Towards Development of a Robust Asynchronous EEG-BCI using Error-Related Potentials

by

Rozhin Yousefi

A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy
Graduate Department of Biomedical Engineering
University of Toronto

© Copyright 2019 by Rozhin Yousefi
Abstract
Towards Development of a Robust Asynchronous EEG-BCI using Error-Related Potentials

Rozhin Yousefi
Doctor of Philosophy
Graduate Department of Biomedical Engineering
University of Toronto
2019

The primary goal of brain-computer interface (BCI) research is to provide a means of communication for individuals with severe motor impairments. For BCIs to be widely adopted by patients, they need to have a reliable accuracy. One method to achieve this goal is to automatically correct erroneous classifications by exploiting error-related potentials (ErrPs). The first objective of this research is to explore how does the introduction of error-based autocorrection impact the accuracy of a multi-class active BCI based on non-motor imagery (MI) cognitive tasks. Another unavoidable step toward making BCIs clinically viable is to develop self-paced BCIs that users can control whenever they intend to. The second objective of this research is to investigate the impact of ErrP-based autocorrection on the accuracy of self-paced BCIs based on non-MI cognitive tasks. The first two studies were designed to answer the first research question. In the first study, participants performed multiple iterations of five different cognitive tasks. To simulate errors, a random subset of 20% of the trials were followed by incorrect feedback. An average area under curve of 0.83 was reached for the detection of ErrPs which confirmed the presence of ErrPs in such BCIs. The second study explored the effect of ErrP-guided error correction in an online three-class active BCI (idle state and two personally selected cognitive tasks). ErrP-based error correction modestly but significantly improved the average online task classification accuracy (+7%) and the information transfer rate (+0.9 bits/min) of the BCI across participants. The third study was designed to answer the second research question. Using a self-paced EEG-BCI based on cognitive tasks, the possibility of improving the BCI performance using ErrPs was investigated. The BCI continuously analyzed the EEG data and displayed real-time feedback as soon as it detected a cognitive task. Then, the BCI analyzed the EEG data after the feedback onset to detect ErrPs. The average of post-error correction success rate across participants improved significantly compared to the pre-error correction value (+7%). The findings of these studies support the addition of ErrP-informed correction to maximize the accuracy of cue-based and self-paced BCIs based on non-MI cognitive tasks.
Acknowledgements

My PhD journey has been a truly life-changing experience for me and it would not have been possible to do without my supervisor’s guidance, Dr. Tom Chau. I would like to express my sincere gratitude for his constant support, encouragement, and kind advice through this stage of my life. I will always be grateful for accepting me as your student, helping me to put behind my unfortunate experiences at the beginning of my PhD, and turning it into most rewarding experience of my academic life.

I would like to thank my committee members, Dr. Anne-Marie Guerguerian, Dr. Tilak Dutta, and Dr. Babak Taati for their continuous support, valuable suggestions, and helpful questions that have made this work stronger. I would also like to thank Dr. Gernot Muller-Putz, who graciously agreed to serve in my final PhD exam committee.

Thanks to all members of the PRISM lab, you have made graduate school such a welcoming and stimulating experience.

Thanks to all those who volunteered their time to participate in my experiments. None of this would have been possible without you.

Many thanks go out to my mom, dad, and brother for their constant support and encouraging me along the way. Special thanks to my sister, Zhino, for always being there for me.

Finally, to my wonderful spouse and my best friend, Alborz, thank you for everything you have done for me. Words fail to express my appreciation for your love and affection.
Contents

1 Introduction 1
  1.1 Motivation ................................................. 1
  1.2 Research questions and objectives ................................. 2
  1.3 Outline of the thesis .................................... 3

2 Background 4
  2.1 Brain-computer interfaces .................................... 4
    2.1.1 EEG as BCI Modality .................................. 5
    2.1.2 BCI types ........................................... 6
    2.1.3 Cue-based versus self-paced BCIs ......................... 7
    2.1.4 Functional activity induced by cognitive tasks ............... 7
  2.2 Limitations of current BCIs ................................ 8
    2.2.1 Error-related potentials ................................ 8
  2.3 Literature review ........................................ 9
    2.3.1 Active BCI ......................................... 9
    2.3.2 ErrP-based error correction in BCI .................. 10
    2.3.3 BCI brain-switches .................................. 10

3 Exploiting error-related potentials in cognitive task-based BCI 11
  3.1 Abstract ................................................ 11
  3.2 Introduction ............................................. 12
  3.3 Methods .................................................. 13
    3.3.1 Participants ....................................... 13
    3.3.2 Instrumental Setup ................................ 13
    3.3.3 Tasks ............................................... 13
    3.3.4 Protocol ............................................ 14
    3.3.5 Data Analysis ...................................... 14
  3.4 Results .................................................. 18
    3.4.1 Error Detection .................................... 18
    3.4.2 Tasks Classification Accuracies: Pre- and Post-Error Correction 20
  3.5 Discussion ............................................... 21
    3.5.1 Presence of ErrP in a cognitive task-based BCI paradigm 21
    3.5.2 The morphology of the ErrP .......................... 23
    3.5.3 Value of ErrP-based error correction .................... 24
4 Online detection of error-related potentials in multi-class cognitive task-based BCIs

4.1 Abstract

4.2 Introduction

4.3 Methods

4.3.1 Instrumental Setup

4.3.2 Participants

4.3.3 Tasks

4.3.4 Protocol

4.3.5 Data Analysis

4.3.6 Performance Metric

4.4 Results

4.5 Discussion

4.5.1 ErrP-based Error Correction

4.5.2 Error-related Potentials

4.5.3 Task Classification

4.5.4 Limitations and Future Work

5 Robust Asynchronous Brain-switch using ErrP-based Error Correction

5.1 Abstract

5.2 Introduction

5.3 Methods

5.3.1 Participants

5.3.2 Instrumental Setup

5.3.3 Tasks

5.3.4 Experimental Protocol

5.3.5 Analysis of Training Session Data

5.3.6 Analysis of Test Session Data

5.3.7 Performance Assessment Metrics

5.4 Results

5.4.1 Offline Training Session

5.4.2 Online Test Session

5.5 Discussion

5.5.1 Asynchronous Protocol Design

5.5.2 BCIs as Brain-switches

5.5.3 Adding Error-correction

5.5.4 ErrP Waveforms

5.5.5 Limitations and Future Directions

6 Conclusion

6.1 Future Work

6.1.1 Investigating ErrPs in more realistic settings and scenarios

6.1.2 Considering collecting more data
6.1.3 Exploring multi-choice asynchronous brain switches and the effect of ErrP-guided
error correction in their performance ........................................... 55
6.1.4 Validating the findings with different age groups as well as potential BCI users . 55
6.2 Peer-reviewed publications ......................................................... 55

Bibliography .......................................................... 57
List of Tables

3.1 Error-related potential classification results: area under the curve (AUC), true positive rate (TPR) and false positive rate (FPR). ................................................................. 19
3.2 Binary task classification accuracies (%) between each mental task and idle state pre- and post-error correction. ................................................................. 22
3.3 ITR (bits/min) values of binary task classifications between each mental task and idle state pre- and post-error correction. ................................................................. 22
3.4 Ternary task classification accuracies (%) between pairs of mental tasks and idle state pre- and post-error correction. ................................................................. 23
3.5 ITR (bits/min) values of ternary task classifications between each mental task and idle state pre and post ErrP-based error correction. ................................................................. 24
4.1 Tasks selected by participants. ................................................................. 29
4.2 Achieved online accuracy (ACC), true positive rate (TPR), and false positive rate (FPR) for ErrP classifiers are reported for every three consecutive blocks and the entire session. The upper limit of the 95% confidence interval of chance (ULC) for every participant is also reported (using cumulative binomial distribution). ................................................................. 32
4.3 Online pre- and post-error correction ternary task classification accuracies for two cognitive tasks and unconstrained rest/idle are reported for every three consecutive blocks and the entire session. Online information transfer rates (ITRs) are reported as well. ................................................................. 33
4.4 An overview of online error detection studies. ................................................................. 35
5.1 The mental task selected by each participant. ................................................................. 43
5.2 Leave-one-out cross validation results of the intention classifier (task vs. idle) for each participant: true positive rate (TPR), true negative rate (TNR), and accuracy (ACC). The cognitive task was defined as the positive class while idle was defined as the negative class. ................................................................. 48
5.3 Leave-one-out cross validation results of the ErrP classifier (error-present vs. error-absent): true positive rate (TPR), true negative rate (TNR), and accuracy (ACC). The presence of error was defined as the positive class while the absence of error was considered the negative class. ................................................................. 48
5.4 Online performance of the asynchronous BCI: pre- and post-error correction success rate (SR), hit rate (HR), and positive predictive value (PPV). ................................................................. 48
List of Figures

2.1 The BCI cycle. .......................................................... 4

3.1 EEG channels (shaded) considered in this study. Channel location and nomenclature were determined according to the 10-10 international system. .................................................. 14

3.2 The user interface. Each icon corresponded to one task. The icon in the middle with no text represented idle state. ................................................................. 15

3.3 Trial timing and user interface. (i) The required task was highlighted for 5 s. In this example, the target is the leftmost icon. (ii) Participant performed the required task for 5 s. The EEG signals recorded during this time interval were used for task classification. (iii) Simulated feedback was displayed for 2 s. Data from this period of time were analyzed for the presence of ErrP. (iv) Participant rested for 3 s and prepared for the next trial. ... 16

3.4 Average event-related potentials for correct (dotted line) and error (dashed line) trials for participant #10 at AFz, Fz and FCz. The solid line is the difference between correct and error responses. Note that in error trials, the second peak is larger and occurs later (630 ms) than in correct trials (600 ms). Time 0 marks the beginning of the visual feedback. ... 19

3.5 The top row depicts the grand average ERPs across all participants for correct (dotted line) and error (dashed line) trials along with their difference (error minus correct; solid line) at AFz, Fz and FCz. The bottom row shows the grand average of the difference waveforms along with the corresponding standard error (shaded region) across participants. Time 0 marks the beginning of the visual feedback. .................................................. 20

3.6 The topographic maps of the average of the (a) correct trials, (b) error trials, and (c) their difference for participant #10 at 330, 400, and 700 ms from feedback onset. ... 21

3.7 Boxplots of binary classification accuracies across participants pre- and post-error correction. 23

3.8 Boxplots of ternary classification accuracies across participants pre- and post-error correction. ................................................................. 25
4.1 Trial interface: (a) The required task was highlighted for 4 s by changing the text font color from gray to red. (b) The color of the icon’s bow-tie changed to magenta to indicate that the participant should start the task. The participant performed the required task for 5 s. Then, the color of the bow-tie changed back to gray. The 5 s of EEG data were used for task classification. Then, real-time feedback was displayed. At this point, depending on the output of the classifier, the timing followed either (c) or (d). (c) In the first case, the task classifier output was correct, so the icon representing the required task remained unchanged while the other two icons fell. (d) In the second case, the task classifier output was incorrect as the icon representing the required task fell. EEG data after feedback onset (from time 0 to 1.4 s) was analyzed to detect error. (e,g) No error was detected so the participant was notified with the following message: “No Error!”. (f,h) Error was detected so the BCI changed its decision. The participant was notified with following message: “Error! BCI changed its decision to x”, where x refers to the output of the binary task classifier and can be “task 1”, “task 2”, or “rest”. “task 1” referred to the task written on the left icon and “task 2” referred to the task written on the right icon.

4.2 Pipeline for training the online task classifier for the $n^{th}$ online block, $n = 1, \ldots, 9$.

4.3 Pipeline for tuning the online ErrP classifier for the $n^{th}$ online block, $n = 1, \ldots, 9$.

4.4 The grand average of responses across all participants for correct (red line) and error (blue line) trials along with their corresponding standard error (shaded region) at FCz. Time 0 marks the beginning of the visual feedback.

4.5 Boxplots of online ternary task classification accuracies across participants pre- and post-error correction. Post-error correction accuracies for blocks 1-9 were improved significantly compared to pre-error correction values ($p=0.002$, Wilcoxon Signed-Rank test).

5.1 The interface during the training session. The top panel depicts a no-error trial (the icon falls upon task performance) where as the bottom panel is an error trial (the icon falls although the user remains idle).

5.2 The timing of trials in the training session. The idle and task interval times, $t_{idle}$ and $t_{task}$, are drawn from discrete uniform distributions, $U(a,b)$.

5.3 The grand average of ErrP waveforms across all participants for error and no-error trials along with their corresponding error bars (shaded region). Time 0 marks the beginning of the visual feedback. The vertical dashed red lines demarcate the segment which was used for classification.
## Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECOG</td>
<td>Electrocorticography</td>
</tr>
<tr>
<td>EEG</td>
<td>Electroencephalography</td>
</tr>
<tr>
<td>ERP</td>
<td>Event-related potential</td>
</tr>
<tr>
<td>ErrP</td>
<td>Error-related potential</td>
</tr>
<tr>
<td>fMRI</td>
<td>Functional magnetic resonance imaging</td>
</tr>
<tr>
<td>fNIRS</td>
<td>Functional near-infrared spectroscopy</td>
</tr>
<tr>
<td>MEG</td>
<td>Magnetoencephalography</td>
</tr>
<tr>
<td>SSEP</td>
<td>Steady-state evoked potential</td>
</tr>
<tr>
<td>SSVEP</td>
<td>Steady-state visual evoked potential</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

1.1 Motivation

Individuals with certain neuromuscular disorders such as amyotrophic lateral sclerosis, brain stem stroke, and spastic quadriplegic cerebral palsy have limited or no means of communication. Most assistive technologies developed for these individuals rely on some form of voluntary muscle control. However, patients who present as locked-in do not have any reliable voluntary motion. One alternative means of communication for these patients is a brain-computer interface since they retain cognitive capabilities [4, 172].

Brain-computer interfaces (BCIs) provide a communication channel between humans and external devices by directly using brain signals, without the involvement of muscles. BCIs translate a user’s intention into command signals on a computer to control a communication device. A BCI cycle starts with measuring modulations of the user’s brain activities. There are a variety of unique signal patterns that can be measured and utilized to control a communication device [171, 164, 115, 4]. There are various measurement modalities to collect changes in brain signals such as functional near-infrared spectroscopy (fNIRS) [166, 114], functional magnetic resonance imaging (fMRI) [170], and electroencephalography (EEG) [107]. EEG is the most common modality used in BCI, given that the associated instrumentation is inexpensive and portable and provides millisecond temporal resolution. In this thesis, EEG modality was used.

EEG-BCIs can be categorized into three types of active, reactive, and passive in terms of the mental activities they use for control [180]. Active and reactive BCIs detect user’s intention for control while passive BCIs typically measure mental states of the brain such as fatigue or stress [113]. Reactive BCIs require an external stimulus to generate specific brain signals that are shown to be detectable, such as P300 and steady-state visual evoked potential (SSVEP) [6]. In active BCIs, users intentionally modulate their brain activity by performing specific tasks that have been shown to produce detectable signal patterns, such as motor imagery (MI) [173, 127], imagined speech [149], or mental arithmetic [32].

In this study, we used non-MI active tasks, and the reason was threefold. First, active BCIs are needless of constantly attending external cues, which makes them more practical for most asynchronous paradigms. Secondly, it has been shown that motor imagery and motor execution involve similar brain regions [106]. This makes use of these tasks for some asynchronous systems, such as brain switches, not practical as voluntary movements can interfere with the control of the system. We note that MI
tasks are viable and intuitive choices for some applications of BCI, such as controlling prosthetic arms or legs [110, 111]. Third, it has been shown that “BCI illiteracy”, inability to control MI-based BCIs, is present in 15 ∼ 30% of population [12]. Cognitive tasks can be investigated as a potential replacement for this group. Besides, MI can be hard or impossible to perform by individuals with congenital motor impairments [23, 24, 22]. Nonetheless, the performances of most asynchronous BCIs developed to this date, regardless of their activation tasks, are not sufficient for daily use adoption.

For EEG-BCIs to become widely adopted among severely disabled individuals, certain challenges must be addressed. First, BCI’s performance must be improved. The performance of BCIs is not ideal, and they require training and recalibration prior to and during operation. One possible way to improve performance while remaining training time is to introduce automatic error correction. It is possible to design an EEG-BCI that can detect its mistakes and change its decision accordingly [142]. Besides, such BCIs can learn from their mistakes and consequently approach their optimal performance [17, 145]. One error correction mechanism for EEG-BCIs is based on the error-related potential (ErrP), which is produced when the user realizes that the choice made by the BCI is incorrect [41]. Our lab and others have shown that ErrP can be detected in EEG signals with a reliable accuracy [18, 182].

Another shortcoming of most EEG-BCIs developed to date is that they operate in a synchronous mode (paced by an external cue). In such systems, users perform mental tasks and hence make selections according to the pace dictated by the BCI. A solution for this problem is to use asynchronous (self-paced) BCIs, which can be activated whenever the user performs a specific mental task and hence, does not require an external cue. However, this type of BCI is more difficult to implement [98]. For instance, an activation mental task should be very specific so that no other brain activity produces similar patterns (and hence falsely activates the BCI), while at the same time, the mental task should not be difficult to perform so that a user in urgent need (to activate the BCI and communicate) can still perform it. In such a paradigm, detecting mistakes (such as accidental activations of the BCI) can help the performance of asynchronous BCIs and increase their practicality.

1.2 Research questions and objectives

The overall objective of this thesis was to develop a reliable asynchronous EEG-based brain-computer interface based on non-motor active tasks by incorporating error-related potentials. The purpose was to advance one step toward a more practical means of communication for the main target population of BCI research, namely, individuals who present as locked-in. To achieve the goal of this research, the following questions were investigated:

I. Which non-motor cognitive tasks are more discriminant against unconstrained rest (also known as idle state)? This information will be important for BCIs designed to work in an asynchronous mode.

II. Is single-trial classification of ErrPs feasible in a multi-class, non-motor active EEG-BCI?

III. How does the introduction of ErrP-based autocorrection impact the accuracy of a multi-class, active EEG-BCI?

IV. How accurately can non-motor cognitive tasks be detected in an asynchronous BCI?
V. How does the introduction of ErrP-based autocorrection impact the accuracy of an asynchronous EEG-BCI?

To answer these questions, the following objectives were defined:

I. We built a multi-class active EEG-BCI based on non-motor cognitive tasks. The tasks included unconstrained rest to determine which cognitive tasks combination provided most discriminant information against unconstrained rest.

II. The presence of ErrPs was investigated in a multi-class non-motor active EEG-BCI, and the feasibility of single-trial ErrP classification was explored. The theoretical added value of ErrP-based error correction to the multi-class EEG BCI, if any, was computed.

III. To determine the benefits of incorporating ErrP-based error correction, a multi-class active EEG-BCI was designed, and online performance of the BCI was compared pre- and post-error correction.

IV. An asynchronous EEG-BCI based on non-motor active tasks was developed.

V. ErrP-based error correction was added to an asynchronous EEG-BCI and the performance was measured pre- and post-error correction.

1.3 Outline of the thesis

Following this introductory chapter, chapter 2 presents a brief review of different types of BCIs, EEG modality, and background literature on asynchronous BCIs and BCIs with ErrP-based error correction. To address the above objectives, three studies were completed during the course of this thesis.

The first study was designed to answer the objectives I and II. Results of the first study, which focused on the offline classification of EEG during non-motor cognitive tasks and detection of ErrPs, are presented in chapter 3. This chapter is reproduced from the following published article: Yousefi R, Sereshkeh AR, Chau T. “Exploiting error-related potentials in cognitive task based BCI”. Biomedical Physics and Engineering Express. 2018 Dec 20;5(1):015023.

