state reports the decoding result of the EEG signals. Gyroscope signals indicate the physical movements on each leg. Laser distance meter measured the distance from the starting position. The sequence of events for one experiment trial is as follows: 1) initiate FES-powered stand up sequence, 2) BCI begins decoding brain signals, 3) subject maintains 10-20 s of standing still at the first cone, 3) BCI-controlled walking to the second pair of cones, 4) 10-20 s of standing still, 5) walking to the final pair of cones, 6) 10-20 s standing still, 7) turn off BCI and initiate FES-powered sit down sequence.
Figure 7.5: Setup of the BCI-Foot-Stroke therapy for the neurorehabilitation of foot drop due to stroke [89]. Each subject participated in 12, 1-hr long sessions over 4 weeks (3 per week). The on-screen computerized cues (Idle and Dorsiflex) instruct the subject to relax or perform repeated attempts of dorsiflexion. Changes in the subject’s EEG signals are decoded by the computer as dorsiflex or idle, and the computer instructs the attached FES system [30] to deliver or stop delivering muscle stimulation, respectively. Note that during this test, only 32 EEG channels are recorded (Figure 7.3-Left).
Figure 7.6: The progression of dorsiflexion active range of motion (AROM), Fugl-Meyer (FM) leg motor score, and 6-minute walk test for each subject throughout the study for neurorehabilitation of foot drop due to stroke (unpublished work [89]). 6 out of 7 subjects showed significant (Left-tailed Mann-Whitney U test, p<0.01) improvement in AROM, 3 subjects in FM score, and 3 subjects in the 6-min walk test, 1 week after the last BCI session.
also has plans to miniaturize our BCI to run on a microcontroller (Arduino Mega) and a fully implantable digital signal processor (DSP). The ability to run BCI on small, portable devices has major implications. It is one of the first steps to bring BCI out of a laboratory or clinic. Consider the following scenario: A person with tetraplegia due to stroke or SCI is implanted with electrodes in the brain, the brain signals are routed via a thin cable to a chest unit similar to how deep brain stimulators (DBS) work (see Figure 7.7) [3], and the BCI software installed on the DSP in the chest unit decodes the brain signals to send wireless commands to control the implanted FES units (e.g. BION) in the user’s arm and leg muscles [120] or control a spinal cord stimulator [53]. This user is then able to stand up, walk and use their arms, while all the equipment are concealed beneath their skin, free from risks of infection and social stigma. There are still practical problems to be solved, such as tissue damage and longevity of electrodes, durability of electronic implants, battery life, reliability of BCI software, and immune response. Nevertheless, this technology is promising in restoring motor functions to the paralyzed individuals.

7.2 Future Works

This dissertation developed the BCI software platform and applied it to two practical BCI applications. However, without better data acquisition hardware or output end-effectors, this middleman is still limited in usefulness. This section describes these limitations and plans to surpass them.

7.2.1 Electrodes

Despite advanced data processing, EEG is still limited by the signal source—badly smeared brain signals that have passed through multiple layers of soft tissues and bone. Useful
Figure 7.7: Schematic of a deep brain stimulator (DBS). Electrode cables are routed from the brain beneath the scalp and skin, through the neck, and to the pulse generators in the chest. Image credit: National Institute of Health.
signals such as $\gamma$-band for fine motor control ([20, 152, 145, 94, 95, 76, 143, 144]) or language ([137, 84]) may have degraded too far below the sensitivity of the amplifiers. Despite advances in amplifier technology (e.g. negative capacitance [68]), it is still better to acquire brain signals from closer to the source, without damaging the brain in the process.

BrainGate (Blackrock Microsystems, UT) is an implantable multielectrode array (MEA), previously known as the Utah array, that uses 100 hair-thin electrodes that sense the neuron spikes and local field potentials (LFP) inside a brain. Clinical trials have demonstrated control of robotic arms by implanted patients [55, 56], and the implant is reported to have worked for at least 5 years. However, this invasive procedure requires the insertion of the MEA into the brain with a pneumatic gun, causing damage to the impacted neurons and elicit scar tissue formation. Revision surgeries also carry a risk of further damage after the scar tissue have adhered to the electrodes.

Electrocorticography (ECoG) uses a grid of flat platinum disc electrodes with spacing between 1 to 10 mm arranged on a flexible plastic sheet, such as those offered by Integra Lifesciences Corp., NJ. The grid is inserted below the dura mater during surgery (see Figure 7.8). It is used clinically to localize intractable epileptic seizures and has been used by BCI researchers between medical interventions to acquire brain signals. The signal appears similar to scalp EEG, but with much better quality, signal-to-noise ratio, and is immune to external electrical and motion artifacts. Currently, BCI researchers only have access to ECoG implanted subjects during the days they undergo seizure evaluations, and have no influence on where the grids are implanted. With more compelling advances in BCI software and hardware designs, the FDA may grant permission for human trials.
7.2.2 Multi-class BCI

So far, the BCIs in this dissertation consist of only two classes, such as Idle vs. Move (BCI-Gait) and Oddball vs. Non-oddball (BCI-Speller). With higher-resolution recording modalities such as ECoG, it may be possible to resolve movements or attempted movements of individual limbs such as fingers [76] or parts of the upper extremity [33]. Briefly, in [33], subjects with ECoG implants were asked to physically move 6 parts of their upper extremity, one at a time: finger flexion, wrist flexion, forearm, elbow, shoulder rotation, and shoulder flexion movements. Each recorded movement lasted only 2-4 minutes. Multi-class decoding would therefore be necessary to distinguish which limbs are moving. Preliminary results showed that the classification method (Section 4.3), when applied to high-density (4 mm) ECoG signals, was able to separate those 6 movements with 93.7% average accuracy (unpublished work). Having 93.7% accuracy on 6 classes is akin to 2.23 bits/trial (a perfect 2-class decoder has 1.0 bit/trial, see Section 4.4 for calculations). More practically, this potentially enables the development of BCI-controlled robotic arm prostheses with multiple
degrees of freedom (DOF) while still maintaining intuitive control and fast training time (2-4 minutes for each movement).

