Event-Related Potential-based Brain Computer Interface Speller based on a Novel Sequential Protocol

Ahmet Can Mercimek

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Abstract

Most BCI spellers based on visual stimulus presentation rely on the oddball effect, which causes the brain to respond with a P300 ERP to a rare random stimulus of interest (e.g., the flashing of the letter the participants intends to input). Naturally the information transfer rate (ITR) of a speller depends on how many such relevant stimuli one can react to in a given time. So, fairly short SOAs are commonly used, resulting in a reduced amplitude of P300s, very big deformations w.r.t. to its text-book shape, and the contamination from near targets (where a P300 like ERP may be elicited). All of which, hampers classification accuracy and correspondingly limits ITRs.

In previous research on a BCI for mouse cursor control, a sequential non-oddball-based stimulation protocol was developed where 8 stimuli (representing different directions of desired movement) were arranged in a circle and were flashed sequentially. The colour of the flashes was randomly chosen and participants were asked to mentally name the colour of the attended stimulus. This produced better recognisable P300s and, so, significant improvements of AUC and ITR.

In this thesis we apply this idea to a BCI speller, where 36 letters are organised around a circle and they are highlighted sequentially in either green or red and users need to mentally name the colour of the target letter. Each revolution required 2 seconds in one experiment and 3 seconds in another experiment. We compared this speller against a traditional 6 × 6 matrix speller where all letters are highlighted twice (row and column) also within 2 seconds or 3 seconds. All participants used both protocols in counterbalanced order. Results show that our sequential speller produces much bigger and cleaner P300s and, in the 2 second condition, this leads to a significantly higher classification accuracy and approximately doubles the ITR w.r.t. the Donchin's speller.

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List of Abbreviations

AMYOTROPHIC LATERAL SCLEROSIS	ALS
AREA UNDER THE CURVE	AUC
BRAIN-COMPUTER INTERFACE	BCI
CANONICAL CORRELATION ANALYSIS	CCA
CEREBRAL PALSY	CP
COMMON SPATIAL PATTERNS	CSP
CONTINGENT NEGATIVE VARIATION	CNV
DIGITAL SIGNAL PROCESSING	DSP
EDGES PARADIGM	EP
ELECTROCARDIOGRAPHY	ECG
ELECTROCORTICOGRAPHY	ECOG
ELECTROENCEPHALOGRAPHY	EEG
ELECTROMYOGRAPHY	EMG
ELECTRO-OCULOGRAPHY	EOG
EVENT-RELATED POTENTIAL	ERP
EVOKED POTENTIALS	EPS
FAST FOURIER TRANSFORM	FFT
FUNCTIONAL MAGNETIC RESONANCE IMAGING	FMRI
GLOBAL BURDEN OF DISEASES	GBD
INDEPENDENT COMPONENT ANALYSIS	ICA
INFORMATION TRANSFER RATE	ITR
INTER-STIMULUS INTERVAL	ISI
LINEAR DISCRIMINANT ANALYSIS	LDA
LOCKED-IN SYNDROME	LIS
MAGNETOENCEPHALOGRAPHY	MEG
MAGNETOENCEPHALOGRAPHY	MEG
MICROVOLT	μV
MOTOR IMAGERY	MI
MOTOR NEURONE DISEASE	MND
MULTIPLE SCLEROSIS	MS
NEAR-INFRARED SPECTROSCOPY	NIRS
PRINCIPAL COMPONENT ANALYSIS	PCA
RANDOM SET PRESENTATION	RASP
RECEIVER OPERATING CHARACTERISTIC	ROC
ROW/COLUMN PARADIGM	RCP
ROW-COLUMN SPELLER	RCS
SIGNAL-TO-NOISE RATIO	SNR
SINGLE CELL PARADIGM	SCP
SLOW CORTICAL POTENTIALS	SCPS
STEADY-STATE VISUAL EVOKED POTENTIAL	SSVEP
SUPPORT VECTOR MACHINES	SVM
TARGET-TO-TARGET INTERVAL	TTI

Chapter 1

Introduction

Certain individuals may develop Motor Neurone Disease (MND), either at birth or in later stages of life, that results in a decrease or complete restriction of their motor functions. Locked-in Syndrome (LIS), Amyotrophic Lateral Sclerosis (ALS), Multiple Sclerosis (MS), and Cerebral Palsy (CP) are motor-neurone diseases that impair motor function and result in a dependent life for the patient. For affected individuals, who face physical limitations and challenging living circumstances, it is crucial to retain communication with their surroundings for psychological well-being and to fulfil their fundamental needs. Efforts are underway to develop devices, software, and concepts that facilitate communication between individuals with disabilities (or other limitations) and their surroundings.