The second study, designed to answer objective III, is detailed in chapter 4. This study focused on the online classification of cognitive tasks in a ternary task EEG-BCI and classification of ErrPs following provided real-time feedback. This chapter is reproduced from the following published article: Yousefi R, Sereshkeh AR, Chau T. “Online detection of error-related potentials in multi-class cognitive task-based BCIs”. Brain-Computer Interfaces (2019): 1-12.

Chapter 5 presents the results of the third study and concentrates on objectives IV and V, which was to explore the potential benefits of adding ErrP-based error correction to a cognitive task-based asynchronous BCI in an online paradigm. This chapter is reproduced from the following article that has been submitted for publication: Yousefi R, Sereshkeh AR, Chau T. “Development of a robust asynchronous brain-switch using ErrP-based error correction”. Journal of Neural Engineering, Under Review.

Finally, the main contributions of this research and suggested directions for future works are summarized in chapter 6.
Chapter 2

Background

2.1 Brain-computer interfaces

A brain-computer interface is a system that can identify certain brain activity patterns. A measurement modality is used to record the user’s brain activity and transmits the data to a computer. The computer interprets the data and generates a corresponding command to control external devices such as moving a robot’s hand, controlling a wheelchair or guiding Pacman through a maze. In more details, a BCI system comprises five consecutive stages as shown in 2.1: (i) signal acquisition, (ii) preprocessing including digitization and filtering to remove artifacts and noise, (iii) data analysis including feature extraction and classification, (iv) the control interface executing the commands, and (v) the feedback obtained by the user about the success or failure of his/her effort to control the system.

Figure 2.1: The BCI cycle.

In the pre-processing stage, it is essential to identify data contaminated with artifacts as muscular movement. Contaminated data can be either discarded or artifacts removal techniques can be applied...
to remove artifact components [40]. In the feature extraction step, discriminant features are identified. These features can be from different domains such as time, wavelet, or frequency, depending on the data. Besides, as the number of data in BCI is typically low, the number of features must also be of a low dimension. Common feature reduction techniques such as fast correlation-based filter solution [177] and sequential floating forward selection [132] are sometimes used to reduce the number of features. Classification methods, including support vector machine (SVM), linear discriminant analysis (LDA), and neural network (NN) are among the most commonly used techniques in BCI [95, 94]. Finally, the control interface stage translates the results of data classification into control commands such as moving a cursor or spelling a word.

2.1.1 EEG as BCI Modality

There are various signal acquisition modalities used in BCI [134]. Selecting which modality to use depends on the application. The most common noninvasive modality is EEG [107], which measures electrical voltage from the surface of the scalp. Another technique that measures the electrical signal from the neural activity is electrocorticography (ECoG) [52]. This modality is invasive and requires surgery to implant electrodes on the cortex. However, compared to EEG, ECoG is less sensitive to artifacts and provides a higher signal to noise ratio (SNR). Another non-invasive technique called magnetoencephalography (MEG) measures magnetic fields induced by electrical field fluctuations of neural activity over time [101]. Compared to EEG, MEG has a higher spatial resolution and is less sensitive to noise but is more expensive and not portable. fNIRS [166, 114] and fMRI [170] are two non-invasive techniques which measure hemodynamic response in the active brain area. Active neurons demand more glucose and oxygen compared to inactive neurons, which result in an increase in oxyhemoglobin concentration. An fNIRS system emits near-infrared light from the surface of the scalp to the brain and measures the reflected light. The attenuation level of the reflected light is affected by fluctuations in oxyhemoglobin and deoxyhemoglobin concentrations of the outer cortical layer. Hemodynamic responses are delayed in nature, which limits their applications. In addition, fMRI is bulky and expensive and has a low temporal resolution. So, overall, fMRI and MEG are not viable modalities for daily BCI use by individuals with disabilities. In this thesis, we employed EEG for data collection during the experiments.

Brain electrical signals arise from the flow of ions in neurons when transmitting information. Cortical pyramidal neurons contribute significantly to the generation of the EEG. During signals transmission, neurons become electrical dipoles. The signals may be excitatory where net voltage increases or inhibitory where net voltage decreases [133].

Hans Berger, a German psychiatrist, created an electroencephalogram for the first time by attaching electrodes to the scalp to measure electrical activity in human brains in 1924. In general, an electroencephalogram consists of a cap placed around the head with a number of electrodes to measure EEG. The measured EEG signal of each electrode is the differential voltage between that electrode and ground (GND) electrode minus the voltage measured from the reference (REF) electrode.

EEG Electrodes can be categorized into two major types based on their development technology. The first type called ‘wet’ electrodes as they require a conductive gel to be applied between them and the skin to lower the impedance to the range of 10 kΩ. However, applying gel can take a long time, and the signal quality drops as the gel dries out by time. The other type of electrodes are called ‘dry’, and they have the advantage of being gel-free and easier to montage, but they are more expensive and provide less signal to noise ratio [55].
At each moment, measured brain EEG signals originate from numerous simultaneous activities. However, certain activities have signature signal patterns which can be detected and used for BCI control.

2.1.2 BCI types

BCIs can be categorized into three types, namely, active, reactive, or passive, according to the mental activities they employ to interpret the user’s state of mind and intention [180].

Active

Active BCIs, also referred to as endogenous BCIs, require the user to consciously perform mental tasks such as motor imagery (MI), word generation, and mental arithmetic. Users are able to control the BCI by performing these tasks as each task is typically associated with a certain command.

Active tasks deployed in BCIs are either motor-related (e.g. motor imagery [126], kinesthetic attention [100], readiness potentials [181]) or cognitive (e.g. word generation [32], music imagery [54], imagined speech [149]). Motor imagery (MI) is the most common mental task for the development of active BCIs [43, 161, 139, 75, 178, 109, 167, 99, 173]. However, for individuals with congenital or long-term motor impairments, MI can be impossible or difficult to perform [22, 23, 24]. It has also been shown that approximately 15-30% of BCI users (even without any motor impairments) are unable to control an MI BCI [12]. An alternative to be explored for these individuals is to use non-MI tasks [32, 34, 33, 29, 149, 148, 100] which we will refer to as cognitive tasks.

Passive

Passive BCIs do not require an external stimulus or intentional brain activity by the user. Passive BCIs simply monitor spontaneously occurring background brain activity, which therefore can provide information on the user’s mental state such as fatigue, attention, or frustration [112, 113].

Reactive

Reactive BCIs, also referred to as exogenous BCIs, involve using external stimuli to elicit specific brain responses. In other words, users of this type of BCIs do not control their brainwaves consciously but instead react to external cues. Two common reactive signals in BCI include P300 and steady-state evoked potentials (SSEPs) [6]. P300 occurs in response to an infrequent stimulus, and SSEPs occur when the stimulus is oscillating at a specific frequency. The stimulus for generating P300 and SSEPs can be visual [183, 174, 187], auditory [85, 46, 116], somatosensory [14, 15], or a combination of them [175, 86].

Actives BCIs may require a lengthy period of user training before achieving proficiency, especially for naïve BCI users [121] but reactive BCIs require minimal training. Active BCIs also typically do not achieve high accuracy when the number of classes exceeds two and the number of training sessions is small. Hence, active BCIs typically have a lower information transfer rate compared to reactive BCIs. However, in reactive BCIs, the user must continuously attend to external stimuli, which may induce fatigue [115] and reduce the practicality of systems for certain applications. One way to exploit the advantages of both types (higher ITR of reactive BCIs and being needless of constantly attending external cues in active BCIs) is to combine them [128]. For example, a brain-switch (an asynchronous
BCI designed to detect one brain pattern) can be developed based on an active task to turn on a fast reactive BCI (such as a p300 speller).

### 2.1.3 Cue-based versus self-paced BCIs

Most existing BCIs are cue-based, also known as synchronous, which means users’ brain activity is analyzed in specific time intervals. In other words, the BCI dictates to the users by external cues when they can interact with the system. This makes analyzing the users’ data and determining their intentions less challenging as activation time intervals are pre-determined.

Self-paced or asynchronous BCIs offer a more natural mode of communication, allowing users to control the timing of the BCI. In an asynchronous BCI, brain signals need to be continuously analyzed to isolate the brain activities associated with intentional control (IC) from any other ongoing brain activity. From numerous simultaneous functions happening in our brain to non-stationary nature of these activities result in many elusive challenges complicating the development of asynchronous systems. This means the BCI must be able to distinguish the IC periods from every other non-control (NC) mental states. The wide variety of NC mental states are typically referred to as idle state.

### 2.1.4 Functional activity induced by cognitive tasks

The human brain is a distributed processing system. Most functional brain imaging studies have focused on finding specific brain regions involved in cognitive tasks. But a newer perspective suggests that brain functions must be studied in a network paradigm which suggests any cognitive task activates different brain regions which are connected as a network [103].

**Mental 3D figure rotation** - It has been confirmed that parietal areas are involved in mental rotation of visual images including superior parietal cortex (predominantly on the right side), posterior parietal cortex (which is part of spatial attention network), transverse occipital sulcus, intraparietal sulcus (IPs) and adjacent regions [179, 160, 158].

**Mental math** - Studies on brain regions involved in arithmetic tasks have demonstrated activities in prefrontal and parietal cortex. Specifically, the angular gyrus of the inferior parietal cortex and inferior prefrontal cortex are activated during the mental numerical calculation. They also have shown that lesions to prefrontal, frontoparietal, and thalamus may lead to impaired arithmetic reasoning [135, 102, 28].

**Mental counting** - Ordered verbal concepts, such as months, weekdays, and numbers activate intraparietal sulcus while other non-ordered verbal do not [70, 152]. In [70], Ischebeck et al. showed that IPS activation was similar for both numbers and months, which means that the IPS activation might not be modulated by the quantity information carried by numbers.

**Mental phonemic fluency** - We refer to phonemic fluency task as word generation. Many studies have investigated various types of fluency tasks. Phenomic fluency tasks are shown to activate left frontal lobe and left temporal lobe, specifically left inferior frontal gyrus and insula, left rolandic operculum and the left middle frontal gyrus [67, 11].

**Unconstrained rest** - It has been shown that the brain is always active even during resting state. The active brain regions during unconstrained rest or mind-wandering form a network called default mode network (DMN). It was called the default mode since it was assumed to become deactivated during tasks. However, recent studies show that DMN plays a role in some other certain tasks such as
thinking about past and future [53].

2.2 Limitations of current BCIs

There are still several challenges that need to be addressed before widespread adoption of BCIs. First, BCIs must be developed sufficiently user-friendly, so non-BCI experts can set them up easily and quickly. EEG is portable and relatively inexpensive compared to other modalities. As technology advances and dry wireless EEG electrodes are becoming more available, EEG-BCIs are getting closer to being practical for daily usage. In this thesis, we used dry EEG systems to move one step forward toward practicality.

Secondly, the user must be able to control the BCI whenever they intend to, which means a practical BCI must work in an asynchronous mode.

Third, brain signals are nonstationary, and thus change over time, which can be the result of changes in mental strategy and mental state. This makes training a reliable BCI more challenging. One partial solution is to collect a sufficient amount of data on different days to train the BCI and continue updating it.

Fourth, BCIs must be reliable in understanding the user’s intentions. However, the performance level of most BCIs developed to this date is not sufficient for wide adoption. Much effort has been devoted to improving the performance of BCIs. Recent improvements in the quality of recorded EEG signals (e.g., signal-to-noise ratio) [55] and classification algorithms [95, 94] have enhanced BCI performance, but further improvements are required. Another approach is to detect the BCI’s errors and correct them. Brain reacts when someone commits an error [37] or observes an error by others [165] or a computer [41] and generates certain signal patterns called error-related potentials (ErrPs). The feasibility of detecting these signals and using them to enhance BCI’s performance has been proven [18].

2.2.1 Error-related potentials

The typical success rate of a BCI in recognizing user’s intentions is less than 100%. Error-related potentials, brain signals elicited when someone perceives that a mistake is made, can be used to correct BCI’s behavior. Falkenstein et al. and Gehring et al. are among the first researchers to investigate the presence of ErrPs in the early 1990s [37, 48]. There are several variants of ErrPs based on the source of the error, including response ErrP, feedback ErrP, observation ErrP, and, interaction ErrP [42].

Response ErrPs occur when a person commits an error during a rapid ipsative or memory task [122]. Feedback ErrPs are generated when the user makes a mistake in a reinforcement learning task and may be unaware of the mistake unless she/he is explicitly informed of the error using feedback [59]. Observation ErrPs occur when an individual is monitoring the performance of another person or a computer and observes a mistake being made [165]. It has been shown that another type of ErrPs, called interaction ErrPs, are elicited when a BCI makes an error in interpreting the user’s intention, and this error is perceived by the user [41].

The feasibility of single-trial detection of ErrPs with reliable accuracy has been previously shown in many studies [18, 9, 43, 185]. Schalk et al. first demonstrated that error-related potentials could be detected in a motor imagery BCI [142]. The detected ErrPs have been used to improve BCI performance via two mechanisms: (i) error correction, where detected mistakes trigger a change to the output [13, 93, 137]; and (ii) classifier adaptation, where the BCI classifier is gradually updated based on the detection
of ErrPs [182, 8]. These mechanisms have been investigated in the context of MI-based active BCIs [43, 83, 8] and reactive BCIs that harness evoked potentials such as the P300 [26, 20, 159] and SSVEPs [155, 183].

Different types of ErrP waveforms have some characteristics in common. First, the error-related negativity (ERN) appears over the frontocentral cortex. It has been demonstrated that ERN can be detected with the same performance after several months without recalibration, suggesting stability of ERN over time [42]. ERN is most likely generated in the anterior cingulate cortex (ACC) [163] with a peak latency varying between 50ms to 250 ms from the error onset [18]. Iturrate et al. investigated ErrPs in three tasks with different difficulty levels [71]. They suggested that some features of ErrP waveforms such as ERN latency varies for the different tasks while the amplitude and overall waveform shape remain similar. ERN is followed by a centroparietal positive peak, which has been shown to be modulated by error awareness [64].

2.3 Literature review

The general purpose of this research was to develop a robust asynchronous EEG-BCI by employing error-related potentials. Previous studies that have investigated active BCIs developed asynchronous brain-switches or adopted error-related potentials to improve BCI performance are reviewed here.

2.3.1 Active BCI

Non-motor imagery active tasks have received little attention in BCI. Since the first step of this research is to develop a multi-class BCI based on active tasks, relevant publications are reviewed here. In one of the first reports on active tasks, published in 1990, Keirn and Aunon collected EEG data during five different active mental tasks and were able to classify the tasks pairwise with a minimum accuracy of 85% [76, 77]. These five tasks included complex math problem solving, geometric figure rotation, mental letter composing, visual counting, and baseline measurement. The power and asymmetry ratio from four frequency bands (delta, theta, alpha, and beta) were extracted from the EEG data, and a Bayes quadratic model was used for classification.

Over the next two decades, several other studies investigated various types of feature extraction and classification methods on the EEG data collected by Keirn and Aunon [57, 119, 7, 120]. To name a few, Palaniappan et al. applied a fuzzy ARTMAP neural network on power spectral density (PSD) and autoregressive (AR) features of the EEG data to choose the three best mental tasks from five available ones [120]. They showed that these best triplets of mental tasks are different for each subject because each subject had a different way of performing each mental task. Also, an improvement of about 5% was reported in some of the binary classification problems [120].

In another effort by Palaniappan, spectral power and asymmetry ratio features from the gamma band (24-37 Hz) were extracted and added to the features from the lower frequency bands which resulted in improved accuracies compared to the original obtained ones [119]. Different types of support vector machines (SVM) have also been investigated on the same dataset, which led to improvements in some of the classification problems [89, 57]. It should be noted that some of the attempts in investigating new techniques on this dataset led to lower accuracies compared to previous work [7]. In conclusion, developing a reliable BCI using non-motor imagery tasks appears feasible, given an appropriate signal processing pipeline.
Some of the other non-motor imagery active mental tasks which have been used for BCI include navigation imagery [32], auditory recall [32], phone imagery [32], and word generation [91]. Also, some studies have investigated more intuitive mental tasks such as speech imagery of vowels [27], syllables [35] or complete words [168] and reported higher than chance average accuracies.

### 2.3.2 ErrP-based error correction in BCI

Schalk et al. first demonstrated that error-related potentials are generated when an error is made by a machine in a BCI context [142]. Feasibility of single-trial detection of error-related potentials is shown in many studies. It has been suggested that ErrPs can be used to improve BCI performance in two ways: (i) to correct the erroneous decisions made by BCI where the BCI reverts the command before being fully executed, (ii) to learn from the mistakes by recalibrating classifying algorithms [13, 93, 137]. So far, most studies have investigated ErrP as a corrective signal in either motor imagery [8, 9, 43, 83] or P300 based BCIs [26, 20, 159, 155, 183]. The results of these studies demonstrated that BCI performance was improved by incorporating ErrP. One essential note is that both sensitivity and specificity of ErrP detection and the ensuing corrective mechanism are important. Even with a high detection accuracy of ErrP, information transfer rate might decrease.

### 2.3.3 BCI brain-switches

Throughout the past decade, asynchronous systems have received increasing attention among the BCI community. The most common modality for developing asynchronous BCIs is EEG. The first study on asynchronous EEG-BCI was performed by Mason and Birch in 2000 [98]. They designed a brain-switch based on the finger movements. A brain-switch is designed to detect one brain pattern and is used as a binary switch. They achieved an average area under the curve (AUC) of 79 %. Most asynchronous studies have explored MI tasks [66, 161, 87, 16, 88, 139, 125, 49]. Some of these studies demonstrated the feasibility of asynchronous MI-related BCIs in motor-impaired patients [69, 125, 88]. Several studies have focused on using SSVEP [31, 128] and P300 signals [129, 90, 144] to develop an asynchronous BCI. There are also several papers that have developed asynchronous BCIs using a combination of MI and non-MI tasks [32, 25, 34, 47, 33, 105, 29]. These studies showed that cognitive tasks such as 3D object rotation, mathematical operations, word generation, spatial navigation, and auditory recall could be classified from idle state with acceptable accuracies.
Chapter 3

Exploiting error-related potentials in cognitive task-based BCI

This chapter is reproduced from the following published article: Rozhin Yousefi, Alborz Rezazadeh Sereshkeh, and Tom Chau. “Exploiting error-related potentials in cognitive task based BCI. “Biomedical Physics & Engineering Express 5.1 (2018): 015023. Hence, there is some material that is repeated from Chapter 1 and 2 (e.g. parts of the literature review). The final published article can be found in the following link: https://iopscience.iop.org/article/10.1088/2057-1976/aaee99/meta.