7.2.3 Online Training

Currently, there is no method in our BCI to change the training parameters once the subject has gone online. Basically, if a subject’s mental imageries change between the training procedure and the online procedure, either the subject recalls the trained imageries, or the entire training procedure has to be repeated. The fundamental problem to the inability to update the training parameters on the fly during online mode is that the BCI cannot truly know the subject’s intentions during the self-paced online mode. Gilja et al [47] demonstrated an interesting way to overcome this problem: During a goal-oriented online task, a subject is assumed to want to complete the task correctly and efficiently (his subjects were monkeys). Therefore, when a BCI misclassifies brain signal ‘x’ as class ‘Y’, it can be instructed to learn that the brain signal ‘x’ belongs to class ‘X’ since the goal-oriented task demands ‘X’ at that exact moment. This correctional term can be added to the existing training parameters to improve or maintain BCI performance over time.

On the other hand, non-goal oriented tasks, such as using the BCI-Speller (Chapter 5) in free spelling mode, might not be able to employ this real-time correction mechanism. However, it can be inferred that when a user selects the Backspace key on the BCI-Speller, the previous selection was most likely misclassified. Furthermore, the human brain may elicit an error-related negativity (ERN) [96], an event-related potential (ERP) that occurs when an error is encountered in a feedback (e.g. a displayed letter on screen is not intended). Such signals can be interpreted by a BCI-Speller to automatically undo the previous selection.

These update and correction techniques not only improve the speed and accuracy of BCIs, but also reduce user frustration and improve their confidence in using the BCI.
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Appendices

A Classwise Classifier

The Bayes rule (see Eqn. 4.6) produces one posterior probability for each class. On the other hand, CPCA generates one projection subspace for each class and therefore one set of posterior probabilities per class from Bayes rule:

\[
P(c_1 | f^*, s_1), P(c_2 | f^*, s_1), \ldots, P(c_m | f^*, s_1) \\
P(c_1 | f^*, s_2), P(c_2 | f^*, s_2), \ldots, P(c_m | f^*, s_2) \\
\vdots \\
P(c_1 | f^*, s_m), P(c_2 | f^*, s_m), \ldots, P(c_m | f^*, s_m) \tag{A.1}
\]

where \(m\) is the number of classes, \(c_1 \ldots c_m\) are the classes, \(s_1 \ldots s_m\) are the subspace for the corresponding classes, and each row sums to 1. This means that for a binary classifier of Idle vs. Move, the Move class has two posterior probabilities, one in each subspace. Since we require the classifier to produce exactly one posterior probability for each class, as we do not only use the classifier decisions but also the posteriors in our BCI, we decided to consolidate the posteriors by using the following algorithm in our classwise classifier:

1. Choose the class with the highest posterior probabilities among all subspaces, i.e. the highest \(P\) in each column in Equation A.1.
2. Normalize the above choices

3. If all $P$ from the choices are equal, continue the steps. Otherwise, this is the set of posteriors to be reported to the BCI. End algorithm.

4. Take the mean over all subspaces, e.g. $P(c_1|f^*) = \frac{1}{m} \sum_i P(c_1|f^*, s_i)$ from Equation A.1.

5. Note that the resulting values are already normalized.

6. This is the set of posteriors to be reported. If the tie is still not resolved, it remains so. End algorithm.

With this algorithm, the classwise classifier is compatible with an ordinary classifier, producing exactly one posterior probability for each class.

For MATLAB implementation, see Appendix G.4.
B Iterative Artifact Rejection Algorithm

This algorithm is run through an EEG recording from a training procedure to remove artifacts. Channels whose EEG amplitude exceeded an outlier voltage threshold in more than 25% of the total trials were removed. The outlier threshold was nominally set to 6 standard deviations (SD) from the mean, and was adaptively changed to keep the number of outlier trials below a pre-specified number (5% of all trials in the BCI-gait and BCI-FES experiments). The above procedure was repeated until no more channels could be removed. To minimize the effect of outliers on statistical estimates, robust (i.e. median-based) mean and standard deviation were used [60]. The above procedure typically resulted in the exclusion of signals from circumferential “hat band” electrodes which usually overlay the mastoid process, the forehead, the occiput, and the temporalis muscles.
C Using CPCA and AIDA in BCI-Speller

For binary pattern recognition problems such as classification of oddball and non-oddball trials, CPCA projects high-dimensional data onto a pair of subspaces locally adapted to individual classes. Due to its nonlinear (piecewise linear) nature, CPCA is well-suited for pattern recognition problems where high-dimensional data are confined to a low-dimensional manifold, and where traditional linear dimensionality reduction techniques may be inadequate. In addition, unlike PCA and other nonlinear dimensionality reduction methods [113], CPCA is a supervised learning technique, and it therefore takes advantage of the known class labels. In this study, implementing CPCA with default parameters [22] typically resulted in the high-dimensional trials being projected onto a 20-D to 30-D subspace. A detailed description of this technique can be found in [22].