BCIs, as in the field of MND, have proved to be distinctly advantageous and valued due to the ability to provide interaction, enabling a patient to fully communicate and interact with their surroundings using only their brain signals. The most common forms of BCIs in MND are spelling tools and systems to interact with or move in the user's surroundings. These systems utilize state-of-the-art machine learning algorithms to analyse different patterns of brain electrical activity such as P300 Event-Related Potential (ERP), seen between 300ms and 600ms milliseconds after receiving relevant stimuli in the brain. As MND worsens, these BCIs can be adjusted to meet the patient's changing demands, ensuring an interaction channel is maintained even in the later stages of the disease. Recent studies have shown that BCIs both contribute functional assistance while boosting the patient's sense of autonomy, mental well-being, and reduced sense of isolation [1]. BCIs are an essential technological innovation in the control and care of MND patients. There is the possibility of more extensive enhancements as new technology and an enhanced understanding of neural processes are established. It is feasible to apply BCI technologies in various health areas, including Assistive Technology for Disabled, Neurofeedback and Mental Health, Medical Rehabilitation, Research and Cognitive Neuroscience. Moreover, is feasible to apply BCI systems in the areas of Education [2], Gaming and Virtual Reality [3], [4], Military and Defense [5], [6], and Consumer Electronics [7], [8], thanks to continued technological advancements.

Depending on whether BCIs are invasive, semi-invasive, or non-invasive, they exhibit various levels of performance and risk. *Invasive BCIs*, such as involving the implant of electrodes directly into the brain, provide high quality signals that allow for accurate control of assistive technologies, which is vital for patients with severe MND [9]. However, there are considerable risks; these include the risks of infection and of inflicting neurological harm [8]. *Semi-invasive BCIs* require the insertion of electrodes under the skull, but not inside the brain tissue. Such an approach offers a better noise-to-signal ratio than non-invasive BCIs at the same time reducing health risks due to the lack of the direct contact with a brain tissue [11]. The safest and most easily accessible BCIs are *non-invasive BCIs*, including EEG-based ones. They do not require surgery and pose the fewest health risks. Nevertheless, the quality of their signals is significantly lower, which may limit their ability to properly understand patient intentions, especially in complicated tasks [12]. The balance choice for each approach depends mainly on the severity of the patient's disease, the target application, and the risk the patient is willing to take.

The three most common non-invasive BCI approaches are based on: SSVEP, MI, and P300. *SSVEP BCIs* are a kind of BCI that utilizes the brain's strong oscillatory reaction to visual stimulation at specific frequencies to create high-speed communication systems or interfaces. A *MI-based BCI* is a method that uses electrodes positioned on the scalp in proximity of motor regions of the brain and measure specific neural patterns when a subject imagines physical activities such as hand or foot movements. It is mostly applied in prosthetic control and rehabilitative techniques. On the other hand, *P300-based BCIs* rely on a prominent event-related potential component resulting from the brain's response to infrequent (attended) stimuli. A P300-based BCI is an excellent choice for a control and communication because of their relatively information bandwidth. BCI technology using the P300 response enables a very isolated individual, such as someone with extreme disabilities, to manage the environment or control a computer (e.g., for spelling and mouse control) in real-time.

SSVEP BCI spellers can achieve reliable brain signals by providing continuous stimuli at particular frequencies, resulting in accurate classification results. Hybrid BCI spellers achieve both high ITR and classificationaccuracy via the combination of multiple BCI paradigms, such as SSVEP, MI, and P300-based (both visual and auditory).

Because of the various disadvantages of other paradigms and the relative advantages of P300-based spellers, which are discussed in detail in Section 2, P300-based spellers were the focus of this thesis. P300-based spellers vary according to the interfaces they use, some interfaces providing easier usability and better results. In addition to the Row/Column paradigm, which was the first of these P300-based interfaces and which we refer to as the *Donchin method* in this thesis, there are various other paradigms such as Single Character, Region-based, Face Flashing, T9, 3D and Virtual Reality. Based on the strengths and weaknesses of these methods, in this thesis we will propose a new paradigm that offers good performance and may create a new area of future BCI-spelling research.