3.1 Abstract

Brain-computer interfaces (BCIs) can make mistakes in recognizing user intention. It has been well-established that for reactive and motor imagery (MI) BCIs, an error-related potential (ErrP) occurs subsequent to such mistakes, and can be used to improve BCI performance. However, the presence of ErrPs in active BCIs based on non-MI cognitive tasks has not been confirmed. In this study, we attempted to elicit ErrPs in a BCI based on non-MI mental tasks. Twelve typically developed young adults participated in two sessions each. Participants performed multiple iterations of five different mental tasks (mental arithmetic, counting, word generation, figure rotation and idle state) to “knock down” one of 4 targets on a graphical interface (each mental task was associated with a different target). To simulate errors, a random subset of 20% of the trials were followed by incorrect feedback (i.e., the wrong target fell). Our findings confirmed the presence of an interaction ErrP, with a negative peak at ∼180 ms, followed by two positive peaks, respectively, at ∼400 and ∼630 ms post-feedback onset. The classification of mental tasks and error versus non-error trials were both performed using a pseudo-online paradigm where the last quarter of trials were used for testing. For binary (task and idle) and ternary (2 tasks and idle) classification, across-participant average accuracies of 76%±12 and 63%±12, respectively, were attained. An average area under curve (AUC) of 0.83 was reached across participants for the detection of ErrPs. After applying ErrP-based error correction, the average binary and ternary classification accuracies of mental tasks improved by 9% and 14%, respectively. Our findings support the addition of ErrP detection and ErrP-informed correction to maximize the accuracy of BCIs based on cognitive tasks.
3.2 Introduction

Individuals with conditions such as amyotrophic lateral sclerosis, and those living with the effects of brain stem stroke, may have limited or no means of communication. Most assistive technologies rely on extant voluntary movements, which are elusive in those who present as locked-in. One alternative means of communication for these individuals is a brain-computer interface (BCI). BCIs provide a communication channel between the brain and external devices, circumventing the need for muscular activity. Electroencephalography (EEG) is the most common modality used in BCIs; the associated instrumentation is generally portable, and offers sub-second temporal resolution.

Much effort has been devoted to improving the performance of BCIs [138]. Some BCIs employ a verification step to reduce error rates, but the communication rate is reduced as a consequence. An alternative approach is to detect errors using certain brain signals called error-related potentials (ErrPs).

Based on the source of the error, a response, feedback, observation, or interaction ErrP may be observed. Response ErrPs occur when a person commits an error during a rapid ipsative or memory task. Feedback ErrPs are generated when the user makes a mistake in a reinforcement learning task and may be unaware of the mistake unless she/he is explicitly informed of the error using feedback. Observation ErrPs occur when an individual is monitoring the performance of another person or a computer and observes a mistake being made. It has been shown that another type of ErrPs, called interaction ErrPs, are elicited when a BCI makes an error in interpreting the user’s intention and this error is perceived by the user [42].

The feasibility of single-trial detection of ErrPs with reliable accuracy has been previously shown in many studies [18, 9, 43, 185]. Schalk et al. first demonstrated that error-related potentials can be detected in a motor imagery (MI) BCI [142]. The detected ErrPs have been used to improve BCI performance via two mechanisms: (i) error correction, where detected mistakes trigger a change to the output [13, 93, 137]; and (ii) classifier adaptation, where the BCI classifier is gradually updated based on the detection of ErrPs [182, 8]. These mechanisms have been investigated in the context of MI-based active BCIs [43, 83, 8] and reactive BCIs that harness evoked potentials such as the P300 [26, 20, 159] and steady-state visually evoked potential [155, 183].

Although reactive BCIs often have higher information transfer rates than active BCIs, the user must continuously attend to external stimuli, which may induce fatigue [115]. In active BCIs, the user consciously performs a task such as MI, word generation or mental arithmetic to control the BCI. Some individuals with congenital or long-term motor impairments may have difficulty eliciting a significant response in the motor cortex [23, 24, 22]. In addition, a lengthy period of user training may be required before achieving proficiency with a motor-based BCI [121]. An alternative is to use non-MI cognitive tasks [32, 34, 33, 29, 149, 148].

Excluding BCIs controlled by actual movements [78, 42], the study of ErrP in active BCIs has been limited to those of the motor imagery variety. Ferrez and Millan achieved an average detection rate of correct versus error trials of 84.7% and 78.8%, for two participants, respectively. By incorporating ErrP-based error correction, the BCI error rate was reduced from 30% to 7% [43]. Kreilinger et al. showed that combining ErrP and MI improved classification accuracies by 11% on average in three participants [83] and confirmed the presence of ErrPs during a continuous feedback paradigm [82]. In a recent study, Bhattacharyya et al. reported ErrP classification accuracies of 80% or higher and showed that the inclusion of ErrP-based error correction led to higher performance in controlling a robotic arm [10]. Collectively, these studies confirm the value of ErrP-driven error correction in active, MI-based
BCIs.

It has been shown that many factors affect the morphology of ErrP waveforms such as the user’s level of engagement during the task [60], as well as the cognitive workload of the task and the feedback paradigm [71]. Schmidt et al. measured ErrPs in a P300-based center speller and a calibration speller (controlled via key press) while the interface and the feedback were kept identical [145]. They found that although the ErrPs for both cases exhibited similarities in terms of the general shape, latencies and amplitudes of error-related negativity and positivity were notably different. As the impact of variations in BCI mental tasks on ErrPs has not been adequately evaluated, it cannot be assumed that a single classifier can be trained to reliably detect ErrPs elicited in different mental task and feedback paradigms.

The main goal of this study was to investigate the possibility of using a participant-dependent classifier for single-trial detection of error potentials subsequent to five different non-MI cognitive tasks. To the best of our knowledge, this is the first study to investigate whether machine-discernible ErrP is elicited subsequent to errors committed by a non-MI cognitive task-driven BCI. We also explored the impact of incorporating ErrP-based error correction on BCI performance using accuracy and information transfer rate (ITR) [171]. Finally, it should be noted that the measurements of this study were all performed using dry EEG electrodes.

3.3 Methods

3.3.1 Participants

This study was approved by the research ethics boards of Holland Bloorview Kids Rehabilitation Hospital and the University of Toronto. Twelve typically developed adults (6 male) with normal or corrected-to-normal vision were recruited for this study (mean age: 28 ± 2 years). Participants attended two sessions on separate days. They were seated in front of a computer screen about 70 cm away and were asked to relax and refrain from excessive blinking or moving during mental tasks periods.

3.3.2 Instrumental Setup

Brain activity was recorded using a 32 channel dry EEG system (actiCAP Xpress Twist, Brain Products, Germany). The locations of the electrodes are shown in figure 3.1. Reference and ground electrodes were placed on the left and the right earlobe, respectively. The sampling rate for data acquisition was set to 1000 Hz.

3.3.3 Tasks

The following five mental tasks were chosen for this study: (I) Backward counting from 10 at a constant pace; (II) Mental arithmetic - iterative mental subtraction of a single-digit number from a 2-digit number (both self-selected), e.g. 94-7=87, 87-7=80, 80-7=73, etc.; (III) Word generation - thinking of as many words as possible that begin with a certain letter (self-selected prior to the trial); (IV) Figure rotation - visualizing the rotation of a particular three-dimensional object (self-selected) around an axis; and, (V) Idle state - rest while allowing normal thought processes to occur and refraining from performing any of the defined mental tasks.
Figure 3.1: EEG channels (shaded) considered in this study. Channel location and nomenclature were determined according to the 10-10 international system.

3.3.4 Protocol

Each participant completed two sessions on separate days. Each session lasted approximately 90 minutes including setup time. In each session, participants completed 180 trials (36 trials per task). During each trial, five icons, each corresponding to one task, were displayed on the monitor (figure 3.2). At the beginning of each trial, the colour of the target icon changed from white to yellow (figure 4.1(i)), indicating the task the participant was to perform. The sequence of targets was pseudo-randomized. Participants had 5 s to prepare themselves for the upcoming task (e.g. choose the two numbers for the mental arithmetic task, choose the letter for the word generation task, or choose the 3D object for the figure rotation task). Then, participants were visually cued (the bowtie of the target icon changed from white to magenta in colour) to perform the mental task (figure 4.1(ii)) for 5 s. Afterward, visual feedback (all icons except one fell down) was displayed for two seconds (figure 4.1(iii)). In correct trials, the remaining icon was that corresponding to the mental task performed. Participants were told that the feedback was the real-time result of classifying their recorded EEG signals whereas in fact, the feedback was randomly generated to be erroneous in 20% of the trials [83, 17, 8]. This contrived mismatch between the completed task and the feedback was deliberately created to evoke error-related potentials. Pseudo-randomization of targets and the randomization of feedback mitigated the potential of any order effects [42].

3.3.5 Data Analysis

Preprocessing

The EEG data from the two sessions were combined for each participant. The data were treated using a 1 to 40 Hz bandpass finite impulse response (FIR) filter which is the recommended bandwidth for this dry EEG system [51]. The data were then partitioned into a training set and a test set. The first 75% of trials (all trials of session I and the first half of session II) were placed in the training set and the rest in the test set to emulate an online evaluation (i.e. pseudo-online).
Figure 3.2: The user interface. Each icon corresponded to one task. The icon in the middle with no text represented idle state.

Ocular and blink artefacts were removed by applying independent component analysis (ICA) and the ADJUST algorithm [108]. Only the training subset of EEG data (i.e., data from session I and the first half of session II) was used for calculating ICA weights.

Error-related Potential Detection

1.3 s of EEG signal post-feedback onset was epoched for ErrP detection. The data were filtered using an FIR bandpass filter with a passband from 1 to 12 Hz (in addition to the aforementioned filtering and artifact removal). This bandwidth has been shown to capture ErrPs [29]. The first 100 ms was averaged and subtracted from the signal to remove the baseline offset. The signal was then downsampled by a factor of 20. The downsampled signal was used as the feature vector. Other common feature extraction techniques, including power spectral density, the Yule-Walker autoregressive (AR) model, and discrete wavelet transform (DWT) features were investigated. However, using the downsampled signal as a feature vector resulted in the highest cross-validation (CV) performance on the training set.

As error potentials were elicited in only 20% of the trials, the data for training the error detector was imbalanced between classes (i.e., there were more trials without error potentials). Hence, instead of accuracy, the area under the curve (AUC) of the receiver operating characteristic (ROC) was selected as the evaluation metric for the ErrP classifier.

Various algorithms including Support Vector Machine (SVM), Linear Discriminant Algorithm (LDA), and regularized LDA (rLDA) classifiers were tested on the training set. We also explored different feature selection techniques (namely, Fast Correlation-Based Filter [177] and Sequential Forward Floating Selection [132] with the training set. Regularized LDA without feature selection yielded the highest average CV classification AUC on the training set. The regularization parameter ($\gamma$) was optimized for each participant by maximizing the average leave-one-out cross-validation (LOOCV) AUC on the training set for different values of $\gamma$ over the range of [0, 1.0] in 0.1 increments. Using the optimal $\gamma$, an rLDA classifier was trained. All the reported metrics were computed on the test set.

Task Classification

All possible binary (each task and idle state) and ternary (each pair of tasks and idle state) combinations of tasks were considered. An asynchronous BCI must allow users to freely mind wander when not
intending to control the BCI. Hence, all classification problems included an idle state. Any task that can be differentiated from an idle state may be a candidate control task for an asynchronous BCI for a given participant.

The 5 s task period of each trial was epoched. Spectral power values were calculated from 1 to 40 Hz in 1 Hz increments, which resulted in 40 features per EEG channel. Other common types of EEG features including DWT and AR features were investigated on the training set. However, features generated using spectral power values yielded the best average CV performance on the training set.

Various feature selection and classification algorithms were tested on the training set and again, rLDA resulted in the highest mean CV accuracy (averaged across participants and all different task combinations). The regularization parameter ($\gamma$) was optimized for each participant using LOOCV on the training set. Using the selected $\gamma$, an rLDA classifier was trained. All the reported metrics were calculated on the test set.

**Theoretical Improvement of the BCI System**

The goal of detecting ErrPs was to correct wrong decisions made by the BCI. Improvement in BCI performance depends on the sensitivity and specificity of ErrP detection. In this section, we explain how we calculated the expected improvement in the task classifier after endowing it with ErrP-based error correction.

A binary task classifier, without any error correction, can be represented by the following confusion matrix:
matrix:

\[
\begin{array}{c|cc}
\text{Actual} & \text{Task}_1 & \text{Task}_2 \\
\hline
\text{Task}_1 & C_{11} & C_{12} \\
\text{Task}_2 & C_{21} & C_{22} \\
\end{array}
\]  
(3.1)

where the matrix entries are counts of the classifier’s predicted label (Task₁ or Task₂) for each trial. Since \( C_{11} + C_{22} \) is the total number of trials with the correctly predicted labels, the accuracy of this classifier (\( ACC_{\text{pre}} \)) can be calculated as:

\[
ACC_{\text{pre}} = \frac{C_{11} + C_{22}}{C_{11} + C_{12} + C_{21} + C_{22}}  
(3.2)
\]

The error detection classifier can also be represented by a confusion matrix:

\[
\begin{array}{c|cc}
\text{Actual} & \text{Error} & \text{No Error} \\
\hline
\text{Error} & TP_e & FN_e \\
\text{No Error} & FP_e & TN_e \\
\end{array}
\]  
(3.3)

where the matrix entries are the counts of true positive (\( TP_e \)), false positive (\( FP_e \)), true negative (\( TN_e \)), and false negative (\( FN_e \)) error detections.

For binary task classification with error correction, trials that are classified incorrectly (\( C_{12} + C_{21} \)) using the task classifier (corresponding to the count of actual errors in the confusion matrix for the error detector, i.e., \( TP_e + FN_e \)), will be corrected if the decision of the error detector is correct (\( TP_e \)). However, some of the trials that are classified correctly using the task classifier (\( TN_e + FP_e \)) will be rendered incorrect if the error detector mistakenly flags an error (\( FP_e \)). Hence, the new binary classification accuracy after error correction can be calculated as follows:

\[
ACC_{\text{post}} = \frac{C_{12} + C_{21}}{\sum_{i=1}^{2} \sum_{j=1}^{2} C_{ij}} \times \frac{TP_e}{TP_e + FN_e} + \frac{C_{11} + C_{22}}{\sum_{i=1}^{2} \sum_{j=1}^{2} C_{ij}} \times \frac{TN_e}{TN_e + FP_e}  
(3.4)
\]

A ternary task classifier, without any error correction, can be represented by the following confusion matrix:

\[
\begin{array}{c|ccc}
\text{Actual} & \text{Task}_1 & \text{Task}_2 & \text{Task}_3 \\
\hline
\text{Task}_1 & C_{11} & C_{12} & C_{13} \\
\text{Task}_2 & C_{21} & C_{22} & C_{23} \\
\text{Task}_3 & C_{31} & C_{32} & C_{33} \\
\end{array}
\]  
(3.5)

The ternary classification accuracy is calculated as follows:

\[
ACC_{\text{pre}} = \frac{\sum_{i=1}^{3} C_{ii}}{\sum_{i=1}^{3} \sum_{j=1}^{3} C_{ij}}  
(3.6)
\]

After the addition of error correction, the error classifier may correctly detect the presence of ErrP (\( TP_e \)) following the trials that were wrongly classified using the task classifier (\( TP_e + FN_e \)). However, in the ternary case, there are two possible ways to revise each identified misclassification. Hence, only
some of the detected misclassifications will be changed to the correct class. We estimated this fraction using the elements of the task classifier confusion matrix in Equation (3.5).

To elucidate, consider an example. $C_{12}$ represents the number of Task 1 trials which are classified as Task 2 by the ternary task classifier. If the error classifier correctly detects error following any of $C_{12}$ trials in an online paradigm, the classifier decision can be changed to the class with the second highest probability score. An estimation of the conditional probability that the correct class (i.e., Task 1) will be predicted given that Task 2 is not the correct class, is given by $\frac{C_{11}}{C_{11} + C_{13}}$. The same logic can be applied to all the other instances of incorrect classifications (i.e., $C_{ij}, i \neq j$). Hence, the new ternary classification accuracy after error correction can be calculated as follows:

$$\text{ACC}_{\text{post}} = \left( \frac{\sum_{i=1}^{3} \sum_{j=1, j \neq i}^{3} \sum_{k=1, k \neq i, j}^{3} C_{ij} \times \frac{C_{ij}}{C_{ij} + C_{ik}}}{\sum_{i=1}^{3} \sum_{j=1}^{3} C_{ij}} \right) \times \frac{TP_e}{TP_e + FN_e}$$

$$+ \frac{\sum_{i=1}^{3} C_{ii}}{\sum_{i=1}^{3} \sum_{j=1}^{3} C_{ij}} \times \frac{TN_e}{TN_e + FP_e}$$

(3.7)

**Performance Metrics**

To evaluate the task classifier, accuracy and information transfer rate were computed. Information transfer rate, sometimes referred to as bit-rate, is a common performance metric in BCI [171]. It takes both accuracy and time into account. However, it is a theoretical metric derived from mutual information which does not depend on the BCI implementation [26]. The following formula was used to calculate ITR in terms of bits per minutes.

$$ITR = \frac{60}{T} \times \left( \log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{N - 1} \right)$$

(3.8)

where $T$ represents the time required to communicate one command in seconds, $N$ is the number of classes and $P$ is the classification accuracy in the range of $[0, 1]$.

To evaluate the error detector, we computed area under the curve, true positive rate and false positive rate. These metrics are conventionally invoked in signal detection and have been applied in the characterization of error potential detectors [183, 185, 184].

### 3.4 Results

#### 3.4.1 Error Detection

Table 4.2 shows the area under the ROC curve (AUC) for each participant for the test set. An average AUC of 0.83 was achieved across all participants. Table 4.2 also presents the true positive rate (TPR) and false positive rate (FPR) achieved for each participant on their respective test set.

To find these optimum values for TPR and FPR for each participant, first, an ROC curve was plotted using the training set for three hundred different discrimination thresholds. To generate each point, TPR and FPR values were calculated by applying LOOCV on the training set. Then, post-error correction accuracies (i.e. after applying ErrP-based error correction on all possible binary LOOCV classification accuracies of task vs. idle on the training set) were computed using equation 3.4 for all points on the ROC. The discrimination threshold which maximized the mean cross-validated binary task classification
Table 3.1: Error-related potential classification results: area under the curve (AUC), true positive rate (TPR) and false positive rate (FPR).

<table>
<thead>
<tr>
<th>Participant #</th>
<th>AUC</th>
<th>TPR</th>
<th>FPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.81</td>
<td>0.33</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0.95</td>
<td>0.84</td>
<td>0.06</td>
</tr>
<tr>
<td>3</td>
<td>0.72</td>
<td>0.40</td>
<td>0.08</td>
</tr>
<tr>
<td>4</td>
<td>0.84</td>
<td>0.68</td>
<td>0.11</td>
</tr>
<tr>
<td>5</td>
<td>0.82</td>
<td>0.72</td>
<td>0.10</td>
</tr>
<tr>
<td>6</td>
<td>0.79</td>
<td>0.75</td>
<td>0.11</td>
</tr>
<tr>
<td>7</td>
<td>0.95</td>
<td>0.95</td>
<td>0.15</td>
</tr>
<tr>
<td>8</td>
<td>0.92</td>
<td>0.89</td>
<td>0.14</td>
</tr>
<tr>
<td>9</td>
<td>0.85</td>
<td>0.78</td>
<td>0.12</td>
</tr>
<tr>
<td>10</td>
<td>0.83</td>
<td>0.61</td>
<td>0.12</td>
</tr>
<tr>
<td>11</td>
<td>0.72</td>
<td>0.61</td>
<td>0.08</td>
</tr>
<tr>
<td>12</td>
<td>0.78</td>
<td>0.78</td>
<td>0.11</td>
</tr>
</tbody>
</table>

AVG±STD: 0.83 ±0.08

accuracy (averaged over all pairwise accuracies) was chosen as optimum on a per participant basis. In the event of a tie, the discrimination threshold with the lower FPR was selected. The reported TPR and FPR values in Table 4.2 were calculated over the test set using the selected discrimination threshold.