To enhance class separability while further reducing the dimension of data, approximate information discriminant analysis [26] was used. AIDA can be seen as an approximation of an information-theoretic technique [99], which seeks a low-dimensional data projection by maximising the mutual information between the class labels and data. However, unlike computationally expensive information-theoretic techniques [99, 136], AIDA retains the computational simplicity characteristics of linear, second-order techniques, such as linear discriminant analysis [37]. More specifically, the feature extraction matrix, $T_{\text{AIDA}}$, is found through eigenvalue/eigenvector decomposition. In this study, 1-D features were extracted in this manner, i.e. $T_{\text{AIDA}} \in \mathbb{R}^{m \times 1}$, where $m$ is the dimension of the subspaces found by CPCA ($m = 20–30$). A detailed account of AIDA can be found in [26].
D Randomization of Characters in BCI-Speller

During operation of the BCI-Speller, the characters are highlighted in a random order, biased to the frequency of the English language alphabet, digits, and punctuations (see Figure D.9) [82, 86]. Before each Stage 1 cycle, the order of characters is re-randomized in an iterative process by using the inverse sampling theorem [27]. To this end, a cumulative distribution function (CDF) $F_X(x), x = \{>, E, T, \ldots\}$, is calculated by integrating the character histogram (see Figure D.9). The inverse sampling theorem states that if $Y$ is a uniformly distributed random variable, then the CDF of $X \triangleq F_X^{-1}(Y)$ is precisely $F_X$, and so uniformly distributed samples can be mapped into arbitrarily distributed samples as long as $F_X$ is known. To order characters according to their frequencies, at each iteration a uniformly sampled random number, $y^* = U[0, 1]$, was mapped according to $x^* = F_X^{-1}(y^*)$, and the character corresponding to $x^*$ was selected without replacement. Since $F_X$ is discontinuous, the mapping $F_X^{-1}$ is implemented as a lookup table. This procedure is then iterated until all the characters have been selected. The characters are subsequently organized into 7 groups (6 characters per group) according to the order they were sampled. Using this technique, the more frequently used characters, e.g. $\{>, E, T, A, O, I\}$ are more likely to be highlighted earlier in a cycle. For example, through Monte Carlo simulations, it can be shown that the average number of illuminations necessary to highlight $>$ (the most frequent character according to Figure D.9) is only 1.6 (out of 7). Note, however, that since the above algorithm is stochastic, the group assignment and order of illumination generally vary over cycles, which prevents the formation of predictable spatio-temporal illumination patterns that are known to weaken the P300 response. Finally, in Stage 2, the characters are illuminated one-by-one in the same biased random order as in Stage 1.
E Monte Carlo Random Walk Simulations

The random walk simulations are performed as a statistical control against the online performances in Motor BCIs, e.g., BCI-Gait (Chapter 6, [141, 71]) and BCI for neurorehabilitation of foot drop due to stroke (Section 7.1.3.2, [89]). Briefly, comparing the simulation results and online performance forms the empirical p-value and ascertains whether a subject performed significantly better than chance. McCrimmon et al [89] developed the following procedure to perform the random walk simulation that follows the statistics of the posterior probabilities during an online session.

1. Let $\bar{P}_k$ be the sequence of averaged posterior probabilities from an actual online session. Let $W \sim U(0, 1)$, i.e., $W$ is sampled from uniform distribution between 0 and 1. Also define $X_{k+1}$ to be $X_k$ lagged by 1 index.

2. Define the following auto-regressive (AR) model:

   $$ X_{k+1} = \alpha X_k + \beta W_{k+1}, \quad X_0 \sim U(0, 1) $$

   (E.2)
where \( \alpha \) and \( \beta \) are constants, and \( X \) is the simulated version of \( \bar{P} \).

3. To find \( \alpha \) and \( \beta \),

(a) The expected value of Equation E.2 is

\[
\mathbb{E}[X_{k+1}] = \mathbb{E}[\alpha X_k + \beta W_{k+1}]
\]
\[
= \alpha \mathbb{E}[X_k] + \beta \mathbb{E}[W_{k+1}]
\]

(E.3)

(b) For a long time sequence, i.e. large maximum \( k \), the means and variances of \( X_k \) and \( X_{k+1} \) are equal. Therefore, let \( \mu \) and \( \nu \) be

\[
\mu = \mathbb{E}[X_{k+1}] = \mathbb{E}[X_k]
\]
\[
\nu = \text{var}(X_{k+1}) = \text{var}[X_k]
\]

(E.4)

(c) Since \( W \sim U(0,1) \), \( \mathbb{E}[W_{k+1}] = 0.5 \). It follows from Equation E.4 that

\[
\mu = \alpha \mu + 0.5 \beta
\]

(E.5)

(d) The covariance of \( X_{k+1} \) and \( X_k \) is

\[
\text{cov}(X_{k+1}, X_k) = \mathbb{E}[X_{k+1}X_k] - \mathbb{E}[X_{k+1}]\mathbb{E}[X_k]
\]

(E.6)

(e) Combine Equations E.3 and E.6:

\[
\mathbb{E}[X_{k+1}X_k] - \mathbb{E}[X_{k+1}]\mathbb{E}[X_k] = \mathbb{E}[X_{k+1}X_k] - \mathbb{E}[X_{k+1}]\mathbb{E}[X_k]
\]
\[
\mathbb{E}[X_{k+1}X_k] = \mathbb{E}[(\alpha X_k + \beta W_{k+1})X_k]
\]
\[
= \mathbb{E}[\alpha X_k^2 + \beta W_{k+1}X_k]
\]
\[
= \alpha \mathbb{E}[X_k^2] + \beta \mathbb{E}[W_{k+1}]\mathbb{E}[X_k]
\]