1.1 Motivation and Objectives

Despite epidemiological studies on MND in the United States of America and Europe, its indices, prevalence and burdens are not well known because the disease is rare. Nonetheless, there are various rates obtained from the studies [13], [14], [15]. The incidence in relation to age is notably high in high-income regions such as Europe, Australasia, and North America, with the exception of the Asia-Pacific region [16]. The peak occurrence of ALS, which can differ based depends on factors such as age, sex, and geography, is often around the age of 70. The rate of new cases of ALS is 1.7 per 100,000 person-years, while the number of people already living with ALS is 4.5 per 100,000 individuals [17], [18]. In addition, based on the 2016 Global Burden of Diseases (GBD) estimates, the overall incidence rate of MND for all age groups is 0.78 per 100,000 person-years [16]. Affected individuals experience significant communication limitations with their surroundings as a result of impairments in their musculoskeletal and neural systems, leading to various challenges. [13], [14], [15], [16], [17], [18]

Researchers working on BCI systems have focused on hardware/software instruments, neuro imaging techniques, signal processing, classification, and interface designs. In our study, we focused primarily on the interface design, the acquisition and effect of the signal by the user. The questions that are the starting point of the method we have developed are listed below:

Q1- What are the advantages and disadvantages of existing P300-based BCI paradigms? How can the difficulties faced by users be mitigated when designing a new interface model? What are the cognitive processes that need to be considered for an interface that can produce a distinctive ERP? What are the cognitive processes that should be considered for an interface that can produce a significant ERP?

Q2- Which points/features are most critical for the effective implementation of P300-based BCIs? How can their interaction (e.g. stimulus design, timing, interface layout) be optimised to improve user performance, comfort and accuracy?

Q3- How do variations in Stimulus Onset Asynchrony (SOA) and Target-Target Interval (TTI) affect P300 amplitude and classification accuracy? What adjustments can be made to maximise both signal quality and user experience?

Q4- What suggestions can be made for a sequential paradigm using a variety of stimulus presentations (e.g. colour combinations) tested in previous studies to address the problems of adjacency, crowding and fatigue associated with the classical Row/Column paradigm?

Q5- Can signal processing (e.g. band filter, PCA), classification methods (e.g. LDA, SVM), which are frequently used in current studies, provide a good alternative for the sequential speller paradigm? How can the possible negative effects of imbalanced dataset be minimised in the classification stage?

1.2 Contributions

This study builds upon the BCI Mouse paradigm created over a decade ago by the members of the Essex BCI (M. Salvaris, C. Cinel, R. Poli, L. Citi, and F. Sepulveda) [19]. However, spelling represents a more difficult task as it requires expanding the command set from the original 8 possible directions of movement of the BCI mouse to the 36 letters and numbers of a BCI speller. Our primary goal was to design a system that is stable, efficient, has a promising ITR and produces classification accuracies in line with current studies.

This has been achieved to a very significant degree. While there are some missing elements in the system (as mentioned in Chapter 6), the system presented in the thesis has been shown to perform better than Donchin paradigm, and in the future might become competitive with some more recent improvements presented in the literature.

The appropriate techniques from Neuroimaging and signal processing methods were identified, and the characteristics of these methodologies that are compatible and incompatible with our system were elucidated. This will provide guidance for neuroimaging and signal acquisition techniques that can be employed in future investigations with similar paradigms.

The results obtained by testing the signal processing, feature selection/extraction and classification techniques used in P300-based BCI systems provide ideas for future similar studies. In particular, the suitability of the classification techniques for sequential systems was tested and the differences from the classification of signals generated by traditional random stimulation approach were determined. We have also investigated techniques to address potential problems in imbalanced datasets, such as Resampling or SMOTE, which can also work effectively in P300-based BCI systems.

The subjects' fatigue levels, concentration, and focus areas on the screen were determined while and after using the paradigm. Based on the verbal feedback, the extent to which these problems could be solved compared to previous research was assessed and possible alternatives for improving the speller were identified.

Our study has revealed that extended periods of time between stimuli, known as inter-stimulus intervals (ISIs), do not consistently yield improved outcomes. In fact, in certain instances, they can hinder the success of classification due to the negative effects of fatigue and decreased concentration. The effects of ISI durations were not investigated for the first time in this study. However, it was observed that longer ISI duration did not produce higher accuracy/ITR for the Circular speller than shorter ISI duration.