Figure 3.4: Average event-related potentials for correct (dotted line) and error (dashed line) trials for participant #10 at AFz, Fz, and FCz. The solid line is the difference between correct and error responses. Note that in error trials, the second peak is larger and occurs later (630 ms) than in correct trials (600 ms). Time 0 marks the beginning of the visual feedback.

The average event-related potentials (ERPs) are demonstrated in Figure 3.4 for correct trials, error trials and their difference for one participant, at three different recording locations of AFz, Fz, and FCz. A small deflection and a positive peak are present at about 180 and 400 ms after feedback onset in both correct and error trials. There is also a second positive peak in both correct and error trials. However, the amplitude and latency of this second peak are noticeably greater in error trials. The design of the experimental protocol, particularly the method of feedback, is known to affect the morphology of ERPs [73, 185, 175]. The difference waveform (error minus correct) consists of a small negativity at ∼330 ms followed by a large positivity at ∼700 ms.

The first row of Figure 3.5 depicts the grand average ERPs across all participants for correct and error trials along with their difference at AFZ, Fz, and FCz. The bottom row of Figure 3.5 shows the grand average of the difference waveforms along with the corresponding standard error across participants. As
Chapter 3. Exploiting error-related potentials in cognitive task-based BCI

3.4.2 Tasks Classification Accuracies: Pre- and Post-Error Correction

Classification accuracies for the binary classifiers (i.e. each cognitive task vs. idle) are reported in table 3.2 for all participants. Post-error correction accuracies for each participant were calculated using equation 3.4. The upper limit of the 99% confidence interval of the corresponding chance estimates was 64% using the binomial cumulative distribution [21]. In seven cases, as marked with † in the table, pre-error correction accuracies did not surpass the chance level while all post-error correction accuracies exceeded chance. There were six cases where applying error correction reduced accuracy as marked with ‡ in the table. When averaged across participants, post-error correction accuracies for two out of four pairs of tasks increased compared to the pre-error correction accuracies (p<0.05, Wilcoxon Signed-Rank test) as depicted in figure 3.7. For further assessment of the ErrP-based error correction, ITRs were computed as explained in section 3.3.5. The time (T) required for completion of a command without error-correction was computed as follows: 5 s (for performing the task) + 0.5 s (time between end of the

Figure 3.5: The top row depicts the grand average ERPs across all participants for correct (dotted line) and error (dashed line) trials along with their difference (error minus correct; solid line) at AFz, Fz and FCz. The bottom row shows the grand average of the difference waveforms along with the corresponding standard error (shaded region) across participants. Time 0 marks the beginning of the visual feedback.

depicted, the first 800 ms of the difference waveform was relatively consistent among participants.

Figure 3.6 portrays the topographic maps of averaged error and correct trials along with their difference for one participant at 330, 400, and 700 ms from feedback onset. These were the time points where the most prominent peaks appeared in the difference waveforms. From these maps, we can see that the positivity at 400 ms occurs in the fronto-central region while the subsequent positivity appears over the centro-parietal region.
Figure 3.6: The topographic maps of the average of the (a) correct trials, (b) error trials, and (c) their difference for participant #10 at 330, 400, and 700 ms from feedback onset.

...task and feedback onset) + 0.5 s (time for completion of feedback). Error-correction added 1.3 s to the aforementioned time. The pre- and post-error correction values of ITR for all the binary tasks classifiers are provided in table 3.3.

Table 4.3 summarizes the results for ternary (each pair of cognitive tasks and idle state) classification before and after error correction. Post-error correction accuracies were calculated using equation 3.7. There were two cases, as marked with † in the table, where the pre-error correction accuracies did not surpass the chance level of 44% (p=0.01 using cumulative binomial distribution [21]), while all post-correction accuracies exceeded chance (table 4.3). There were also two cases where the addition of error correction led to a decrease in accuracy (marked with ‡ in the table). As shown in figure 3.8, when averaged across participants, ErrP-based error correction increased ternary classification accuracies (p<0.05, Wilcoxon Signed-Rank test). For all the ternary tasks classifiers, the pre- and post-error correction values of ITR are provided in table 3.5.

### 3.5 Discussion

#### 3.5.1 Presence of ErrP in a cognitive task-based BCI paradigm

Our findings confirm the presence of an ErrP following erroneous feedback in an active BCI based on non-MI cognitive tasks, and that the ErrP can be detected on a single-trial basis. After combining data...
Table 3.2: Binary task classification accuracies (%) between each mental task and idle state pre- and post-error correction.

<table>
<thead>
<tr>
<th>Participant</th>
<th>Arithmetic</th>
<th>Counting</th>
<th>Word Gen.</th>
<th>Figure Rot.</th>
</tr>
</thead>
<tbody>
<tr>
<td>#</td>
<td>Pre Post</td>
<td>Pre Post</td>
<td>Pre Post</td>
<td>Pre Post</td>
</tr>
<tr>
<td>1</td>
<td>79 86</td>
<td>63† 75</td>
<td>88 92</td>
<td>87 91</td>
</tr>
<tr>
<td>2</td>
<td>97 94‡</td>
<td>87 93</td>
<td>86 93</td>
<td>92 93</td>
</tr>
<tr>
<td>3</td>
<td>67 75</td>
<td>53† 68</td>
<td>87 85</td>
<td>577 70</td>
</tr>
<tr>
<td>4</td>
<td>64 82</td>
<td>70 83</td>
<td>64 81</td>
<td>69 82</td>
</tr>
<tr>
<td>5</td>
<td>64 84</td>
<td>56† 82</td>
<td>78 86</td>
<td>75 86</td>
</tr>
<tr>
<td>6</td>
<td>68 85</td>
<td>77 86</td>
<td>79 86</td>
<td>72 85</td>
</tr>
<tr>
<td>7</td>
<td>72 88</td>
<td>70 88</td>
<td>75 88</td>
<td>78 87</td>
</tr>
<tr>
<td>8</td>
<td>97 86‡</td>
<td>72 87</td>
<td>96 86‡</td>
<td>81 87</td>
</tr>
<tr>
<td>9</td>
<td>70 85</td>
<td>56† 84</td>
<td>86 87</td>
<td>75 86</td>
</tr>
<tr>
<td>10</td>
<td>97 87‡</td>
<td>78 82</td>
<td>80 83</td>
<td>95 87‡</td>
</tr>
<tr>
<td>11</td>
<td>56† 78</td>
<td>61† 80</td>
<td>72 83</td>
<td>72 83</td>
</tr>
<tr>
<td>12</td>
<td>83 87</td>
<td>72 86</td>
<td>75 86</td>
<td>94 88‡</td>
</tr>
<tr>
<td>AVG</td>
<td>76 85</td>
<td>68 83</td>
<td>81 86</td>
<td>79 85</td>
</tr>
<tr>
<td>STD</td>
<td>14 5</td>
<td>10 6</td>
<td>9 3</td>
<td>11 6</td>
</tr>
</tbody>
</table>

| p<0.05†     | No Yes No Yes |

† Accuracies which did not exceed the chance level.
‡ The post-error correction accuracies which were lower than their corresponding pre-error correction accuracies.

*p-values were corrected with Holm-Bonferroni method.

Table 3.3: ITR (bits/min) values of binary task classifications between each mental task and idle state pre- and post-error correction.

<table>
<thead>
<tr>
<th>Participant</th>
<th>Arithmetic Pre Post</th>
<th>Counting Pre Post</th>
<th>Word Gen. Pre Post</th>
<th>Figure Rot. Pre Post</th>
</tr>
</thead>
<tbody>
<tr>
<td>#</td>
<td>2.59 3.42</td>
<td>0.49 1.55</td>
<td>4.71 4.91</td>
<td>4.43 4.63</td>
</tr>
<tr>
<td>2</td>
<td>8.06 5.53</td>
<td>4.43 5.21</td>
<td>4.16 5.21</td>
<td>5.98 5.21</td>
</tr>
<tr>
<td>3</td>
<td>0.85 1.55</td>
<td>0.03 0.79</td>
<td>4.43 3.21</td>
<td>0.14 0.98</td>
</tr>
<tr>
<td>4</td>
<td>0.57 2.63</td>
<td>1.19 2.81</td>
<td>0.57 2.45</td>
<td>1.07 2.63</td>
</tr>
<tr>
<td>5</td>
<td>0.57 3.01</td>
<td>0.10 2.63</td>
<td>2.40 3.42</td>
<td>1.89 3.42</td>
</tr>
<tr>
<td>6</td>
<td>0.96 3.21</td>
<td>2.22 3.42</td>
<td>2.59 3.42</td>
<td>1.45 3.21</td>
</tr>
<tr>
<td>7</td>
<td>1.45 3.87</td>
<td>1.19 3.87</td>
<td>1.89 3.87</td>
<td>2.40 3.64</td>
</tr>
<tr>
<td>8</td>
<td>8.06 3.42</td>
<td>1.45 3.64</td>
<td>7.58 3.42</td>
<td>2.99 3.64</td>
</tr>
<tr>
<td>9</td>
<td>1.19 3.21</td>
<td>0.10 3.01</td>
<td>4.16 3.64</td>
<td>1.89 3.42</td>
</tr>
<tr>
<td>10</td>
<td>8.06 3.64</td>
<td>2.40 2.63</td>
<td>2.78 2.81</td>
<td>7.14 3.64</td>
</tr>
<tr>
<td>11</td>
<td>0.10 1.97</td>
<td>0.35 2.29</td>
<td>1.45 2.81</td>
<td>1.45 2.81</td>
</tr>
<tr>
<td>12</td>
<td>3.42 3.64</td>
<td>1.45 3.42</td>
<td>1.89 3.42</td>
<td>6.73 3.87</td>
</tr>
<tr>
<td>AVG</td>
<td>2.99 3.26</td>
<td>1.28 2.94</td>
<td>3.22 3.55</td>
<td>3.13 3.43</td>
</tr>
<tr>
<td>STD</td>
<td>3.19 1.00</td>
<td>1.28 1.13</td>
<td>1.89 0.81</td>
<td>2.36 1.04</td>
</tr>
</tbody>
</table>

| p<0.05*     | No Yes No No |

* p-values were corrected with Holm-Bonferroni method.

from both sessions for each participant, an average AUC of 0.83 was achieved for ErrP detection which is comparable to that reported in existing literature. Zeyl and Chau reported an average AUC of 0.81 in a visual P300 speller [185]. An accuracy of 80% was achieved for ErrP detection by Bhattacharyya et al. in a motor imagery BCI in one study [9] and 93% in another [10]. They attributed their high accuracy in [10] to protracted training times of at least 60 hours.

Also noteworthy is the fact that error potentials were detected with dry electrodes in this study. While literature has cited better signal-to-noise ratio with wet rather than dry electrodes [19], the latter requires less preparation time and arguably offers better comfort to users due to the lack of gel. The ErrP detection accuracies with the dry electrodes were comparable to findings reported in the aforementioned studies, all of which deployed gel-based measurements [185, 9, 10].
Chapter 3. Exploiting error-related potentials in cognitive task-based BCI

Figure 3.7: Boxplots of binary classification accuracies across participants pre- and post-error correction.

Table 3.4: Ternary task classification accuracies (%) between pairs of mental tasks and idle state pre- and post-error correction.

| Participant # | Arithmetic + Counting | Arithmetic + Word Gen. | Arithmetic + Figure Rot. | Counting + Word Gen. | Counting + Figure Rot. | Word Gen. + Figure Rot. | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post | Pre | Post |
|---------------|-----------------------|------------------------|--------------------------|-----------------------|------------------------|--------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1             | 72                     | 80                     | 67                       | 76                    | 81                     | 86                       | 57  | 69  | 69  | 74  | 57  | 69  | 69  | 74  | 75  | 78  | 75  | 78  |
| 2             | 72                     | 88                     | 74                       | 90                    | 85                     | 91                       | 44  | 62  | 45  | 64  | 46  | 62  | 45  | 64  | 56  | 91  | 90  | 93  |
| 3             | 47                     | 69                     | 49                       | 68                    | 53                     | 69                       | 44  | 62  | 45  | 64  | 46  | 62  | 45  | 64  | 56  | 91  | 90  | 93  |
| 4             | 52                     | 69†                    | 41                       | 55                    | 46                     | 64                       | 47  | 70  | 56  | 72  | 46  | 64  | 47  | 70  | 56  | 72  | 50  | 68  |
| 5             | 52                     | 69                    | 56                       | 73                    | 57                     | 72                       | 54  | 72  | 59  | 77  | 63  | 77  | 59  | 77  | 63  | 77  | 63  | 77  |
| 6             | 57                     | 71                    | 59                       | 77                    | 61                     | 78                       | 62  | 79  | 60  | 76  | 60  | 76  | 60  | 76  | 62  | 75  | 62  | 75  |
| 7             | 59                     | 83                    | 54                       | 74                    | 63                     | 82                       | 56  | 78  | 63  | 83  | 63  | 83  | 63  | 83  | 63  | 83  | 63  | 83  |
| 8             | 69†                    | 86                    | 89                       | 86‡                   | 81                     | 86                       | 72  | 86  | 61  | 76  | 78  | 82  | 61  | 76  | 78  | 82  | 61  | 76  |
| 9             | 57                     | 71                    | 69                       | 80                    | 61                     | 74                       | 67  | 79  | 50  | 69  | 67  | 78  | 50  | 69  | 67  | 78  | 67  | 78  |
| 10            | 70                     | 80                    | 83                       | 83                    | 87                     | 84‡                   | 69  | 77  | 70  | 74  | 81  | 82  | 70  | 74  | 81  | 82  | 81  | 82  |
| 11            | 45                     | 71                    | 54                       | 73                    | 48                     | 72                       | 51  | 73  | 43‡ | 71  | 48  | 72  | 43‡ | 71  | 48  | 72  | 48  | 72  |
| 12            | 65                     | 78                    | 69                       | 76                    | 83                     | 78                       | 61  | 74  | 74  | 76  | 76  | 81  | 74  | 76  | 76  | 81  | 76  | 81  |
| AVG           | 60                     | 76                    | 64                       | 76                    | 67                     | 78                       | 60  | 76  | 61  | 76  | 67  | 78  | 67  | 78  | 67  | 78  | 67  | 78  |
| STD           | 10                     | 7                     | 14                       | 9                     | 15                     | 8                       | 10  | 7   | 11  | 7   | 13  | 7   | 11  | 7   | 13  | 7   | 13  | 7   |

† Accuracies which did not exceed the chance level.
‡ The post-error correction accuracies which were lower than their corresponding pre-error correction accuracies.
* p-values were corrected with Holm-Bonferroni method.

3.5.2 The morphology of the ErrP

The overall morphology of the ErrPs was similar to that of observation and interaction error potentials reported by [71, 72] and [118]. The morphological resemblance to observation error potentials may be due the fact that, in this study, feedback was shown to the participants 0.5 s after they stopped performing the required tasks, and hence had greater opportunity to “monitor” the computer’s response. Literature has reported that these two types of ErrPs share very similar morphologies [78, 118]. There were however departures from literature in terms of latencies, which are expected given the different experimental protocols used to elicit error responses [72]. The latencies in this study were longer than most of those reported in literature, which is likely attributable to the gradual falling of the icon over
Table 3.5: ITR (bits/min) values of ternary task classifications between each mental task and idle state pre and post ErrP-based error correction.

<table>
<thead>
<tr>
<th>Participant #</th>
<th>Arithmetic Counting</th>
<th>Arithmetic Word Gen.</th>
<th>Arithmetic Figure Rot.</th>
<th>Counting Word Gen.</th>
<th>Counting Figure Rot.</th>
<th>Word Gen. Figure Rot.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
<td>Pre</td>
<td>Post</td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>1</td>
<td>4.50</td>
<td>5.45</td>
<td>3.40</td>
<td>4.52</td>
<td>6.93</td>
<td>7.07</td>
</tr>
<tr>
<td>2</td>
<td>4.50</td>
<td>7.69</td>
<td>4.98</td>
<td>8.35</td>
<td>8.25</td>
<td>8.70</td>
</tr>
<tr>
<td>3</td>
<td>0.58</td>
<td>3.14</td>
<td>0.75</td>
<td>2.96</td>
<td>1.18</td>
<td>3.14</td>
</tr>
<tr>
<td>4</td>
<td>1.06</td>
<td>3.14</td>
<td>0.18</td>
<td>1.17</td>
<td>0.50</td>
<td>2.32</td>
</tr>
<tr>
<td>5</td>
<td>1.06</td>
<td>3.14</td>
<td>1.55</td>
<td>3.89</td>
<td>1.69</td>
<td>3.69</td>
</tr>
<tr>
<td>6</td>
<td>1.69</td>
<td>3.50</td>
<td>0.98</td>
<td>4.74</td>
<td>2.30</td>
<td>4.97</td>
</tr>
<tr>
<td>7</td>
<td>1.98</td>
<td>6.22</td>
<td>1.30</td>
<td>4.09</td>
<td>2.64</td>
<td>5.96</td>
</tr>
<tr>
<td>8</td>
<td>3.82</td>
<td>7.69</td>
<td>9.75</td>
<td>7.07</td>
<td>6.93</td>
<td>7.07</td>
</tr>
<tr>
<td>9</td>
<td>1.69</td>
<td>3.50</td>
<td>3.82</td>
<td>5.45</td>
<td>2.30</td>
<td>4.09</td>
</tr>
<tr>
<td>10</td>
<td>4.04</td>
<td>5.45</td>
<td>7.57</td>
<td>6.22</td>
<td>8.98</td>
<td>6.50</td>
</tr>
<tr>
<td>11</td>
<td>0.42</td>
<td>3.50</td>
<td>1.30</td>
<td>3.89</td>
<td>4.50</td>
<td>3.69</td>
</tr>
<tr>
<td>12</td>
<td>3.01</td>
<td>4.97</td>
<td>3.82</td>
<td>4.52</td>
<td>7.57</td>
<td>4.97</td>
</tr>
<tr>
<td>AVG</td>
<td>2.36</td>
<td>4.73</td>
<td>3.37</td>
<td>4.74</td>
<td>4.48</td>
<td>5.18</td>
</tr>
<tr>
<td>STD</td>
<td>1.54</td>
<td>1.64</td>
<td>2.90</td>
<td>1.88</td>
<td>3.07</td>
<td>1.91</td>
</tr>
</tbody>
</table>

\(p < 0.05^*\) Yes No No Yes Yes No

\(^*\) p-values were corrected with Holm-Bonferroni method.

0.5 s, resulting in a delayed perception of the BCI decision.

The ERP waveforms for error and correct trials generally consisted of an initial negativity around 180 ms followed by two positive peaks, the first prior to 400 ms and a second, broader peak at 600 ms or shortly thereafter. The initial negative peak was similar in magnitude for both error and correct trials and could be a component of a motion-onset evoked potential resulting from the initiation of the visual feedback (i.e., falling icon). Its magnitude and latency is similar to the N2 component of motion-onset evoked potentials reported elsewhere [56]. The initial negative peak could also be a feedback-related negativity, which has been previously observed in both correct and error trials in a P300 speller [183].

The first positive peak may be a combination of a movement-evoked positivity and a surprisal response, as seen in [74] where the authors elicited simultaneous motion-onset and P300 potentials. The earlier peak on average in the correct trials may be attributable to the motion of the falling non-target icons (i.e., correct feedback) occurring in the periphery of the participant’s visual field as peripheral stimuli are known to elicit faster responses than perifoveal stimuli [58]. The second, wider positive peak around 600 ms was generally unique to error trials and is a response characteristic previously associated with observing erroneous feedback [183, 145]. The prominence of this latter positivity over the centro-parietal region is in line with the finding in a previous ErrP study [184].