(E.7)
(f) Since $W_{k+1}$ and $X_k$ are independent, and since $\text{var}(X_k) \equiv \mathbb{E}[X_k^2] - (\mathbb{E}[X_k])^2$,

$$
\mathbb{E}[X_{k+1}X_k] = \alpha \text{var}(X_k) + (\mathbb{E}[X[k]])^2 + \beta \mathbb{E}[W_{k+1}] \mathbb{E}[X_k] = \alpha (\nu + \mu^2) + \beta 0.5 \mu
$$

(E.8)

(g) Solve for $\alpha$ and $\beta$ using the two Equations E.5 and E.8.

$$
\alpha = \frac{\mathbb{E}(\tilde{P}_{k+1}\tilde{P}_k)}{\text{var}(\tilde{P})} \\
\beta = 2\mathbb{E}[\tilde{P}] (1 - \alpha)
$$

(E.9)

Note that $\mathbb{E}(\tilde{P}_{k+1}\tilde{P}_k)/\text{var}(\tilde{P})$ is simply the lag-one auto-correlation of $\tilde{P}$.

4. With the values of $\alpha$ and $\beta$ known, we can iterate Equation E.2 from $k = 0$. However, since $X$ is supposed to be a probability, we first need to constraint each iteration to $[0, 1]$. We redefine Equation E.2 to:

$$
X_{k+1} = f(\alpha X_k + \beta W_{k+1}), \quad X_0 \sim U(0, 1)
$$

(E.10)

where

$$
f(x) = \begin{cases} 
0 & : x < 0 \\
1 & : x > 0 \\
x & : \text{otherwise}
\end{cases}
$$

(E.11)

5. We feed $X$, the simulated version of $\tilde{P}$, into the BCI binary-state machine (Figure 4.3) using the same thresholds $T_I$ and $T_W$. The output is a sequence of BCI states, $S$.

6. We compute cross-correlation of $S$ and cues (ground truth), $Q$, and obtain the maxi-
mum correlation coefficient \( \hat{\rho} \) at lag \( \tau \).

\[
\tau \equiv \arg\max_t [\text{corrcoef}(S_{k+t}, Q)] \\
\hat{\rho} \equiv \text{corrcoef}(S_{k+\tau}, Q)
\]  

(E.12)

7. Steps 4 through 6 are repeated using new random samples of \( X_0 \) and \( W \), for a total of \( N \) runs. \( N \) is usually 10000-100000.

8. Let \( n \) be the number of occurrences when the simulated maximum cross-correlation coefficient \( \hat{\rho} \) is equal to or greater than the actual maximum cross-correlation, \( \rho \), as obtained by a human subject during an online session. We define empirical p-value, \( p \equiv n/N \).
F Reshape

Typical dimension reduction techniques require a 1-dimension array as the input. A data matrix composing of channels and time frequency sample points must therefore be converted to an array.

Let data matrix $M$ be $C \times T$, i.e. $C$ rows of channels by $T$ columns of sample points. In the following example, we have 3 channels (a, b, c) and 4 sampled points (1, 2, 3, 4).

$$M = \begin{pmatrix} a_1 & a_2 & a_3 & a_4 \\ b_1 & b_2 & b_3 & b_4 \\ c_1 & c_2 & c_3 & c_4 \end{pmatrix}$$

By reshaping $M$, we produce:

$$\text{reshape}(M) = \begin{pmatrix} a_1 & b_1 & c_1 & a_2 & b_2 & c_2 & a_3 & b_3 & c_3 & a_4 & b_4 & c_4 \end{pmatrix}^T$$

which is compatible with our dimension reduction technique.
G MATLAB Algorithm

G.1 Principal Component Analysis

This is an efficient implementation of the traditional PCA using eigen decomposition. It considers both small-sample-size case and small-dimension case. Note that the principal component vectors of $X$ is the eigenvectors of the covariance of $X$.

```matlab
function [Un, Eval] = princomp2 (X)

% Principal Component Analysis of data X
% (n observations by p dimensions).
% Eval = Eigenvalues
% Un = Eigenvectors

[n,p] = size(data);
X = X - ones(n,1)*mean(X,1);

% Efficient Eigen Decomposition Method
if p >= n % Small sample size
    [V,D] = eig(X*X');
    [d,I] = sort(diag(D), 'descend');
    Eval = d(1:n-1) / (n-1);
    Un = X' * V(:,I(1:n-1)) * diag(d(1:n-1).^(-1/2));
else % Small dimension
    [Un,D] = eig(X'*X);
    Eval = diag(D)/(n-1);
    [Eval,I] = sort(Eval, 'descend');
    Eval = Eval;
    Un = Un(:,I);
end
```
G.2 Dimension Reduction by Classwise PCA

This is an implementation of dimension reduction by CPCA [23, 22], with threshold set to the one-half of the mean of non-zero eigenvalues. This code uses the output of traditional PCA (see Section G.1).

```matlab
function DRmatC = cpca(TrainData, TrainLabels)

% function DRmatC = cpca(TrainData, TrainLabels)
% Classwise Principal Component Analysis based on work done by Zoran Nenadic. Cut-off criteria: Half of mean of non-zero eigenvalues.

Nobs = length(TrainLabels);
classes = unique(TrainLabels);
Nclass = length(classes);
Ndim = size(TrainData,2);
NtrialA = zeros(1,Nclass);
for c = 1:Nclass
    NtrialA(c) = length(find(TrainLabels == classes(c)));
end

% Calculate PCA for each class
for c = 1:Nclass
    idc = find(TrainLabels==classes(c));
    [coeff, latent] = princomp2(TrainData(idc,:));
    coeffrC{c} = coeff(:, latent > mean(latent));
    sampmu{c} = mean(TrainData(idc,:),1);
end

sampmuall = mean(TrainData,1);

% Calculate between-class covariance
Data_b = zeros(Nclass,Ndim);
for c = 1:Nclass
    Data_b(c,:) = sqrt(NtrialA(c) / Nobs) * (sampmu{c} - sampmuall);
end
W_b = princomp2(Data_b);

% Calculate principle subspace basis
DRmatC = cell(1,Nclass);
for c = 1:Nclass