1.3 Thesis Structure

The thesis has the following structure:

Chapter 2 provides the relevant background. In Section 2.1, firstly, the working principles of the current BCI paradigm types are illustrated by providing examples. After giving examples of SSVEP, MI, Hybrid, detailed examples of P300-based BCI systems are presented and their history and contributions to the field are indicated. Individual figures showing different P300-based BCI paradigms are presented and a comparison between the interfaces is provided. This is followed by a brief overview of BCI systems and their history.

Chapter 3 provides information on BCI methods, including signal acquisition, signal processing and classification techniques. The methods used in the field of BCI are described in general terms and more details are provided for the preprocessing, feature extraction and classification methods we have chosen to use in our study. The experimental protocol is introduced and detailed information about the processes of the interface used is presented.

In Chapter 4, from the preliminary stages to the evaluation results, our three-second experiment is comprehensively described in detail. It is explained how the features required for classification were determined. The results are analysed in detail and the factors affecting the ERP amplitudes, AUCs and character classification of the Circular method are discussed. After analysing the results, the Circular and Donchin methods were compared. The advantages and weaknesses of our proposed new method (Circular) and the Donchin method were identified and the findings were used to guide the next study.

In Chapter 5 we describe our second study. Based on the results of the 3-second experiment, we reduced the duration of the experiment to 2 seconds to allow the subjects to focus better and be less tireed. Every step of the 2-second experiment was executed as for the 3-second experiment described in Chapter 3. The results of the performance increase in the Circular method are listed and the reasons are analysed.

Chapter 6 is the concluding chapter. Within it, the results obtained in Chapter 4 are shown to be promising, and that the stage is set for publishing them. However, the results of the proposed study show that the paradigm has some shortcomings and aspects that are open to improvement, and these findings are explained in detail in Chapter 5. Based on the acquired results and feedback from the participants, further investigations and proposed improvements are also discussed in the chapter.

1.4 Ethical Matters

Since BCI systems obtain, use, interpret and produce results from the brain signals of the subjects, they need to be user-approved and user-friendly. Ethical approval and follow-up of all processes from the acquisition of signals to the publication of the test results obtained should be carried out and possible risks should be prevented. For example, unauthorised and misuse of data, experiement that may harm the subject, or failure to take precautions against health problems such as allergies and panic. These procedures must be implemented for the protection of personal data security.

In this study, the EEG device, other hardware instruments and laboratory environment were provided by the BCIs-Neural Engineering laboratory at the University of Essex and all experiments were conducted in accordance with the guidelines of the University of Essex Ethics Committee. The study was approved by the Ethics Committee of the University of Essex on 18th of January, 2019. The Ethical Approval form for Experiment 1 in Appendix A was changed due to Covid and a different Ethics Approval form for Experiment 2 was created on November 16, 2021.

Chapter 2

Background and Literature Review

This chapter provides an overview of previous and current research in the topic of BCI spellers, including their categorization and the entire BCI process, from data collection to feedback. These processes are commonly summarised as data collection, signal processing, feature selection/extraction and classification.

2.1 Brain Computer Interface

A brain-computer interface (BCI) is a system that translates brain activity into (in almost real time) functionally useful outputs. It is a system that modifies, restores, enhances, complements and/or improves brain normal outputs, accordingly manipulating the sequence of interactivity between the brain with its outside or internal environments. It can thus adjust brain activity using precisely trained stimulus action to induce functionality related signals to the brain [20].

BCI is a interdisciplinary field involving mathematics, statistics, computer science, bioengineering, neurology, physiology, neuroscience, and electronics engineering, and is evolving every day with the discovery of the mystery of the brain. Despite the rapid advances in this field, due to the complex nature of the brain, it also contains various challenges that require solutions and further exploration. Section 2.1.1 introduces the basic concept of BCI systems and provides an overview of their first studies. Section 2.1.2 provides a comprehensive and organised overview of the objectives, approaches, and rates of success of current studies.

2.1.1 Development of BCI

Following Hans Berger's discovery of electroencephalography (EEG) in the 1920s [21] , there was an increased focus on studying the functions, operations, and neurological illnesses of the brain with more detail. The BCI research initiated by Professor Jacques J. Vidal in the early

1970s [22] , funded by DARPA, the US military research agency, and conducted under the roof of the University of California, can be considered as the first studies in this field. It has been shown that a computer-generated visual stimulus can elicit a certain response from individuals, potentially creating a means of communication between a human and a computer.

2.2 Types of Brain-Computer Interface

Brain-computer interface (BCI) systems can be categorised based on type of signals, the methods of signal acquisition.