### 3.5.3 Value of ErrP-based error correction

From the classification accuracies reported in tables 3.2 and 4.3, it can be seen that cognitive task performance varied across individuals which is consistent with literature [24]. For the majority of participants, regardless of cognitive task, the introduction of error correction significantly increased binary task classification accuracy. The instances where accuracy was compromised by error correction were those where the original binary task classification accuracy was already very high (≥ 95%). In a practical system, error correction would be invoked judiciously; task classifiers that perform well would typically not be endowed with error correction. For the ternary case, all but one specific task triplet (arithmetic, word generation and idle) for one participant (P8) did not benefit from the introduction of error correction.
This participant-ternary task combination already achieved 89% accuracy prior to error correction. In sum, the combination of task classifier and ErrP detection improved the accuracies of the binary and ternary classifier by 9% and 14% on average, respectively. This finding supports the continued integration of ErrP-based error correction in cognitive task-based BCI systems.

For a comprehensive evaluation of a BCI, both speed and accuracy must be taken into account. ITR includes both of these factors. The average values of ITR after ErrP-based error correction for the binary classifiers changed by 0.64 (bits/min). However, this change was only significant for one out of the four classifiers. For the ternary classifiers, the average ITR increased by 1.56 (bits/min). The improvement was significant for three out of six classifiers. The authors suggest the use of error correction, even in cases where accuracy is significantly enhanced but ITR remains unchanged, given the speed-accuracy trade-off. An accuracy enhancement can potentially reduce the user’s frustration when controlling a BCI.

### 3.5.4 Future work

For future studies, the authors suggest implementing the proposed BCI in an online paradigm (with real-time feedback of the initial task decision, error detection decision, and updated task decision) to fully assess the performance of cognitive task-based, active BCIs with ErrP-based error correction. Also, additional sessions (i.e. more trials) may improve both the task classification and error detection. In this study, the regularization parameter was optimized separately for each participant and for each classification problem. Additional sessions and extra trials may enhance the generalizability of the classification models and mitigate the need for such customization. Last but not least, evaluating the performance of this BCI on individuals who present as locked-in is necessary prior to clinical translation.
Chapter 4

Online detection of error-related potentials in multi-class cognitive task-based BCIs

This chapter is reproduced from the following published article: Rozhin Yousefi, Alborz Rezazadeh Sereshkeh, and Tom Chau. “Online detection of error-related potentials in multi-class cognitive task-based BCIs.” Brain-Computer Interfaces (2019): 1-12. Hence, there is some material that is repeated from Chapter 1 and 2 (e.g. parts of the literature review). The final published article can be found in the following link: https://www.tandfonline.com/doi/abs/10.1080/2326263X.2019.1614770.

4.1 Abstract

One method for improving the accuracy and hence the rate of communication of a brain-computer interface (BCI) is to automatically correct erroneous classifications by exploiting error-related potentials (ErrPs). The merit of such a correction scheme has been demonstrated in both active (e.g., motor imagery) and reactive (e.g., P300) BCIs. Here, we investigated the effect of ErrP-guided error correction in a three-class, active BCI based on cognitive rather than motor imagery tasks using electroencephalography (EEG). Ten able-bodied adults participated in three sessions of data collection. For each participant, a ternary BCI differentiated among idle state and two personally selected cognitive tasks (e.g., mental arithmetic, counting, word generation, and figure rotation). Real-time feedback of the BCI decision was displayed to the participant following each task. EEG data after feedback onset were used to detect ErrPs and correct the BCI’s output in the case of detected errors. ErrP-based error correction modestly but significantly improved the average online task classification accuracy (+7%) as well as the information transfer rate (+0.9 bits/min) of the ternary BCI across participants. Our findings support further study of ErrPs in active BCIs based on cognitive tasks.
4.2 Introduction

Brain-computer interfaces (BCIs) can provide a channel of communication for individuals who are not able to communicate conventionally [4, 172]. Changes in the brain signal patterns during different mental tasks can be measured by a BCI and translated into meaningful commands or messages. Different modalities can be used to measure brain activities. Electroencephalography (EEG), which measures the electrical activity of the brain, is the most common modality for BCI development [115].

BCIs can be categorized based on the type of mental activities invoked [180]. Reactive BCIs use the brain activity elicited in reaction to an external stimulus. Two common examples of reactive BCIs are P300 spellers [74, 96] and steady-state visual evoked potential (SSVEP) [187] BCIs. Reactive BCIs require minimal training and can provide a relatively high information transfer rate (ITR) [115]; however, the user must continuously attend to external stimuli which can be easily fatiguing.

Active BCIs use self-regulation of brain activity without external stimuli. They require longer training times compared to reactive BCIs, especially for naïve BCI users, and provide a relatively lower ITR [115]. However, this category of BCI is more conducive to self-paced control where users dictate the timing of interaction.

Motor imagery (MI) is the most common mental task for the development of active BCIs [167, 99, 173]. However, for individuals with congenital or long-term motor impairments, MI can be impossible or difficult to perform [22, 23, 24]. It has also been shown that approximately 15-30% of BCI users (even without any motor impairments) are unable to control an MI BCI [12]. One potential alternative is to use non MI-based mental tasks, such as mental arithmetic, word generation, and figure rotation, which we will refer to as cognitive tasks.

One reason for the lower ITR of active compared to reactive BCIs is the low accuracy when the number of classes exceeds two and the number of training sessions is small. Recent improvements in the quality of recorded EEG signals (e.g., signal-to-noise ratio) [55] and classification algorithms [95, 94] enhanced BCI performance, but further improvement is required before BCIs become practical and widely adopted. Using error-related potentials (ErrPs) to detect BCI mistakes has been investigated to enhance BCI performance [18].

Monitoring or committing of errors elicits discernible electrical signals in medial frontal and central brain regions [37, 165]. The morphology of these error-related potentials (ErrPs) depends on many factors such as the experimental protocol [73, 71] and frequency of the error [17]. Errors made by a BCI are known to evoke ErrPs [142]. Many studies have demonstrated the feasibility of single-trial detection of BCI-induced ErrPs [18, 82, 184, 183]. Detected ErrPs can be used to correct an erroneous command, prevent its execution, or to promote error-based learning [18]. ErrP-based error correction has been explored in different contexts including reactive BCIs (P300 [183] and SSVEP [157]), continuous feedback [82, 30, 156], human-robot interaction [140, 79] and MI-based active BCIs [43, 83], yielding in most cases, improved decoding of user intention.

One of the defining criteria of any BCI is providing real-time feedback [123]. The importance of real-time feedback in BCI training has frequently been cited in the literature [117, 50, 150]. Closing the human-machine feedback loop can enhance the neural response. For instance, Kaiser et al. showed that the provision of long-term training with real-time visual feedback to low BCI performers (< 70%) in an MI-BCI paradigm over ten sessions led to an increase in cortical hemodynamic activity and beta band activity [75]. It has also been shown that long-term training with feedback can preserve activation in the sensorimotor cortex of patients with spinal cord injury [36]. Surprisingly, despite the evidence of
the effectiveness of real-time feedback and the extensive number of online reactive or MI-based active BCIs, there has been a paucity of studies of active BCIs with non-MI tasks (which may be necessary for individuals with a disinclination to MI). Most of non-MI studies have collected their data in an offline paradigm. Among the limited non-MI BCI studies, most have exploited the hemodynamic response, measured by functional near-infrared spectroscopy (fNIRS), and have explored a combination of cognitive and MI active tasks to control the BCI [146, 104, 65].

In this paper, we present a ternary BCI based on non-MI active tasks, which is capable of correcting its mistakes by detecting ErrPs. After two offline training sessions with five cognitive tasks (mental arithmetic, word generation, mental counting, figure rotation and unconstrained rest/idle), participants were asked to choose their top two preferences (other than idle) for the online session. The variety of cognitive tasks increased the likelihood of finding tasks for each user which produced distinctive brain signal patterns. To the best of our knowledge, this is the first report of the integration of a non-MI active BCI with ErrPs (generated by actual BCI feedback). Also, unlike previous ErrP studies, all the measurements were made using dry rather than gel-based EEG electrodes. Dry electrodes have lower signal-to-noise ratio, but require less preparation time, making them an appealing option for practical use where user time, attention and patience may be limited [19].

4.3 Methods

4.3.1 Instrumental Setup

EEG was recorded using a dry EEG system (actiCAP Xpress Twist, Brain Products, Germany) at 32 different locations according to the 10/10 international system: FP1, FP2, AFz, AF3, AF4, F1, Fz, F2, F7, F8, FT7, FT8, T7, T8, FC5, FC1, FC2, FC6, C1, Cz, C2, CP5, CP1, CPz, CP2, CP6, Pz, P3, P4, POz, and Oz. Reference and ground electrodes were placed on the left and the right earlobes, respectively. The EEG sampling rate was set to 1000 Hz.

4.3.2 Participants

Ten adults without any known disabilities with normal or corrected-to-normal vision participated in this study (5 male, mean ± standard deviation age of 29 ± 3 years). All participants were fluent in English. None of the participants had any reported history of neurological disorders. Participants were asked to refrain from drinking alcoholic or caffeinated beverages at least 3 hours before each session. The study was approved by the research ethics boards of the University of Toronto and the Holland Bloorview Kids Rehabilitation Hospital. All participants provided informed, written consent. Participants attended two offline sessions and one online session on separate days, each approximately 90 minutes in length. The time between offline sessions varied from 7 days to a month. The online sessions were collected about six months after offline sessions.

4.3.3 Tasks

The following popular BCI mental tasks were chosen for this study: (I) Mental arithmetic: Participants were asked to mentally subtract a single-digit number from a 2-digit number (both self-selected per trial), and then iterate, each time subtracting the same single-digit number from the previous result (e.g., 94-7=87, 87-7=80, 80-7=73, etc.); (II) Backward counting: Participants were asked to count backward from
10 at a constant pace; (III) Word generation: Participants were asked to mentally name as many words as possible that begin with a letter chosen by the participants randomly before the trial started; and, (IV) Figure rotation: Participants were asked to visualize the rotation of a three-dimensional object (freely chosen per trial) around an axis. In addition to these tasks, we also considered an idle/unconstrained rest state where participants allowed normal thought processes to occur but refrained from performing any of the defined mental tasks.

During the offline sessions, participants performed all the aforementioned tasks. Prior to the online session, participants chose two of the tasks based on their personal preference, as listed in table 4.1. Participants were informed of their offline performance but they were free to choose any task combination among the six possibilities [176]. Interestingly, all participants chose a task combination that was among their top three in terms of accuracy. Then, a participant-specific ternary BCI was developed based on the participant’s preferred tasks and idle state, using the data collected during the offline sessions.

Table 4.1: Tasks selected by participants.

<table>
<thead>
<tr>
<th>Participant #</th>
<th>Task 1</th>
<th>Task 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>Word generation</td>
<td>Figure rotation</td>
</tr>
<tr>
<td>P2</td>
<td>Mental arithmetic</td>
<td>Figure rotation</td>
</tr>
<tr>
<td>P3</td>
<td>Word generation</td>
<td>Figure rotation</td>
</tr>
<tr>
<td>P4</td>
<td>Backward counting</td>
<td>Word generation</td>
</tr>
<tr>
<td>P5</td>
<td>Mental arithmetic</td>
<td>Word generation</td>
</tr>
<tr>
<td>P6</td>
<td>Word generation</td>
<td>Figure rotation</td>
</tr>
<tr>
<td>P7</td>
<td>Mental arithmetic</td>
<td>Figure rotation</td>
</tr>
<tr>
<td>P8</td>
<td>Mental arithmetic</td>
<td>Word generation</td>
</tr>
<tr>
<td>P9</td>
<td>Mental arithmetic</td>
<td>Word generation</td>
</tr>
<tr>
<td>P10</td>
<td>Mental arithmetic</td>
<td>Word generation</td>
</tr>
</tbody>
</table>

4.3.4 Protocol

Offline Sessions

In each offline session, participants completed 36 trials per task (a total of 180 trials). At the beginning of each trial, participants were cued with the trial type (i.e., one of the mental tasks or idle). After 4 s of trial type presentation, participants were cued to start performing the mental task or idling for 5 s. At the end of the mental task period, participants were shown visual feedback. In 20% of the trials, evenly distributed across different tasks, the feedback was configured to randomly display the wrong task, i.e., one that was different from that which the participant performed. Since participants were told that the feedback was the result of real-time classification of their recorded EEG, the mismatch between the detected task and the actual mental task they performed (in 20% of trials) was intended to evoke error-related potentials. The details of the experimental design, as well as the obtained classification results for offline sessions, were previously reported [176].

Online Session

Online sessions consisted of 135 trials divided into nine blocks of 15 trials. After each block, which lasted approximately 5 min, participants were able to rest and start the next block when ready. For each participant, a BCI was built based on three tasks (their two preferred cognitive tasks and the idle state). The detailed timeline of each trial and the interface designed for this experiment are shown in
Each task was displayed with an icon with the name of the corresponding task. At the beginning of the trial, the participant was notified of the trial type (i.e., one of the two mental tasks or idle) as the relevant icon was highlighted for 4 s by changing the text font color from gray to red (figure 4.1a). Then, the participant performed the task for 5 s. The bow-tie color on the icon was changed to magenta to cue the participant (figure 4.1b). The 5 s of task data were analyzed in real-time as explained in section 4.3.5. Visual feedback was displayed to inform the participant of the classification result. A correct classification would be indicated when the icon corresponding to the performed mental activity remained upright while the others fell (figure 4.1c). If an icon other than the one associated with the required task fell, it meant task classification was not correct (i.e. wrong feedback). After the feedback onset, 1.4 s of EEG data were tested for the presence of any error-related signals. If an error was not detected, a message, “No Error!”, was shown (figures 4.1e and 4.1g). If an error was detected, the task data were re-classified using a binary classifier based on the two remaining tasks to determine the second-best choice. The participant was informed of the new BCI output with a message (figures 4.1f and 4.1h).

There was a score board below the icons to increase the engagement of the participants. They received one point if the task classification result was correct, but they would lose that point if an error was detected in the same trial. If the task classification result was wrong, they would not receive any point. But if an error was detected and the result of the task reclassification was correct, they received one score. So, to summarize, at the end of a trial, they would receive one point if the end result was correct. If it was not, they would not get a point. The scores were added up until the end of each block.

### 4.3.5 Data Analysis

#### Task Classifier

Prior to an online session, a ternary task classifier and three binary task classifiers (for all possible pairs of tasks) were trained based on the data from the offline sessions for each participant. 72 examples per task per participant were available from the offline sessions. Offline task data were filtered using an FIR filter (order 96) between 1 to 40 Hz. Then, artifacts including eye blinks, ocular movement, and discontinuities were removed by applying independent component analysis (ICA) and the ADJUST algorithm [108].

To extract features, power spectral density (PSD) estimates of task data were calculated for all channels. The area under the PSD in 1 Hz bins from 1 to 40 Hz served as the associated band power estimate and yielded 40 features per channel. Classifiers were trained using regularized linear discriminant analysis (rLDA). The regularization parameter ($\gamma$) was optimized over the range of 0 to 1 in 0.1 increments using a leave-one-out cross-validation (LOOCV) on the data from the offline sessions. During each participant’s online session, their respective classifier was retrained after every block (15 trials) to incorporate same day data but $\gamma$, being time-consuming to optimize, was kept constant.

At the beginning of each participant’s online session, 3 min of EEG baseline was collected. ICA weights were computed using this baseline segment. Then, contaminated components with artifacts were identified using the ADJUST algorithm. During each trial, the 5 s task interval was epoched and filtered using an FIR filter (order 96) between 1 to 40 Hz. Then, the PSD features described above were extracted from each trial. Finally, the ternary task classifier was applied and the output was shown to
the participants. Figure 4.2 summarizes the steps of training the task classifier.

**ErrP Classifier**

Prior to each participant’s online session, an ErrP classifier was trained using the participant’s data from the offline sessions. There were 72 trials with error potentials and 288 trials without for each participant as the error rate was fixed at 20%. For each trial, the 1.4 s of EEG signal after feedback onset, referred to as feedback data, was epoched and filtered using an FIR bandpass filter with a passband from 1 to 12 Hz. ICA and ADJUST algorithm were applied to identify artifact components. 100 ms of feedback data was averaged and subtracted from the feedback data to remove the baseline offset.

The actual time samples were used as features by downsampling the data by a factor of 20, which resulted into 70 features per channel. An rLDA was used to train the ErrP classifier. The regularization parameter ($\gamma$) was chosen for each participant by calculating the average LOOCV accuracy for different values over the range of 0 to 1 in 0.1 increments and selecting the value which yielded the highest accuracy.

Figure 4.3 outlines the ErrP classifier. Each participant’s ErrP classifier was also retrained after every block (15 trials) with the same $\gamma$. During each participant’s online session, after displaying a visual feedback of the task classifier output, 1.4 s of the EEG data were analyzed to find the presence of ErrP. The same preprocessing and feature extraction steps (listed above) were applied, except that the ICA weights were calculated from the 3 min EEG baseline recorded at the beginning of the online session. After classifying the the data, if the output score of the classifier was higher than a specified decision threshold, that trial would count as an error.

A rLDA classifier generates an score between 0 to 1 for each class which indicates the probability of the input belonging to that class. Then, the score is compared with a decision threshold (default value of 0.5 in a binary classifier) to predict the class of the input. However, in this study, the default value did not always yield the best online results for ErrP classification in pilot testing. Hence, this decision threshold was optimized after every online block. The threshold used for the first block was equal to 1 which means the classifier only detected error if the output score was 1. The reason for choosing this threshold for the ErrP classifier was to minimize the number of false positives at the beginning of the online session (when there is still no same-day data to train the classifier) to prevent frustration of participants. We made this decision following the pilot sessions, where we noticed that without having same day data, the ErrP classifier was highly susceptible to false positives (i.e., changing the correctly predicted label of the task classifier to an incorrect label). For completeness, true positives were counted when an error potential was detected following an erroneous task classification.

As demonstrated in figure 4.3, to optimize the decision threshold prior to block $n$, LOOCV was performed for every trial in the previous online blocks. To elaborate, for each of the $(n-1) \times 15$ online trials, a classifier was trained using all the available data (offline sessions plus the online data) for the given participant, except the trial under consideration. Then, the held-out trial was classified using the trained classifier. Classifications scores for the online trials were computed for different decision thresholds and the post-error correction accuracy was computed. The decision threshold was varied over the range of 0 to 1 (300 values evenly spaced between 0 and 1) and the value yielding the maximum post-error correction accuracy was selected for use in the subsequent block. The threshold value fluctuated across its full range according to the participant’s most recent performance.
4.3.6 Performance Metric

In addition to accuracy, information transfer rate (ITR) was estimated. ITR is a common BCI performance metric as it takes both accuracy and time into account [171]. ITR was calculated in bits per minutes using the following equation:

$$ITR = \frac{60}{T} \times (\log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{N - 1})$$  \hspace{1cm} (4.1)

where $P$ represents the classification accuracy in the range of $[0,1]$, $T$ is the time required to communicate one command in seconds, and $N$ is the number of classes.