```
G.3 Discriminant Feature Extraction by AIDA and LDA

This is an implementation of discriminant feature extraction (DFE) by AIDA [99, 26] and by LDA [40]. This code uses the output of traditional PCA or CPCA (see Sections G.1 and G.2).

```matlab
% Feature extraction based on Approximated Information Discriminant Analysis by Zoran Nenadic
% TrainData is (obs x dim) (Each row is an observation). m = final dimension
% UseLDA = 1 use LDA, 0 use AIDA
function Fmat = aida(TrainData, TrainLabels, m, UseLDA)
    if size(TrainData, 2) <= m
        % There is no valid reason to do feature extraction if input dimension
        % is already equal to output dimension
        Fmat = eye(size(TrainData,2));
        return
    end
    ntotal = length(TrainLabels);
    Data = TrainData .';
    classes = unique(TrainLabels);
    Nclass = length(classes);
    Nparm = size(TrainData,2);
    Memship = zeros(ntotal,1);
    for i = 1:Nclass
        lind = (Memship == (i-1));
        Memship(TrainLabels == classes(i)) = i-1; % Re-number the labels
    end
    n = size(Data,1);
    M = zeros(n,1);
    Sw = zeros(n,n);
    Sb = zeros(n,n);
    Si = zeros(Nparm,Nparm,Nclass);
    p_i = zeros(1,Nclass);
    Mi = zeros(Nparm,Nclass);
    for j = 1:Nclass
        lind = (Memship == (j-1));
```

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nind = nnz(lind);
p_i(j) = nind/ntotal; %empirical prior
Mi(:,j) = mean(Data(:,lind),2); %class mean
Si(:,j) = cov(Data(:,lind)'); %class covariance
M = M + p_i(j) * Mi(:,j); %overall weighted mean
Sw = Sw + p_i(j) * Si(:,j); %within class cov
Sb = Sb + p_i(j) * (Mi(:,j) * Mi(:,j)'); %between class cov
end
Sb = Sb - M * M';
S = Sw + Sb;
if UseLDA
    V = eig(Sb,Sw);
    Fmat = V/norm(V);
else
    W = inv(sqrtmat(Sw));
    Znew = zeros(n,n);
    Zi = zeros(Nparm,Nparm,Nclass);
    for k = 1:Nclass
        Zi(:,k) = W * Si(:,k) * W;
        Znew = Znew - p_i(k) * logmat(Zi(:,k));
    end
    Znew = logmat(W*S*W) + Znew;
    [V,D] = eig(Znew);
    [~,iD] = sort(diag(D),'descend');
    V = V(:,iD(1:m));
    Anew = V'*W;
    Anew = Anew/norm(Anew);
    Fmat = Anew.*;
end

Note that the following two support functions are required:

function f = logmat(M)
% Logarithm of Matrix
% f = logmat(M);
[V,D] = eig(M);
Lambda = diag(D)+eps;
f = V*diag(log(Lambda))*V';
return;
function f = sqrtmat(M)

% Square root of Matrix

% f = sqrtmat(M);

[V, D] = eig(M);
Lambda = diag(D);
f = V*diag(sqrt(Lambda))*V';
return;

G.4 Classwise Bayesian Classifier

The Bayesian classifier is modified to accommodate CPCA and is optimized to be about 60% faster than MATLAB’s builtin function when it was originally written (ca. 2009). It also adds the capabilities of using additional likelihood functions such as Parzen window (kernel density estimation, [37, 14]) and k-nearest-neighbor.

% [Decision, Posterior, WinningSubspaceID] = classify2 ( testdata, traindata, trainlabels, Classifier, Prior, Cparm )
%
% Classifies testdata using the classifier or pdf of your choice
%
% Decision: The class label that the classifier decides your test data
% belongs to.
%
% Posterior: The posterior probabilities among all classes.
%
% WinningSubspaceID: The index (starts from 1) of subspace, if applicable,
% that the decision is based upon. If only 1 subspace, returns 1.
%
% testdata: Test data (each row is a different test data). The dimension
% (number of columns) should be fairly low, around 1~3. This parameter can
% be a cell containing test data sets from different subspaces. The number
% of subspaces must be identical to that of traindata.
%
% traindata: Training data (each row is a training sample). This parameter
% can be a cell containing training sets from different subspaces. However,
% the labels must still be identical. If it is a cell, highest posterior
% from each subspace is chosen and re-normalized among all subspaces.
% trainlabels: Class labels corresponding to the rows of training data.
% Classifier: Can be 'knn', 'wknn', 'parzen', 'quadratic', 'linear',
% 'diaglinear', 'diagquadratic'. Default: 'quadratic'. This is the
% probability density function or the likelihood function.
% Prior: Prior probabilities. Can be 'empirical', 'equal', or a horizontal
% vector. Default: 'empirical'
% Cparm: Classifier parameter. For knn and wknn, this is the number of
% neighbors. For parzen, this is the width multiplier. If Cparm == 0, it
% will be chosen automatically.
% Cparm: (advanced usage) For quadratic and linear, leave blank to use
% training data. If Cparm is a struct with the following structure,
% sufficient statistics mode is used:
% Cparm.classes(c) for the label name of cth class. This can be an
% integer or character
% Cparm.stats{s,c,1} for the mean of sth subspace, cth class
% Cparm.stats{s,c,2} for the variance of sth subspace, cth class
% If sufficient statistics mode is used, only quadratic or linear
% discriminants can be used, traindata and trainlabels are ignored. If
% Prior other than 'equal' is needed, it must be specified numerically.