In this study, $N=3$. The time ($T$) required for completion of a command without error-correction was calculated as follows: $5$ s (for performing the task) $+ 0.5$ s (time between end of the task and feedback onset) $+ 0.5$ s (time for completion of feedback). EEG data used for error-correction were $1.4$ s in duration and started from feedback onset. Since the complete presentation of feedback required $0.5$ s, the error-correction phase added $0.9$ s ($1.4$ s $- 0.5$ s) to the aforementioned time.

4.4 Results

For each participant, the online performance of their ErrP classifier is reported in table 4.2. Accuracies are reported for the entire session as well as for every three consecutive blocks to reveal potential performance changes in the classifier, which was retrained on a block-by-block basis. An average accuracy of $0.74$ was achieved across all blocks for all participants. The chance level for error detection accuracies varied across participants as they had different task classification accuracies. Chance levels were calculated using the binomial cumulative distribution and are shown in table 4.2.

Table 4.2: Achieved online accuracy (ACC), true positive rate (TPR), and false positive rate (FPR) for ErrP classifiers are reported for every three consecutive blocks and the entire session. The upper limit of the 95% confidence interval of chance (ULC) for every participant is also reported (using cumulative binomial distribution).

<table>
<thead>
<tr>
<th>Participant</th>
<th>Blocks 1-3</th>
<th>Blocks 4-6</th>
<th>Blocks 7-9</th>
<th>Block 1-9</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>ACC 0.78</td>
<td>TPR 0.59</td>
<td>FPR 0.11</td>
<td>ACC 0.89</td>
</tr>
<tr>
<td>P2</td>
<td>ACC 0.58</td>
<td>TPR 0.11</td>
<td>FPR 0.08</td>
<td>ACC 0.87</td>
</tr>
<tr>
<td>P3</td>
<td>ACC 0.51</td>
<td>TPR 0.69</td>
<td>FPR 0.74</td>
<td>ACC 0.56</td>
</tr>
<tr>
<td>P4</td>
<td>ACC 0.62</td>
<td>TPR 0.61</td>
<td>FPR 0.36</td>
<td>ACC 0.73</td>
</tr>
<tr>
<td>P5</td>
<td>ACC 0.62</td>
<td>TPR 0.11</td>
<td>FPR 0.00</td>
<td>ACC 0.78</td>
</tr>
<tr>
<td>P6</td>
<td>ACC 0.67</td>
<td>TPR 0.40</td>
<td>FPR 0.12</td>
<td>ACC 0.73</td>
</tr>
<tr>
<td>P7</td>
<td>ACC 0.82</td>
<td>TPR 0.78</td>
<td>FPR 0.15</td>
<td>ACC 0.89</td>
</tr>
<tr>
<td>P8</td>
<td>ACC 0.82</td>
<td>TPR 0.67</td>
<td>FPR 0.10</td>
<td>ACC 0.91</td>
</tr>
<tr>
<td>P9</td>
<td>ACC 0.47</td>
<td>TPR 0.35</td>
<td>FPR 0.29</td>
<td>ACC 0.71</td>
</tr>
<tr>
<td>P10</td>
<td>ACC 0.71</td>
<td>TPR 0.58</td>
<td>FPR 0.14</td>
<td>ACC 0.54</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Blocks 1-3</th>
<th>Blocks 4-6</th>
<th>Blocks 7-9</th>
<th>Block 1-9</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ACC TPR FPR</td>
<td>ACC TPR FPR</td>
<td>ACC TPR FPR</td>
<td>ACC ULC TPR FPR</td>
</tr>
<tr>
<td>Mean</td>
<td>0.66 0.49 0.21</td>
<td>0.78 0.62 0.20</td>
<td>0.77 0.70 0.23</td>
<td>0.74 – 0.59 0.21</td>
</tr>
<tr>
<td>SD</td>
<td>0.12 0.24 0.21</td>
<td>0.13 0.29 0.27</td>
<td>0.13 0.28 0.20</td>
<td>0.12 – 0.23 0.21</td>
</tr>
</tbody>
</table>

† Accuracies which did not exceed the chance level.

Figure 4.4 displays the grand averaged responses of correct and error trials across all participants at channel FCz. The shaded regions denote the standard error for the averaged trials. Time 0 marks the beginning of the visual feedback.
The averaged error waveform had a very small deflection at about 300 ms (294 ± 33 ms being the mean and standard deviation of the latency across trials) after feedback onset. There were also two positive peaks present at about 500 ms (496 ± 52 ms) and 800 ms (818 ± 90 ms) in both correct and error trials but their amplitudes differed.

Online ternary task classification accuracies are presented for pre- and post-error correction in table 4.3. The results are shown for every three consecutive blocks (45 trials) as well as for the entire session for all participants. The pre-correction accuracies changed significantly in blocks 4-6 (p=0.006) and 7-9 (p=0.002) compared to blocks 1-3, according to a 2-sided Wilcoxon Signed-Rank test. The upper limit of the 95% confidence interval of chance was 44% and 40% for three blocks and the entire session, respectively. Online accuracies that did not surpass chance are marked with † in table 4.3. Post-error correction accuracies were increased compared to pre-error correction accuracies except in three cases which are marked in the table (‡). The addition of ErrP-based error correction improved the average accuracy from 60% to 67% (p=0.002, Wilcoxon Signed-Rank test). ITR values for the entire online session for each participant are provided in the last column of table 4.3. The information transfer rate was also significantly improved from 2.70 to 3.59 (bits/min) (p=0.006, Wilcoxon Signed-Rank test). The boxplots of pre- and post-error correction accuracies are plotted in figure 4.5 for different groupings of blocks as well as for the entire session.

Table 4.3: Online pre- and post-error correction ternary task classification accuracies for two cognitive tasks and unconstrained rest/idle are reported for every three consecutive blocks and the entire session. Online information transfer rates (ITRs) are reported as well.

<table>
<thead>
<tr>
<th>Participant</th>
<th>Accuracies</th>
<th>ITR (bits/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Blocks 1-3</td>
<td>Blocks 4-6</td>
</tr>
<tr>
<td>P1</td>
<td>0.62</td>
<td>0.80</td>
</tr>
<tr>
<td>P2</td>
<td>0.58</td>
<td>0.78</td>
</tr>
<tr>
<td>P3</td>
<td>0.42†</td>
<td>0.45</td>
</tr>
<tr>
<td>P4</td>
<td>0.31†</td>
<td>0.44†</td>
</tr>
<tr>
<td>P5</td>
<td>0.58</td>
<td>0.76</td>
</tr>
<tr>
<td>P6</td>
<td>0.56</td>
<td>0.73</td>
</tr>
<tr>
<td>P7</td>
<td>0.60</td>
<td>0.82</td>
</tr>
<tr>
<td>P8</td>
<td>0.67</td>
<td>0.76</td>
</tr>
<tr>
<td>P9</td>
<td>0.31†</td>
<td>0.51</td>
</tr>
<tr>
<td>P10</td>
<td>0.47</td>
<td>0.42†</td>
</tr>
<tr>
<td>Mean</td>
<td>0.51</td>
<td>0.65</td>
</tr>
<tr>
<td>STD</td>
<td>0.13</td>
<td>0.17</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Participant</th>
<th>Accuracies</th>
<th>ITR (bits/min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Blocks 1-3</td>
<td>Blocks 4-6</td>
</tr>
<tr>
<td>P1</td>
<td>0.73</td>
<td>0.84</td>
</tr>
<tr>
<td>P2</td>
<td>0.58</td>
<td>0.82</td>
</tr>
<tr>
<td>P3</td>
<td>0.44†</td>
<td>0.45</td>
</tr>
<tr>
<td>P4</td>
<td>0.40†</td>
<td>0.53</td>
</tr>
<tr>
<td>P5</td>
<td>0.62</td>
<td>0.78</td>
</tr>
<tr>
<td>P6</td>
<td>0.64</td>
<td>0.69†</td>
</tr>
<tr>
<td>P7</td>
<td>0.76</td>
<td>1.00</td>
</tr>
<tr>
<td>P8</td>
<td>0.59</td>
<td>0.70</td>
</tr>
<tr>
<td>P9</td>
<td>0.62</td>
<td>0.56</td>
</tr>
<tr>
<td>P10</td>
<td>0.59</td>
<td>0.70</td>
</tr>
</tbody>
</table>

† Accuracies which did not exceed the chance level.
‡ The post-error correction accuracies which were lower than their corresponding pre-error correction accuracies.
4.5 Discussion

4.5.1 ErrP-based Error Correction

Several studies have investigated the impact of incorporating ErrP-based error detection in BCIs based on P300 [9, 26, 20, 155], code-modulated visually evoked potential [157], and motor imagery [9, 43, 82, 83, 142, 10], confirming the feasibility of error detection on a single-trial basis [18]. When an error is detected following a trial, at least three different strategies can be employed. The first strategy is to change the BCI output to the second most probable outcome upon error detection [20, 155, 183]. In this strategy, the post-error correction accuracy is limited by the accuracy of the ErrP classifier. The second strategy, which has been adopted by most studies, is to discard and repeat the trials detected as errors [9, 26, 43, 83]. Compared to the first strategy, the discard and repeat approach may lead to a higher post-error correction accuracy given that classification is less constrained by the performance of the ErrP classifier. However, trial repetitions prolong the time required to transmit information and hence may reduce ITR. The third strategy uses ErrP data to update the BCI classifier [18]. For example, in binary cases, ErrP detection can be used to identify misclassifications and provide new labels for the data. Then, in a semi-supervised manner, these labeled samples can be used to update the classifier parameters [93]. In this study, we deployed the first strategy to enhance an online active BCI.

For comparison purposes, studies that performed online error correction in active BCIs [9, 43, 83, 10] are summarized in table 4.4. All of these studies applied the second error correction strategy (i.e. discarding the wrong trials) and used motor imagery tasks for BCI development. Ferrez and Millán showed that applying error correction for two participants reduced the error rate from 32% to 7% which subsequently tripled the bit rate [43]. Kreilinger et al. demonstrated an improvement in accuracy of 11% post-error correction averaged over three participants [83] but ITR values were not reported. Given the modest number of participants in these studies, the significance of these results cannot be ascertained. Bhattacharyya et al. [9, 10] conducted two studies of ErrP-based error correction reporting higher ErrP-corrected performance in controlling a robotic arm. However, they did not report pre- and post-correction accuracies and ITR values, but rather robot targeting metrics to estimate the improvement. Nonetheless, these studies collectively indicate potential value of ErrP-based error correction in active, MI-based BCIs.

In this study, the average TPR and FPR values of 0.59 ± 0.23 and 0.21 ± 0.21 were achieved for error detection. These average values are within the range of those reported in existing literature (see table 4.4). Bhattacharyya et al. [10] obtained higher error potential detection, which can be attributed to their higher BCI task classification accuracy, making errors more rare and hence eliciting stronger and more easily detectable brain responses. Their high BCI performance was attributable to the extensive user training time (60-80 hours). The BCI’s task classification error rate inversely relates to the performance of the ErrP classifier (i.e. higher BCI error rate tends to suppress the ErrP classification accuracy [17]). Hence, in general, it can be expected that when a BCI performs poorly, the performance of the associated error detector diminishes as well. This relationship between the performance of the task classifier and error detector may explain, in part, the below-chance error detection for P3 and P9; their BCI accuracies were among those of the bottom three participants.
Chapter 4. Online detection of error-related potentials in multi-class cognitive task-based BCIs

Table 4.4: An overview of online error detection studies.

<table>
<thead>
<tr>
<th>Study</th>
<th>TPR</th>
<th>FPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed study</td>
<td>0.59</td>
<td>0.21</td>
</tr>
<tr>
<td>Bhattacharyya et al. [9]*</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Ferrez &amp; Millan [43]</td>
<td>0.78</td>
<td>0.15</td>
</tr>
<tr>
<td>Kreilinger et al. [83]</td>
<td>0.53</td>
<td>0.11</td>
</tr>
<tr>
<td>Bhattacharyya et al. [10]</td>
<td>0.94</td>
<td>0.04</td>
</tr>
</tbody>
</table>

* Did not report FPR and TPR values.

4.5.2 Error-related Potentials

Although ErrP waveforms reported in literature share some similar characteristics (such as the presence of a negative and positive peak), there can be many variations as well. The ErrP waveform morphology may vary among participants [1] and according to feedback design [72]. Even for the same participant and feedback design, the BCI error rate may cause variations in the characteristics of the ErrP waveforms [17].

Feedback design determines the mental process required to assess the BCI’s performance [1] and thus impacts ErrP signal morphology. It is argued that the error-related negativity and sometimes the positivity are affected by the detectability of an error (in other words, the conspicuity of the difference between correct and error feedback) [38].

As shown in figure 4.4, there was a small initial negative deflection in error trials and two prominent positive peaks in both correct and error trials. The positivities had greater amplitude in error trials. The waveform characteristics are similar to observations in some studies [17, 72, 118] while different to others [183]. For example, two positive peaks observed by this study and [17, 72, 118] somewhat form one broader peak because of their bandwidth and latency. But, these two peaks are distinct from each other in [183]. These waveform differences arise from variations across studies in error portrayal by the interface (i.e. the feedback design) and error comprehension by the user (i.e. the user-specific mental processing of error occurrence).

The depicted shaded error bars in figure 4.4 arise from both inter- and intra-participant response variations. The differences may be attributable to the fact that classification error rate was different for each individual. It has been confirmed that a less frequent error elicits a larger amplitude (c.f. oddball paradigm) [17]. Even the error rate for each task varied for one participant resulting in a task-specific differences between error-related potentials. Furthermore, it has been suggested that the error-related negativity is correlated with a participant’s cognitive modeling of correct and erroneous feedback [141], which may have also contributed to inter-participant variation in the ErrP waveform.

4.5.3 Task Classification

The cognitive tasks selected for this study are among the most common used in BCIs while the achieved online ternary accuracies with error correction (table 4.3) are on par with previously reported offline ternary EEG studies. Articles on active tasks can be categorized according to the mental tasks invoked: motor imagery [167, 99, 173, 142], cognitive tasks [77, 61, 63], and combinations of MI and cognitive tasks [186, 57, 119, 5, 25, 68, 32, 34, 33, 29, 39, 104, 65, 44, 45, 143]. At the time of writing, only two cognitive EEG studies [75, 36] were conducted online but did not report online task classification accuracies but rather the time required to reach the targets. The remainder of the studies were conducted offline. Keirn et al. [77] collected data from seven participants performing six different cognitive
tasks. Several studies subsequently applied various feature extraction and classification techniques to this dataset [61, 63, 186, 57, 119, 5], achieving a wide range of task classification accuracies. Notably, Dyson et al. reported an average offline binary classification accuracy of 68% between an idle state and a mental task (one of motor imagery, auditory imagery, mental arithmetic or navigation imagery) [34] while Agarwal et al. [2] achieved an average offline ternary classification accuracy of 69% in discriminating among left/right MI and word generation. Our task classifier reached comparable ternary accuracies online.

The significant improvement of task classification accuracies in blocks 4-6 and 7-9 compared to blocks 1-3 (figure 4.5) supports the practice of supplementing the training set with same-day data as brain signals are non-stationary and may change from day to day [115].

4.5.4 Limitations and Future Work

To the best of our knowledge, the active BCI developed in this study is the first online ternary BCI based on cognitive tasks with ErrP-based automatic error correction. Our results are comparable with those in literature in terms of multi-class task classification and ErrP detection accuracies. Future research should include more training sessions and continuous updating of the classifier. We also suggest that the proposed paradigm be investigated in a functional and asynchronous context, such as controlling a robot or wheelchair, to ascertain its feasibility as a practical interface.
Figure 4.1: Trial interface: (a) The required task was highlighted for 4 s by changing the text font color from gray to red. (b) The color of the icon’s bow-tie changed to magenta to indicate that the participant should start the task. The participant performed the required task for 5 s. Then, the color of the bow-tie changed back to gray. The 5 s of EEG data were used for task classification. Then, real-time feedback was displayed. At this point, depending on the output of the classifier, the timing followed either (c) or (d). (c) In the first case, the task classifier output was correct, so the icon representing the required task remained unchanged while the other two icons fell. (d) In the second case, the task classifier output was incorrect as the icon representing the required task fell. EEG data after feedback onset (from time 0 to 1.4 s) was analyzed to detect error. (e,g) No error was detected so the participant was notified with the following message: “No Error!”. (f,h) Error was detected so the BCI changed its decision. The participant was notified with following message: “Error! BCI changed its decision to x”, where x refers to the output of the binary task classifier and can be “task 1”, “task2”, or “rest”. “task 1” referred to the task written on the left icon and “task 2” referred to the task written on the right icon.
CHAPTER 4. **Online detection of error-related potentials in multi-class cognitive task-based BCIs**

Figure 4.2: Pipeline for training the online task classifier for the \( n^{th} \) online block, \( n = 1, \ldots, 9 \).

Figure 4.3: Pipeline for tuning the online ErrP classifier for the \( n^{th} \) online block, \( n = 1, \ldots, 9 \).
Figure 4.4: The grand average of responses across all participants for correct (red line) and error (blue line) trials along with their corresponding standard error (shaded region) at FCz. Time 0 marks the beginning of the visual feedback.

Figure 4.5: Boxplots of online ternary task classification accuracies across participants pre- and post-error correction. Post-error correction accuracies for blocks 1-9 were improved significantly compared to pre-error correction values ($p=0.002$, Wilcoxon Signed-Rank test).
Chapter 5

Robust Asynchronous Brain-switch using ErrP-based Error Correction

This chapter is reproduced from the following published article: Rozhin Yousefi, Alborz Rezazadeh Sereshkeh, and Tom Chau. “Development of a Robust Asynchronous Brain-switch using ErrP-based Error Correction”. Journal of Neural Engineering, Under Review.

5.1 Abstract

The ultimate goal of most researches in brain-computer interface (BCIs) is to provide individuals with severe motor impairments with a communication channel that they can control whenever they intend to. Unavoidable step toward reaching this goal is to develop an asynchronous BCI, a system that allows users to reliably control it in a self-paced manner independently of a cue stimulus. However, due to technical difficulties, despite many years of research, asynchronous BCIs have been explored in only a small percentage of BCI studies. Also, the performance of most asynchronous BCIs developed to this date are not adequate for daily use adoption. In this paper, to address this issue, we presented an asynchronous BCI using electroencephalography (EEG) and based on non-motor imagery cognitive tasks and investigated the possibility of improving its performance using error-related potentials (ErrP). Ten able-bodied adults attended two sessions of data collection each, one for training and one for testing the proposed BCI. For each participant, an asynchronous BCI differentiated among idle state and a personally selected cognitive tasks (mental arithmetic, word generation or figure rotation). The BCI continuously analyzed the EEG data and displayed real-time feedback as soon as it detected a cognitive task. Then, the BCI analyzed the EEG data after the feedback onset using an ErrP classifier to correct erroneous classifications. The average of post-error correction success rate across participants improved significantly from 78 ± 11% to 85 ± 12% compared to the pre-error correction value (p < 0.05). Our findings support the addition of ErrP-correction to maximize the performance of asynchronous BCIs.

5.2 Introduction

Brain-computer interfaces (BCIs) measure brain activities and translate them to meaningful commands. The main goal of BCI research is to provide a communication channel for individuals with severe motor
impairments who are not able to communicate through conventional ways [124].

Ideally, it is desirable for a BCI to allow the users to reliably control the system whenever they intend to and without having to wait for a cue from the system. This type of BCI is called self-paced or asynchronous [115]. However, due to technical difficulties, most BCIs developed to date are cue-based or synchronous which means that the system dictates the time of interactions.