function [Decision, Posterior, WinningSubspaceID] = classify2 ( testdata, traindata, trainlabels, Classifier, Prior, Cparm )

if ~iscell(testdata)
tmp = testdata;
clear('testdata');
testdata{1} = tmp;
end

if ~isempty(who('Cparm')) && isstruct(Cparm) && isfield(Cparm,'classes') && isfield(Cparm,'stats')
SWsuffstat = 1;
else
SWsuffstat = 0;
end

if SWsuffstat
[Nsubspace, Nclass, tmp] = size(Cparm.stats);
classes = Cparm.classes;
if Nclass ~= length(Cparm.classes)
    error('Cparm.classes need to be the same length as number of classes');
end
Ndim = size(Cparm.stats{1,1,1});
if isempty(who('Prior')) || isempty(Prior) || strcmpi(Prior,'equal')
    Prior = ones(1,Nclass) ./ Nclass;
else
    Prior = Prior ./ sum(Prior);
end
else
    if ~iscell(traindata)
        tmp = traindata;
        clear('traindata');
        traindata{1} = tmp;
    end
    Nsubspace = length(traindata);
    Nobs = size(traindata{1},1);
    Ndim = size(traindata{1},2);
    for s = 2:Nsubspace
        if size(traindata{s},2) ~= Ndim
            Ndim = min([Ndim, size(traindata{s},2)]);
        end
    end
    if Nobs ~= length(trainlabels)
        error('Number of training samples from traindata and trainlabels disagree.');
    end
    for s = 2:Nsubspace
        if size(traindata{s},1) ~= Nobs
            error('One or more cell element in traindata has different number of training samples.');
        end
        if size(traindata{s},2) ~= Ndim
            traindata{s} = traindata{s}(:,1:Ndim);
        end
    end
classes = unique(trainlabels);
Nclass = length(classes);
if Nclass <= 1
    error('At least two unique labels are required.');
for c = 1:Nclass
    NtrainA(c) = length(find(trainlabels==classes(c)));
end
if isempty(who('Prior')) || strcmp(Prior,'empirical')
    Prior = NtrainA ./ Nobs;
elseif isempty(Prior) || strcmp(Prior,'equal')
    Prior = ones(1,Nclass) ./ Nclass;
end
end
if Nsubspace == 0
    error('At least one set of training is required. ');
end
if isempty(who('Classifier'))
    Classifier = 'quadratic';
end
Posterior = nan(size(testdata{1},1),Nclass,Nsubspace);
f = nan(size(testdata{1},1),Nclass,Nsubspace);
logf = nan(size(testdata{1},1),Nclass,Nsubspace);
switch Classifier
    case 'knn'
        if ~isempty(who('Cparm')) && ~isstruct(Cparm)
            Kn = Cparm;
        else
            Kn = [];
        end
        for s = 1:Nsubspace
            N = 0;
            for c = 1:Nclass
                f(:,c,s) = knnprob(testdata{s},traindata{s},trainlabels,Kn,classes(c));
                N = N + f(:,c,s) * Prior(c);
            end
            for c = 1:Nclass
                Posterior(:,c,s) = f(:,c,s) .* Prior(c) ./ N;
            end
        end
case 'wknn'
    if isempty(who('Cparm')) &~ isstruct(Cparm)
        Kn = Cparm;
    else
        Kn = [];  
    end
    for s = 1:Nsubspace
        N = 0;
        for c = 1:Nclass
            f(:,c,s) = knnprob(testdata{1},trindata{1},trainlabels,Kn,classes(c));
            N = N + f(:,c,s) * Prior(c);
        end
        for c = 1:Nclass
            Posterior(:,c,s) = f(:,c,s) .* Prior(c) ./ N;
        end
    end

    case 'parzen'
    if isempty(who('Cparm')) &~ isstruct(Cparm)
        Width = Cparm;
    else
        Width = [];  
    end
    for s = 1:Nsubspace
        N = 0;
        for c = 1:Nclass
            f(:,c,s) = parzenwinpdf(testdata{1},trindata{1}(trainlabels==classes(c),:),Width);
            N = N + f(:,c,s) * Prior(c);
        end
        for c = 1:Nclass
            Posterior(:,c,s) = f(:,c,s) .* Prior(c) ./ N;
        end
    end

    case 'quadratic'  
    if SWsuffstat
        for s = 1:Nsubspace
            N = 0;
            for c = 1:Nclass
                f(:,c,s) = normalpdf(testdata{1},Cparm.stats{s,c,1},Cparm.stats{s,c,2});
            end
        end
    end
\[ N = N + f(:,c,s) \times \text{Prior}(c); \]

\text{end}

\text{else}

\text{for c = 1:Nclass}

\[ [f(:,c,s), \text{logf}(:,c,s)] = \text{normalpdf}\{\text{testdata}\{s\},\text{traindata}\{s\}\{\text{trainlabels}==\text{classes}\{c\},:}\}; \]

\[ N = N + f(:,c,s) \times \text{Prior}(c); \]