In asynchronous BCIs, the challenge is to detect the user’s intention for control without knowing its onset. Hence, the brain activity must be continuously analyzed to identify intentional control (IC) from non-control (NC) states [97]. In this paper, we refer to the umbrella of NC states as idle. NC states vary greatly as there are many simultaneous ongoing processes in the brain. These variations make training a robust classifier more challenging compared to synchronous setups, which usually include only a limited number of mental states.

BCIs can be categorized into three types of active, reactive and passive in terms of the mental activities they use for control [180]. Active and reactive BCIs detect user’s intention for control while passive BCIs typically measure mental states of the brain such as fatigue or stress [113]. Reactive BCIs require an external stimulus to generate specific brain signals that are shown to be detectable, such as P300 and steady-state visual evoked potential (SSVEP) [6]. In active BCIs, users intentionally modulate their brain activity by performing specific tasks that have been shown to produce detectable signal patterns, such as motor imagery (MI) [173, 127], imagined speech [149], or mental arithmetic [32].

Reactive BCIs typically have higher information transfer rate (ITR) [171] compared to active BCIs; however, requiring stimuli for operation limits their functionality. For instance, developing an asynchronous BCI solely based on reactive brain responses such as P300 [129] or SSVEP [31] requires the constant presence of stimuli, which reduces the practicality of such asynchronous BCIs for everyday use by the target population. One way to exploit the advantages of both types (higher ITR of reactive BCIs and being needless of constantly attending external cues in active BCIs) is to combine them [128]. For example, a brain-switch (an asynchronous BCI designed to detect one brain pattern) can be developed based on an active task to turn on a fast reactive BCI (such as a p300 speller). In conclusion, in order to fill the gap between laboratory BCIs and practical BCIs for everyday use, there is a definite need for accurate asynchronous BCIs without any dependency on external cues.

There have been several efforts in developing asynchronous active BCIs. Most of these studies have investigated motor related tasks, such as motor execution [66], motor movement intention [69, 92], and motor imagery [161, 87, 16, 88, 62]. Few asynchronous studies have used non-MI tasks [47, 105, 39] such as sound imagery [154], conceptual perception [81], and emotion imagery [3].

In this study, we used non-MI active tasks to develop an asynchronous brain-switch, using electroencephalography (EEG). Participants could select one of three mental tasks including word generation, arithmetic, and figure rotation to control their BCI. The reason that non-MI tasks were chosen was three-fold. First, non-MI tasks have not thoroughly been studied in the context of asynchronous paradigm. Secondly, it has been shown that motor imagery and motor execution involve similar brain regions [106]. This makes use of these tasks for some asynchronous systems, such as brain switches, not practical as voluntary movements can interfere with the control of the system. We note that MI tasks are viable and intuitive choices for some applications of BCI such as controlling prosthetic arms or legs [110, 111]. Third, it has been shown that “BCI illiteracy”, inability to control MI-based BCIs, is present in 15 ∼ 30% of population [12]. Cognitive tasks can be investigated as a potential replacement for this group. Besides, MI can be hard or impossible to perform by individuals with congenital motor impairments.
Chapter 5. Robust Asynchronous Brain-switch using ErrP-based Error Correction

Nevertheless, the performances of most asynchronous BCIs developed to this date, regardless of their activation tasks, are not sufficient for daily use adoption.

The problem of improving the performance of BCIs has been approached from various directions such as improving measurement modalities [115, 164], artifact removal [40], and classification pipeline [95]. Another approach, which has gained many attractions over the last decade, is to detect BCI mistakes when they occur [41, 83]. It has been shown that the brain reacts when someone commits an error [37] or observes an error by others or a computer [165]. This reaction produces a specific pattern of signals which can be reliably detected using EEG [48]. These EEG signals are called error-related potentials (ErrPs). Feasibility of single-trial detection of ErrPs have been shown in many BCI studies [18], including synchronous active [43] and reactive BCI [183], but it has been very limited for asynchronous BCIs [10]. Specifically, to the best of our knowledge, it has not been investigated in the context of asynchronous brain-switches.

The contribution of this study is threefold. First, we investigate the feasibility of a user-specific asynchronous brain-switch that uses EEG signals to continuously detect intentional control events. Secondly, we explore the possibility of single-trial detection of ErrPs in this asynchronous paradigm. Finally, we investigate the impact of error-correction on the performance of the developed asynchronous brain-switch.

5.3 Methods

5.3.1 Participants

Ten adults (six females) without any reported history of neurological disorders participated in this study (mean ± standard deviation age of 29 ± 3 years). All participants were fluent in English with normal or corrected-to-normal vision. The study was approved by the research ethics boards of the University of Toronto and the Holland Bloorview Kids Rehabilitation Hospital. All participants provided informed written consent. Participants attended two sessions of data collection on the same day, each approximately 50 minutes in length including setup time. Participants were provided a 15 to 20 minute break between the two sessions.

5.3.2 Instrumental Setup

A 32-channel dry EEG system (actiCAP Xpress Twist, Brain Products, Germany) was used for EEG measurement at the following locations according to the 10/10 international system: FP1, FP2, AFz, AF3, AF4, F1, Fz, F2, F7, F8, FT7, FT8, T7, T8, FC5, FC1, FCz, FC2, FC6, C1, Cz, C2, CP5, CP1, CPz, CP2, CP6, Pz, P3, P4, POz, and Oz. Reference and ground electrodes were placed on the left and the right earlobes, respectively. The EEG sampling rate was set to 1000 Hz.

5.3.3 Tasks

Three mental tasks, namely, mental arithmetic, word generation and figure rotation were chosen for this study, based on our previous work [176] that confirmed their separability from an idle state. At the beginning of each training session, the participant selected one of the tasks based on her/his personal preference to control the BCI. The selected tasks are listed in table 5.1.

(I) Arithmetic - Participants were asked to mentally subtract a single-digit number from a 2-digit number (both self-selected), and then iterate, each time subtracting the same single-digit number from
the previous result (e.g., 69-8=61, 61-8=53, 53-8=45, and so on). (II) Word generation - Participants were asked to mentally name as many words as possible that begin with a certain self-selected letter. (III) Figure rotation - Participants were asked to visualize the rotation of a particular three-dimensional object of their choosing (e.g., a chair) around an axis.

Table 5.1: The mental task selected by each participant.

<table>
<thead>
<tr>
<th>Participant #</th>
<th>Task</th>
<th>Participant #</th>
<th>Task</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Arithmetic</td>
<td>6</td>
<td>Arithmetic</td>
</tr>
<tr>
<td>2</td>
<td>Figure Rotation</td>
<td>7</td>
<td>Word Generation</td>
</tr>
<tr>
<td>3</td>
<td>Figure Rotation</td>
<td>8</td>
<td>Arithmetic</td>
</tr>
<tr>
<td>4</td>
<td>Arithmetic</td>
<td>9</td>
<td>Figure Rotation</td>
</tr>
<tr>
<td>5</td>
<td>Figure Rotation</td>
<td>10</td>
<td>Arithmetic</td>
</tr>
</tbody>
</table>

5.3.4 Experimental Protocol

Training Session

The first session of data collection was dedicated to gathering training data. This session included 60 trials. The interface displayed to participants during trials is shown in figure 5.1. During a trial, participants were instructed to allow normal thought processes to occur until they observed a cue (the color of the bow-tie on the icon in the middle of the screen changed from gray to magenta as shown in figure 5.1). They were instructed to start performing their selected mental task after the cue appeared and continue until the icon fell. The onset of the cue was randomly chosen, between 10 to 16 s after the beginning of the trial, to simulate an asynchronous setup. The duration of the mental task (from the onset of the cue until the icon’s fall) was also chosen randomly, between 5 to 12 s as shown in figure 5.2. These trials will herein be referred to as no-error trials.

We did not perform any real-time analysis during the training session. However, in order to generate and collect error-related potentials, participants were told that their EEG data were being continuously analyzed in real-time and whenever the BCI detected the task (even if it was before the onset of the task cue), the icon in the middle of the screen would fall. During 30% of the trials, chosen randomly, the icon fell during the idle state, while the color of the bow-tie was still gray. Since the participant had not started the task execution, he/she would perceive icon-falling as an error, and hence, ErrPs were evoked. These trials will be referred to as error trials.

Test Session

After the training data collection session for each participant, an intention classifier (task vs. idle) and an ErrP classifier (error vs. no error) were developed, as outlined in section 5.3.5. The ensuing test session included 50 trials. Each trial was a maximum of 30 s long. The interface was similar to that of the training session, except that participants were not prompted with a cue to begin the task. Rather, participants could start performing the task whenever they desired. They also had the option of remaining idle for the entire length of the trial.

The BCI continuously analyzed the EEG data using the intention classifier. To elaborate, after 5 s from the beginning of the trial, the BCI started analyzing the EEG data from the last 5 s, once every second. As soon as the BCI detected the task, feedback was presented, i.e., the icon fell. Then, the BCI
analyzed the EEG data after the feedback onset using the ErrP classifier. If an error was detected, the icon would return. Whether the BCI detected an error or not, the trial would end at this point.

If the BCI detected no task after 30 s, the trial would end. If a participant decided to perform the mental task in a trial (rather than remaining idle for the entire length of the trial), he/she was required to start the task at least 5 s before the end of the trial, i.e., no later than 25 s after the beginning of the trial. To assist participants with timing, the text (showing the name of the task) on the icon would disappear at 25 s. Participants were instructed to not start the task after that point as the remaining time would be less than 5 s, and not sufficient for intention classification.

After the end of each trial, participants reported whether the BCI detected the presence of the task correctly or not. Incorrect detection include cases where the participant performed the task, but the icon did not fall, and cases where the icon fell before the participant started the mental task. For trials where the BCI detected the task and the icon fell (whether it was correct or not), participants also needed to report if the BCI detected the error correctly or not.

5.3.5 Analysis of Training Session Data
Artifact Removal

First, the raw EEG data were filtered using a finite impulse response (FIR) filter (order 96) between 1 to 40 Hz, and the EEG data for all training trials were extracted. Then, independent components analysis (ICA) was applied and the ADJUST algorithm [108] was deployed to identify components associated with eye blinking, ocular movement, and generic discontinuities [108]. After removing these artifacts, the remaining components were used to reconstruct the EEG data. These ICA weights were also used
Chapter 5. Robust Asynchronous Brain-switch using ErrP-based Error Correction

Figure 5.2: The timing of trials in the training session. The idle and task interval times, $t_{\text{idle}}$ and $t_{\text{task}}$, are drawn from discrete uniform distributions, $U(a,b)$, to remove artifacts during the online test session.

**Feature Extraction**

From each trial, idle and task segments (as described in 5.3.4) were extracted. Note that 30% of the trials contained only idle segments (i.e., no task). Each segment was further decomposed into 5 s epochs with 1 s overlap. For example, consider a trial where the user performed the task between 10 and 17 s. The idle segment would span from 0 to 10 s, consisting of six 5 s, overlapping epochs (0 to 5 s, 1 to 6 s, . . . , 5 to 10 s). Likewise, the task segment would consist of three 5 s, overlapping epochs (10 to 15 s, 11 to 16 s, and 12 to 17 s). This segmentation approach yielded $\sim 580$ epochs of idle and $\sim 180$ epochs of task per participant.

All task and idle epochs were downsampled by a factor 10. Then, discrete wavelet transform (DWT) coefficients were calculated using the Daubechies 5 (db5) wavelet with four levels of decomposition. The root-mean-square (RMS) of the coefficients of each decomposition level were used as features for classification. These four levels represent the following pseudo-frequency ranges: 40-25 Hz, 25-12.50 Hz, 12.5-6.75 Hz, 6.75-3.38 Hz. A total of 128 DWT features (32 EEG electrodes $\times$ 4 DWT features) were generated from each epoch.

For the ErrP analysis, in all trials, 900 ms of data after the feedback onset were extracted. The first 200 ms of each epoch was averaged and subtracted from the whole epoch to remove the baseline offset. Then, the data from 200 to 900 ms were extracted and labeled as error-free or containing error depending on whether the feedback was correct or wrong. Since, wrong feedback was displayed in 30% of the trials, for each participant, there were 18 and 42 epochs of error and no-error data, respectively. The same types of DWT features as described above (for the idle and task epochs) were extracted from
each error and no-error epoch.

**Intention Classification**

All the task and idle trials of the training session were used to build an intention classifier using a regularized linear discriminant analysis (rLDA) model. As the classifier was built between the training and test sessions on the same day, in the interest of time, the regularization parameter ($\gamma$) was kept constant at a value of 0.1.

In general, given an unlabeled input, a binary rLDA classifier calculates a score for each class (where the scores sum to unity). The score can be considered the probability that the input example belongs to a given class. The classifier assigns to the unlabeled input, the label of the class with a score greater than 0.5. However, this default threshold is not necessarily optimal in terms of sensitivity and specificity. To optimize the decision threshold, $\theta$, as a hyperparameter for the intention classifier, leave-one-out cross-validation (LOOCV) was applied to the training data with a $\gamma$ of 0.1. Then, classification outcomes of the intention classifier (subscripted with $I$) were tabulated as true positive ($TP_I$), false positive ($FP_I$), true negative ($TN_I$), and false negative ($FN_I$) values for $\theta \in \{0.1, 0.2, \ldots, 0.9\}$. The threshold, $\theta^*_I$ which yielded the highest F-score (equation 5.2) using LOOCV was selected for use in the test session (section 5.3.6).

$$\theta^*_I = \arg \max_{\theta_I} F(\theta_I) \tag{5.1}$$

where

$$F(\theta_I) = \frac{2}{\left(\frac{TP_I(\theta_I) + FP_I(\theta_I)}{TP_I(\theta_I)}\right) + \left(\frac{TP_I(\theta_I) + FN_I(\theta_I)}{TP_I(\theta_I)}\right)} \tag{5.2}$$

**Error Potential Classification**

Similar to intention classification, rLDA was used for ErrP classification. Since the number of training examples for the ErrP classification was approximately one order of magnitude lower than that available for the intention classifier, it was possible, time-wise, to optimize both the regularization parameter $\gamma_e$ and the decision threshold $\theta_e$, where the subscript denotes the error potential classifier. To determine optimum values, we followed the procedure below:

- For a given $\theta_e, \gamma_e \in \{0.1, 0.2, \ldots, 0.9\}$, $TP_e$, $FP_e$, $TN_e$, and $TP_e$ were computed via LOOCV with the ErrP training data. For notational convenience, the explicit dependence of each classification outcome on $\theta_e$ and $\gamma_e$ is not shown.

- The classification outcomes of the combined system (subscripted with $C$), i.e., the combination of ErrP and intention classifiers, were tabulated as:

$$TP_C = TP_I \times \frac{TN_e}{TN_e + FP_e}$$

$$TN_C = TN_I + FP_I \times \frac{TP_e}{TP_e + FN_e}$$

$$FP_C = FP_I \times \frac{TP_e}{TP_e + FN_e}$$

$$FN_C = FN_I + TP_I \times \frac{FP_e}{FP_e + TN_e}$$

- F-scores were calculated using the above outcomes.
The hyperparameter pair \((\gamma_e^* \text{ and } \theta_e^*)\) which achieved the highest F-score and the ErrP classifier using \(\gamma_e^*\) and trained with all available ErrP trials were retained for the online test session.

### 5.3.6 Analysis of Test Session Data

During the test session, EEG signals were continuously analyzed with a window size of 5 s. The window was moved forward every 1 s. For each 5 s epoch, signals were filtered using the same FIR filter (1 to 40 Hz) as in the training session. Then, the ICA weights calculated in the training session were deployed to remove artifacts using the ADJUST algorithm. Feature extraction was performed as in the training phase. Features were classified with the intention classifier developed in the training phase. The classifier returned the scores for each class. The scores were compared with the decision threshold, \(\theta_I^*\), optimized for the intention classifier (as explained above 5.3.5), yielding the classifier’s output (task or idle). If the epoch was classified as idle, then the trial resumed, and after 1 s, the next 5 s epoch was analyzed. However, if the epoch was classified as a task, the participant received visual feedback (the icon in the middle of the screen fell, as described in section 5.3.4).

For error detection, 900 ms of EEG signals post-feedback onset were epoched to determine the presence of an error. After filtering and removing artifact (as above), baseline offset was removed, and features were calculated (section 5.3.5). Features were fed to the previously trained ErrP classifier and scores for the error-present and error-absent classes were compared to the optimized threshold, \(\theta_e^*\), for the ErrP classifier. If no error was detected, no action ensued. If an error was detected, the fallen icon was restored, thereby notifying the participant of the corrective action.

### 5.3.7 Performance Assessment Metrics

In the training session, the label of every epoch was known. Hence, it was possible to report true positive rate (TPR) and true negative rate (TNR) on an epoch-by-epoch basis. However, in the online test of the asynchronous BCI, the exact time of task onset was unknown as participants were free to initiate activity at will. Hence, it was not possible to label each epoch. Instead, we defined three other metrics to evaluate the BCI’s performance. These metrics were calculated on trial-by-trial basis rather than at the level of individual epochs: (i) Success rate - The number of trials classified according to the participant’s intention divided by the total number of trials. (ii) Hit rate (HR): The number of positive trials, i.e., where participants actually performed the mental task, that were correctly identified as positive over the total number of actual positive trials. (iii) Positive predictive value (PPV): Positive trials that were correctly identified as positive over the total number of trials predicted as positive.

### 5.4 Results

#### 5.4.1 Offline Training Session

Table 5.2 lists the LOOCV results of the intention classifier for each participant in terms of true positive rate (TPR), true negative rate (TNR), and accuracy (ACC) for all participants. The TNR (i.e., detection of idle) for all participants was high, ranging from 0.92 to 1. In contrast, TPR (i.e., detection of task) varied greatly, from 0.50 to 0.99 among participants.

Table 5.3 presents LOOCV accuracies of the ErrP classifiers for every participant as well as the corresponding TPR and TNR values.
Table 5.2: Leave-one-out cross validation results of the intention classifier (task vs. idle) for each participant: true positive rate (TPR), true negative rate (TNR), and accuracy (ACC). The cognitive task was defined as the positive class while idle was defined as the negative class.

<table>
<thead>
<tr>
<th>Participant #</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPR</td>
<td>0.84</td>
<td>0.99</td>
<td>0.62</td>
<td>0.98</td>
<td>0.93</td>
<td>0.83</td>
<td>0.50</td>
<td>0.74</td>
<td>0.90</td>
<td>0.85</td>
<td>0.82</td>
<td>0.16</td>
</tr>
<tr>
<td>TNR</td>
<td>0.99</td>
<td>0.97</td>
<td>0.93</td>
<td>1.00</td>
<td>0.99</td>
<td>0.94</td>
<td>0.92</td>
<td>0.92</td>
<td>0.99</td>
<td>0.97</td>
<td>0.96</td>
<td>0.03</td>
</tr>
<tr>
<td>ACC</td>
<td>0.95</td>
<td>0.99</td>
<td>0.85</td>
<td>0.99</td>
<td>0.97</td>
<td>0.91</td>
<td>0.82</td>
<td>0.88</td>
<td>0.96</td>
<td>0.94</td>
<td>0.93</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table 5.3: Leave-one-out cross validation results of the ErrP classifier (error-present vs. error-absent): true positive rate (TPR), true negative rate (TNR), and accuracy (ACC). The presence of error was defined as the positive class while the absence of error was considered the negative class.