\text{end}

\text{end}

\text{for c = 1:Nclass}

\[ \text{Posterior}(:,c,s) = f(:,c,s) \times \text{Prior}(c) / N; \]

\text{end}

\text{if any}(N==0)

\[ \text{tmp, I} = \text{max}(\text{logf}(:,s)+\text{log}(	ext{Prior}(c))[:,:],2); \]

\[ \text{notI} = [1:I-1,1+1:N\text{class}]; \]

\[ \text{Posterior}(N==0,I,s) = 1; \]

\[ \text{Posterior}(N==0,\text{notI},s) = 0; \]

\text{end}

\text{end}

\text{case 'linear' } % \text{Our linear is 60\% faster than MATLAB's}

\text{for s = 1:Nsubspace}

\[ N = 0; \]

\text{if SWsuffstat}

\[ \text{Sigma} = \text{Prior}(1) \times \text{Cparm.stats}\{s,1,2\}; \]

\text{for c = 2:Nclass}

\[ \text{Sigma} = \text{Sigma} + \text{Prior}(c) \times \text{Cparm.stats}\{s,c,2\}; \]

\text{end}

\text{else}

\[ \text{Sigma} = \text{Prior}(1) \times \text{cov}(\text{traindata}\{s\}\{\text{trainlabels}==\text{classes}\{1\},:}\}; \]

\text{for c = 2:Nclass}

\[ \text{Sigma} = \text{Sigma} + \text{Prior}(c) \times \text{cov}(\text{traindata}\{s\}\{\text{trainlabels}==\text{classes}\{c\},:}\); \]

\text{end}

\text{end}

\text{if SWsuffstat}

\text{for c = 1:Nclass}

\[ f(:,c,s) = \text{normalpdf}\{\text{testdata}\{s\},\text{Cparm.stats}\{s,c,1\},\text{Sigma}\}; \]

\[ N = N + f(:,c,s) \times \text{Prior}(c); \]

\text{end}
else
  for c = 1:Nclass
    \[ f(:,c,:) \] = \text{normalpdf}(\text{testdata}\{s\},\text{traindata}\{s\}(
      \text{trainlabels}==\text{classes}(c,:),\Sigma);
  N = N + f(:,c,:) \times \text{Prior}(c);
  end
end
for c = 1:Nclass
  \text{Posterior}(:,c,:) = f(:,c,:) \times \text{Prior}(c) \div N;
end
if any(N==0)
  \[ \text{tmp}, I \] = max(log2(f(:,:,s))\times log2(\text{Prior}(c)),[],2);
  \text{notI} = [1:1-I,1+1:Nclass];
  \text{Posterior}(N==0,I,s) = 1;
  \text{Posterior}(N==0,\text{notI},s) = 0;
end
else
  for s = 1:Nsubspace
    \[ \text{Dec}, \text{tmp}, \text{Posterior}(:,s) \] = \text{classify}(\text{testdata}\{s\},\text{traindata}\{s\},\text{trainlabels},
      \text{Classifier},\text{Prior});
  end
end

\[ \text{Y, Isub} \] = max(\text{Posterior},[],3); \quad \text{Main decider: Strongest posterior wins}
\text{Z} = \text{mean}(\text{Posterior},3); \quad \text{Tie breaker if needed: Strongest mean wins}
\text{Posterior} = \text{Y} \div (\text{sum(Y,2)} \times \text{ones(1,Nclass)});

% Detect ties (If winner is unique, I1 should == I2)
\[ \text{Y, I1} \] = max(\text{Posterior},[],2);
\[ \text{Y, I2} \] = max(fliplr(\text{Posterior}),[],2);
\text{I2} = Nclass+1-I2;

% Tie breaking
\text{Posterior(11'==I2,:) = Z(11'==I2,:)};

% Decision
\[ \text{Y, I} \] = max(\text{Posterior},[],2);
\text{Isub} = \text{Isub}';
\text{WinningSubspaceID} = \text{Isub}((0:Nsubspace:Nsubspace*(\text{size(Isub,2)-1)})+1);
\text{Decision}(,:,:1) = \text{classes}(1);
G.5 Signal Power

This function calculates the power of a real-valued signal between two frequency cutoffs,

\[ P = \frac{1}{f_2 - f_1} \int_{f_1}^{f_2} X(f)df \]  
\hspace{1cm} (G.13)

where \( X(f) \) is the Fourier transform of \( x(t) \). Note that the power is normalized by the duration of the signal. Thus, increasing or decreasing the duration of the signal will not affect its power.

```matlab
function P = signalpower(signal, Fs, frange)

% signal = Time domain signal in vertical format (n x 1)
% Fs = Sampling rate (Hz)
% frange = (1 x 2 array). The lower and upper cutoffs in Hz.
% Output P = the power of the signal between the two frequencies.
if ~exist('frange','var') || isempty(frange)
    frange = [-inf inf];
end
L = size(signal,1);
NFFT = 2^nextpow2(L);
X = fft(signal,NFFT,1);
d = Fs/NFFT;
f = [0:d:Fs/2, -Fs/2+d:-d];
P = zeros(size(frange,1), size(signal,2));
for i = 1:size(frange,1)
    Y = X((f >= frange(i,1) & f <= frange(i,2)) | (f < -frange(i,1) & f > -frange(i,2)), :);
    P(i,:) = sum(abs(Y).^2,1) / NFFT / L;
end
```
H Sample Output

H.1 Cross Validation

Below is a sample of a 10-run 10-fold stratified cross validation on a subject’s training data for BCI-Speller. The data dimension is 480 (8 channels × 60 time points). There are 623 non-oddball trials and 107 oddball trials (about 6:1 ratio). Each classifier’s performance is displayed. The software also converts a confusion matrix into information transfer rate (ITR). Note that the confusion matrix sums to one vertically.

<table>
<thead>
<tr>
<th>Stratified 10-fold Cross Validation Report</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of total trials: 623 (class 0), 107 (class 1), 730 (total)</td>
</tr>
<tr>
<td>Number of tested trials: 623 (class 0), 107 (class 1), 730 (total)</td>
</tr>
<tr>
<td>Data dimension: 480</td>
</tr>
<tr>
<td>Included 730 test trials: 1:730</td>
</tr>
<tr>
<td>Dimension reduction: cpca ()</td>
</tr>
<tr>
<td>Prior probabilities: [empirical]</td>
</tr>
<tr>
<td>K-fold Uncertainty: ±1 stdv between the 10 runs.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy</th>
<th>ITR (b/tr)</th>
<th>ITR (max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>aida(3) quad</td>
<td>94.8± 0.4% (#8)</td>
<td>0.39 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>aida(3) line</td>
<td>96.7± 0.2% (#4)</td>
<td>0.39 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>aida(2) quad</td>
<td>95.6± 0.3% (#7)</td>
<td>0.34 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>aida(2) line</td>
<td>96.6± 0.2% (#5)</td>
<td>0.34 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>aida(1) quad</td>
<td>96.7± 0.3% (#3)</td>
<td>0.39 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>aida(1) line</td>
<td>96.6± 0.2% (#6)</td>
<td>0.39 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>lda(1) quad</td>
<td>96.7± 0.2% (#2)</td>
<td>0.39 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
<tr>
<td>lda(1) line</td>
<td>96.7± 0.3% (#1)</td>
<td>0.39 b/tr (0.601 max)</td>
<td>0.601 max</td>
</tr>
</tbody>
</table>

Below is a sample of a 10-run 10-fold stratified cross validation on a subject’s training data for BCI-Avatar. The data dimension is 312 (24 channels × 13 frequency bins). There are 60 Idle trials and 60 Walk trials. Each classifier’s performance is displayed. The software also
converts a confusion matrix into information transfer rate (ITR). The software also displays
additional information, such as optimal frequency range and whether to use logarithm. A
feature extraction heat map in condensed form is also generated for a quick overview of the
important electrodes participating in encoding Idle vs. Walk motor imageries.

Stratified 10-fold Cross Validation Report
Number of total trials: 60 (class 3), 60 (class 4), 120 (total)
Number of tested trials: 60 (class 3), 60 (class 4), 120 (total)
Data dimension: 312
Included 24 channels: F5, F1, Fz, F2, F6, FC3, FCz, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P1, Pz, P2, P6, POz
Included 13 time/freq: 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29
Included 2 classes: 3, 4
Included 120 test trials: 1:120
Dimension reduction: cpca()
Prior probabilities: [empirical]

K-fold Uncertainty: ±1 std dev between the 10 runs.

-----------------------------------+------------------------------------+
| aida(3) quad, 99.3±0.3% (#2) | aida(3) line, 98.3±0.0% (#5) |
| ITR= 0.944 b/tr (1 max) | ITR= 0.894 b/tr (1 max) |
| 100.0± 0.0% 1.5± 0.5% | 100.0± 0.0% 3.3± 0.0% |
| 0.0± 0.0% 98.5± 0.5% | 0.0± 0.0% 96.7± 0.0% |

-----------------------------------+------------------------------------+
| aida(2) quad, 99.4±0.4% (#1) | aida(2) line, 98.3±0.0% (#6) |
| ITR= 0.944 b/tr (1 max) | ITR= 0.894 b/tr (1 max) |
| 100.0± 0.0% 1.2± 0.8% | 100.0± 0.0% 3.3± 0.0% |
| 0.0± 0.0% 98.8± 0.8% | 0.0± 0.0% 96.7± 0.0% |

-----------------------------------+------------------------------------+
| aida(1) quad, 99.3±0.3% (#3) | aida(1) line, 98.3±0.0% (#7) |
| ITR= 0.944 b/tr (1 max) | ITR= 0.894 b/tr (1 max) |
| 100.0± 0.0% 1.5± 0.5% | 100.0± 0.0% 3.3± 0.0% |
| 0.0± 0.0% 98.5± 0.5% | 0.0± 0.0% 96.7± 0.0% |

-----------------------------------+------------------------------------+
| lda(1) quad, 99.3±0.3% (#4) | lda(1) line, 98.3±0.0% (#8) |
| ITR= 0.944 b/tr (1 max) | ITR= 0.894 b/tr (1 max) |
| 100.0± 0.0% 1.5± 0.5% | 100.0± 0.0% 3.3± 0.0% |
| 0.0± 0.0% 98.5± 0.5% | 0.0± 0.0% 96.7± 0.0% |

-----------------------------------+------------------------------------+

Passing the following into TrainDB ..
Feature extraction: aida(2) quadratic
Channels: F5, F1, Fz, F2, F6, FC3, FCz, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4, P5, P1, Pz, P2, P6, POz
Frequency range: 4.00 - 30.00 Hz
Pre-processing filter: 2.00 - 50.00 Hz (Butterworth order 2)
Zscore usage: 0
Log-power usage: 1

TrainDB A29B created.
Figure H.10: A sample feature extraction image accompanying the cross validation during the data analysis procedure of BCI-Avatar.