<table>
<thead>
<tr>
<th>Participant #</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>TPR</td>
<td>0.83</td>
<td>0.83</td>
<td>0.61</td>
<td>0.72</td>
<td>0.72</td>
<td>0.89</td>
<td>0.94</td>
<td>0.57</td>
<td>0.83</td>
<td>1.00</td>
<td>0.79</td>
<td>0.14</td>
</tr>
<tr>
<td>TNR</td>
<td>0.86</td>
<td>0.93</td>
<td>0.91</td>
<td>0.95</td>
<td>0.81</td>
<td>0.95</td>
<td>1.00</td>
<td>0.83</td>
<td>0.98</td>
<td>1.00</td>
<td>0.92</td>
<td>0.07</td>
</tr>
<tr>
<td>ACC</td>
<td>0.85</td>
<td>0.90</td>
<td>0.82</td>
<td>0.88</td>
<td>0.78</td>
<td>0.93</td>
<td>0.98</td>
<td>0.75</td>
<td>0.93</td>
<td>1.00</td>
<td>0.88</td>
<td>0.08</td>
</tr>
</tbody>
</table>

5.4.2 Online Test Session

Table 5.4 reports the online performance of the BCIs in terms of success rate, hit rate, and precision for every participant. Without considering the error correction mechanism, successful trials include two different scenarios: (1) trials where the BCI detected the task correctly (i.e., after the participant started performing the task); (2) trials during which the participant decided not to perform the mental task, and the BCI correctly classified the trial as no-control, i.e., every 5 s interval of the trial (with 1 s steps) was correctly labeled as idle.

The online error detection step produced two different scenarios post-intention classification: (1) The intention classifier detected the mental task correctly, but the ErrP classifier detected an error and changed the predicted label (task or idle) to the wrong one; (2) The participant did not perform the task, and the intention classifier mistakenly detected the task, but the ErrP classifier detected the error and corrected the output. The trade-off between these two scenarios determined whether the proposed error correction technique improved the trial success rate or not.

The average post-error correction success rate of 85 ± 11% was achieved across participants which was 7% higher than the average pre-error correction value (p=0.047, Wilcoxon Signed-rank).

As shown in table 5.4, the positive predictive value (PPV) was significantly increased by 9% (p=0.016, Wilcoxon Signed-rank).

Table 5.4: Online performance of the asynchronous BCI: pre- and post-error correction success rate (SR), hit rate (HR), and positive predictive value (PPV).

<table>
<thead>
<tr>
<th>Participant #</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>Mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-error correction</td>
<td>SR</td>
<td>0.68</td>
<td>0.84</td>
<td>0.56</td>
<td>0.66</td>
<td>0.86</td>
<td>0.86</td>
<td>0.74</td>
<td>0.92</td>
<td>0.86</td>
<td>0.88</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>HR</td>
<td>0.83</td>
<td>1.00</td>
<td>0.75</td>
<td>1.00</td>
<td>1.00</td>
<td>0.85</td>
<td>0.76</td>
<td>0.91</td>
<td>1.00</td>
<td>0.98</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>PPV</td>
<td>0.80</td>
<td>0.80</td>
<td>0.57</td>
<td>0.66</td>
<td>0.83</td>
<td>0.93</td>
<td>0.97</td>
<td>1.00</td>
<td>0.84</td>
<td>0.87</td>
<td>0.13</td>
</tr>
<tr>
<td>Post-error correction</td>
<td>SR</td>
<td>0.82</td>
<td>0.96</td>
<td>0.62</td>
<td>0.90</td>
<td>0.86</td>
<td>0.76</td>
<td>0.74</td>
<td>0.92</td>
<td>0.96</td>
<td>0.92</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>HR</td>
<td>0.78</td>
<td>0.97</td>
<td>0.70</td>
<td>0.94</td>
<td>1.00</td>
<td>0.79</td>
<td>0.76</td>
<td>0.91</td>
<td>0.94</td>
<td>0.97</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>PPV</td>
<td>1.00</td>
<td>0.97</td>
<td>0.63</td>
<td>0.91</td>
<td>0.83</td>
<td>0.95</td>
<td>0.97</td>
<td>1.00</td>
<td>1.00</td>
<td>0.93</td>
<td>0.11</td>
</tr>
</tbody>
</table>

Figure 5.3 illustrates the grand average of all error and no-error trials from both training and test.
5.5 Discussion

5.5.1 Asynchronous Protocol Design

An ideal asynchronous BCI must perform purely based on the user’s intention without the user deciding in advance or being told by the system when to start intentional control. However, most previous asynchronous BCIs do not meet this condition because knowledge of the exact time intervals of intentional control is needed for reporting typical assessment metrics such as TP and FP rates.

In many of the reported asynchronous BCI studies, a cue was informed participants what task to perform and when to perform it [161, 16, 39]. In [80], Koo et al. asked their participants to decide the task and when they would like to perform it, prior to a trial. Subsequently, during the trial, a timer was shown to the participants. One can argue that the timer was essentially a synchronous cue, as participants needed to start the task at a specific time, albeit determined pre-trial.

Other studies have tried to avoid cues. For example, several studies designed a goal-oriented protocol where participants had to reach a target, such as going through a maze [87, 136] or controlling a wheelchair [47, 178, 162], a virtual avatar [88, 169] or a robot [16]. Hence, without telling the participants specifically what to do, their performance could be measured.

Finally, in some asynchronous BCI studies, participants were asked to press a button before or after the mental task period. Song and Sepulveda [154] displayed a circular progress bar during each trial to help their participants with timing. Participants were given 30 s and they were free to perform the
activation task for 3 s at anytime during that period. They were required to press a button when they finished the task. In [109], Muller-Putz et al. told participants that they had 180 s for each trial and that they were free to start a foot imagery task anytime during that period, but were required to press a button few seconds before they intended to start. A beep sound was played as a feedback whenever the task was detected.

In our study, we tried to minimize any type of motor movement or distraction and designed a protocol according to the aforementioned definition of an ideal asynchronous BCI. In other words, in our study, the beginning of intentional control was unknown. We considered this a worthwhile compromise for the opportunity to study the feasibility of a real asynchronous brain-switch. Prior asynchronous BCI studies have used different metrics for performance assessment. TP and FP rates [161, 109], mean time to reach a target [87, 16, 169, 162], and information transfer rate [87]. In this study, the BCI's performance was evaluated based on hit rate, precision, and success rate on a trial-by-trial basis (also known as event-by-event basis as described by [161]).

5.5.2 BCIs as Brain-switches

The performance of the asynchronous BCI was comparable to that of previous EEG brain-switches. Mason and Birch developed a brain-switch based on finger movement. They achieved offline TP rates in the range of 0.38 to 0.81 and FP rates in the range of 0.03 to 0.12 over five participants [98]. In [153], Solis-Escalante et al. developed a MI-based asynchronous BCI that was trained based on motor execution data. Six out of nine participants obtained offline TP rates between 0.50 to 0.88 and the average FPR was 0.09±0.04. Muller-Putz et al. reported hit rates between 0.69 and 0.8 and precision values between 0.75 and 0.93 for a single-channel MI-based asynchronous system [109]. In this study, we achieved comparable results. The average hit rate and precision of 91% and 83% was obtained before applying error-correction.

5.5.3 Adding Error-correction

In [10], Bhattacharyya et al. confirmed that adding error detection improved the performance of their asynchronous BCI. Error-correction increased the success rate (the number of times of successful target attainment over the total number of attempts) from 55 % to 86 %. Our study also showed that adding ErrP-based error detection significantly improved the average trial success rate by 7% from 78% to 85% over participants. These results suggest the feasibility and benefits of adding error detection to asynchronous BCIs.

There is an imperative difference between the effect of error correction in asynchronous and synchronous BCIs. In synchronous BCIs, error correction can be used to correct the results of all classes. However, for example, in an asynchronous brain-switch, error detection is only possible in the case of false positives (e.g., when the BCI makes the mistake of detecting IC). Hence, ErrP-based error detection can potentially correct false positives while cannot detect and correct false negatives.

5.5.4 ErrP Waveforms

In this study, whenever the activation task was detected, visual feedback was shown to the participant in the form of a falling icon. However, participants’ reactions were different based on whether the error response was detected correctly or not as shown in figure 5.3. The dip at around 300 ms in both error and
no-error waveforms can be attributed to the motion-onset visual evoked potentials (mVEP) due to the falling icon [84]. Although participants were constantly looking at the icon in the center, the mVEP was stronger in no-error cases. This can be explained by the fact that during no-error trials, their attention level was higher as they were actively trying to knock down the icon. We postulate that the no-error waveform shape is a P300 response from the visual feedback. It comprises two positive peaks at $\sim 500$ ms and $\sim 700$ ms. It has been confirmed that P300 waveforms have two sub-components called P3a and P3b which originate from attention and memory-related storage activities, respectively [130]. The error waveform shares similar morphological characteristics with other error waveforms reported in literature, such as the outcome error observed in [156] and error in a virtual moving square experiment [72].

The latencies of mVEP and P300 components were about 200 ms longer than reported in literature. This delay might be attributable to the fact that feedback was gradual, and the icon fell over 500 ms and it took participants about a 200 ms to notice the fall.

5.5.5 Limitations and Future Directions

For future studies, the authors suggest the use of additional sessions as greater data samples may enhance both intention and ErrP classifiers’ performance. In fact, with more sessions, one may gain insight about the maximum achievable classifier performance. Also, calibrating the thresholds and regularization parameters for both classifiers after one or more online blocks may potentially improve the results.

Future research can also explore the effect of increasing the number of classes in the brain switch, e.g., a two-choice switch. Such a BCI could be used by clinical populations to activate an assistive device or a call bell for assistance. The effect of error correction on a multi-class asynchronous BCI can also be investigated.

Finally, prior to any clinical translation, the results herein should be replicated with different age groups, and more importantly, individuals who present as locked-in.
Chapter 6

Conclusion

This thesis explored the possibility of detecting error-related potential in synchronous and asynchronous BCIs based on non-motor imagery cognitive tasks and investigated the extent that error detection and correction can improve BCI performance. The major contributions of this thesis are as follows:

1. Investigated the presence of ErrPs in an EEG study with five non-MI cognitive tasks (mental arithmetic, counting, word generation and figure rotation and idle state) and estimated the potential improvement in EEG classification of cognitive tasks by exploiting ErrPs. To simulate errors, a random subset of 20% of the trials were followed by incorrect feedback. The classification of mental tasks and error versus non-error trials were both performed using a pseudo-online paradigm where the last quarter of trials were used for testing.

I. Our findings confirmed the presence of an interaction ErrP, with a negative peak at 180 ms, followed by two positive peaks, respectively, at 400 and 630 ms post-feedback onset. There were however departures from literature in terms of latencies, which are expected given the different experimental protocols used to elicit error responses [1]. The latencies in this study were longer than most of those reported in literature, which can be attributed to the gradual feedback, resulting in a delayed perception of the BCI decision.

II. For binary (task and idle) and ternary (2 tasks and idle) classification, across-participant average accuracies of 76%±12 and 63%±12, respectively, were attained. Dyson et al. reported an average offline binary classification accuracy of 68% between an idle state and a mental task (one of motor imagery, auditory imagery, mental arithmetic or navigation imagery) [34] while Agarwal et al. [2] achieved an average offline ternary classification accuracy of 69% in discriminating among left/right MI and word generation. Our task classifier reached comparable ternary accuracies online.

III. An average area under curve (AUC) of 0.83 ± 0.08 was reached across participants for the detection of ErrPs. The results are comparable to that reported in existing literature. Zeyl and Chau reported an average AUC of 0.81 in a visual P300 speller [185]. An accuracy of 80% was achieved for ErrP detection by Bhattacharyya et al. in a motor imagery BCI in one study [9] and 93% in another [10]. They attributed their high accuracy in [10] to protracted training times of at least 60 hours.

IV. After applying ErrP-based error correction, the average binary and ternary classification accuracies of mental tasks improved by 9% and 14%, respectively.
V. Our findings supported the addition of ErrP detection and ErrP-informed correction to maximize the accuracy of BCIs based on cognitive tasks.

2. Designed and tested a three-class active online EEG-BCI based on cognitive rather than MI tasks and investigated the effect of ErrP-based error correction, i.e., to automatically correct erroneous classifications by exploiting ErrPs. To the best of our knowledge, this was the first report of exploiting ErrPs to improve the performance of an active BCI based on non-MI cognitive tasks.

I. For each participant, a ternary BCI differentiated among idle state and two personally selected cognitive tasks (e.g., mental arithmetic, counting, word generation, and figure rotation). An average ternary classification accuracy of 60%±14 was obtained across participants, with nine out of ten participants surpassing the chance level.

II. For ErrP classification, an average TPR of 0.59±0.23 and FPR of 0.21±0.21 was obtained across participants with seven out of ten participants surpassing the chance level. These average values are within the range of those reported in existing literature [10, 9, 83, 43]. Bhattacharyya et al. [10] obtained higher error potential detection, which can be attributed to their higher BCI task classification accuracy, making errors more rare and hence eliciting stronger and more easily detectable brain responses. Their high BCI performance was attributable to the extensive user training time (60-80 hours). The BCI’s task classification error rate inversely relates to the performance of the ErrP classifier (i.e. higher BCI error rate tends to suppress the ErrP classification accuracy [17]). Hence, in general, it can be expected that when a BCI performs poorly, the performance of the associated error detector diminishes as well.

III. ErrP-based error correction modestly but significantly improved the average online task classification accuracy (+7%) as well as the information transfer rate (+0.9 bits/min) of the ternary BCI across participants. Ferrez and Millán showed that applying error correction for two participants reduced the error rate from 32% to 7% which subsequently tripled the bit rate [43]. Kreilinger et al. demonstrated an improvement in accuracy of 11% post-error correction averaged over three participants [83] but ITR values were not reported. Given the modest number of participants in these studies, the significance of these results cannot be ascertained. Bhattacharyya et al. [9, 10] conducted two studies of ErrP-based error correction reporting higher ErrP-corrected performance in controlling a robotic arm. However, they did not report pre- and post-correction accuracies and ITR values, but rather robot targeting metrics to estimate the improvement. Nonetheless, these studies collectively indicate potential value of ErrP-based error correction in active, MI-based BCIs.

3. Designed and tested an asynchronous BCI using EEG and based on non-motor imagery cognitive tasks and investigated the possibility of improving its performance using ErrPs. To the best of our knowledge, this was the first report on exploiting ErrPs to improve the performance of an asynchronous brain switch.

I. Without using ErrP, an average success rate of 0.78±0.12 and a positive precision value of 0.83±0.13 was reached across participants. The performance of the asynchronous BCI was comparable to that of previous EEG brain-switches. Mason and Birch developed a brain-switch based on finger movement. They achieved offline TP rates in the range of 0.38 to 0.81 and FP rates in the range of 0.03 to 0.12 over five participants [98]. In [153], Solis-Escalante et al. developed a MI-based
asynchronous BCI that was trained based on motor execution data. Six out of nine participants obtained offline TP rates between 0.50 to 0.88 and the average FPR was 0.09±0.04. Muller-Putz et al. reported hit rates between 0.69 and 0.8 and precision values between 0.75 and 0.93 for a single-channel MI-based asynchronous system [109].

II. For ErrP classification, an average TPR of 0.79 ± 0.14 and TNR of 0.92 ± 0.07 was obtained across participants.

III. The average of post-error correction success rate and positive precision value across participants both improved significantly to 0.85 ± 0.11 and 0.92 ± 0.11 compared to the pre-error correction values (p < 0.05 using the Wilcoxon signed-rank test). In [10], Bhattacharyya et al. confirmed that adding error detection improved the performance of their asynchronous BCI. Error-correction increased the success rate (the number of times of successful target attainment over the total number of attempts) from 55 % to 86 %. Our study also showed that adding ErrP-based error detection significantly improved the average trial success rate by 7% from 78% to 85% over participants. These results suggest the feasibility and benefits of adding error detection to asynchronous BCIs.

IV. Our findings supported the addition of ErrP-correction to improve the performance of asynchronous BCIs.

6.1 Future Work

6.1.1 Investigating ErrPs in more realistic settings and scenarios

All studies within this dissertation were conducted in a quiet room to minimize the effects of distraction and help participants maximize their focus on task performance. However, such environment is not necessarily representative of environments of regular BCI use such as homes, classrooms, or outdoor, where there is an abundance of distractions. For future studies, presence and effect of ErrPs in BCIs used in such realistic settings and scenarios can be investigated. Future research can also investigate ErrPs when BCIs are used to control an assistive device such as a robot or wheelchair. It has been shown in literature that different experimental protocols and feedback design can affect the characteristics of ErrP waveforms [73]. Hence, the reliability of ErrP detection and its potential in improving the BCI performance can be explored and optimized for various assistive devices. Note that the assistive device does not need to necessarily be controlled by the user’s brain signals. In other words, ErrPs potentially can be exploited to improve the performance of non-BCI assistive devices which make mistakes.

6.1.2 Considering collecting more data

For future studies, we suggest the use of additional sessions and collecting more data. Increasing the number of trials can potentially enhance classifier performance in various ways. First, a more effective mathematical model can be trained for classification using more data. For example, in all of the studies in this thesis, the regularization parameter was optimized separately for each participant and for each classification problem. Additional sessions and extra trials may enhance the generalizability of the classification models and mitigate the need for such customization. Secondly, users’ brains can also learn from the BCI decisions and feedback which may result to a better performance [147]. Our findings in Chapter 4 showed improvement in the ErrP classification performance in later test blocks compared to
earlier one, which is possibly due to the increased training data. Additional sessions would shed further light on the achievable ErrP classifier performance and robustness. Additionally, upon the availability of enough trials, more sophisticated classification models, e.g., deep learning networks, can potentially be trained and tested.

6.1.3 Exploring multi-choice asynchronous brain switches and the effect of ErrP-guided error correction in their performance

In this thesis, we explored a binary asynchronous brain switch and demonstrated that exploiting ErrP can significantly improve its performance. For future studies, we suggest investigating multi-choice asynchronous brain switches, where more than one cognitive task can be used to activate the BCI. Using ErrP-guided error correction in such setting can potentially improve the BCI performance as it can be used not only to correct false positives, but also to correct the BCI decisions when the presence of an activation (i.e., a cognitive task) against the idle state is detected correctly but the type of the cognitive tasks is detected erroneously.

6.1.4 Validating the findings with different age groups as well as potential BCI users

The results presented in this thesis are promising. However, they are yet ready for clinical translation. The findings herein must be first replicated with individuals from different age groups, and more importantly, individuals who present as locked-in, as the main target population of BCI research. It has been previously shown that the characteristics of some brain responses, such as P300, can be different in various age groups [131]. All the studies in this thesis were conducted on young adults. Future research can investigate the changes in the characteristics of ErrPs and their detectability in BCIs based on active tasks in the pediatric and elderly populations. To date, the sample size and number of BCI studies on candidate BCI users, individuals who present as locked-in and with limited or no voluntary movement, have been limited [107, 151]. Testing ErrP-guided error correction in active BCIs with different clinical populations is required to determine what modifications will be required upon their eventual clinical implementation.

6.2 Peer-reviewed publications

Three peer-reviewed journal articles have resulted from this work. They are listed as follows:


In addition to these, two other peer-reviewed journal articles were completed during my Ph.D., but are not part of my thesis. They are listed as follows:


Bibliography


[158] Georgios A Tagaris, Wolfgang Richter, Seong-Gi Kim, Giuseppe Pellizzer, Peter Andersen, Kâmil Uğurbil, and Apostolos P Georgopoulos. Functional magnetic resonance imaging of mental rotation