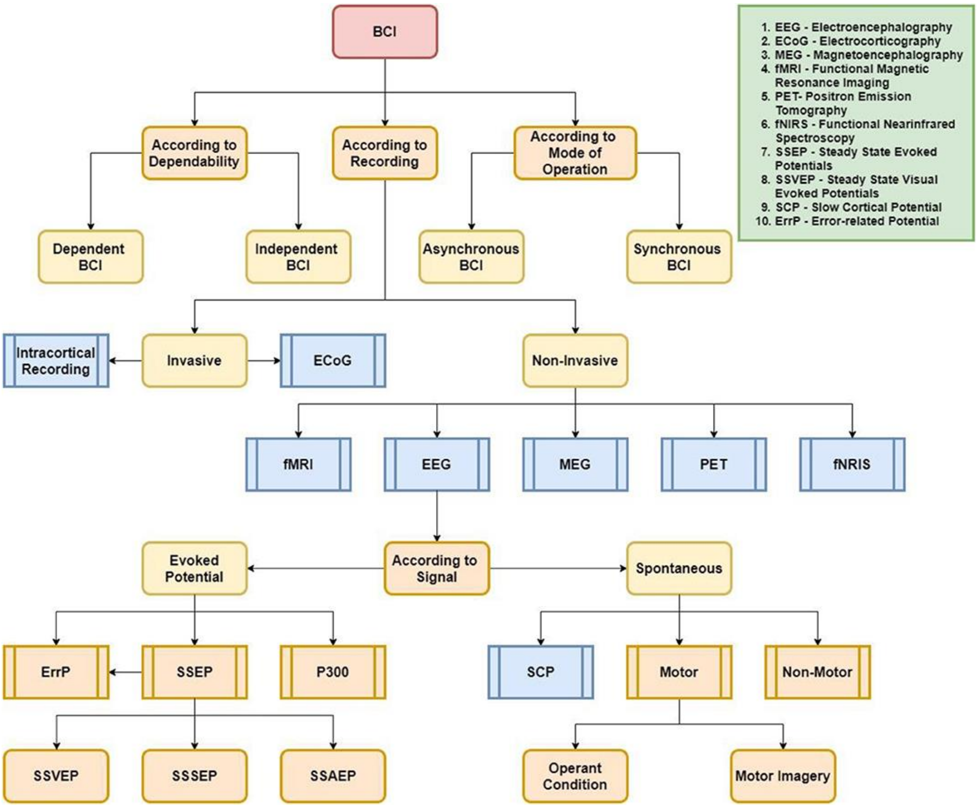


Figure 2-1 Taxonomy of BCI systems according to mode of operation, neuroimaging techniques, and dependability [23] .

Diverse methodologies exist for categorising BCI types. Figure 2.16 shows the BCI structure classified according to mode of operation, neuroimaging techniques, and motor-control-dependence [24]. The subsequent sections provide an overview of various types of BCIs and elucidate the rationale behind the selection of specific types.

2.2.1 Dependent and Independent

Dependent brain-computer interfaces necessitate the user to possess a certain degree of influence over their muscle activity or respond to an external stimulus in order to function. These systems are frequently utilised in rehabilitation environments to improve or recover motor function in individuals with impairments. A dependent BCI system is using visual evoked potentials of a user reaction to a visual stimulus to enable a user to control a computer cursor. Since the user needs to detect the external stimulus of operation and to respond to it, as a result, it is classified as dependent [12].

In contrast, an independent BCI system is a device able to operate without a user commanding it with muscle control or needing to respond to an external stimulus. Such a system is especially beneficial for people with serious motor disorders, such as those diagnosed with ALS or LiS, since it allows them to communicate and control a machine independently of their physical capabilities. This type of BCI is based on “motor imagery,” meaning that the user imagines moving a body part, and the BCI system detects these intentions and uses them to control an external equipment [25], [26].

Dependent and independent BCIs both have their own strengths and weaknesses, and the decision between them is based on the user's particular requirements and capabilities. Dependent BCIs may be more accessible for certain persons, but their effectiveness is constrained by the user's capacity to detect stimuli or control muscular activity. Independent BCIs provide increased autonomy but may necessitate additional instruction and focus to operate efficiently.

The proposed Circular speller method represents a dependent BCI, similar to many existing spellers, in the context of developing a new speller paradigm. This also helps in the comparison with Donchin's speller, which is dependent. We can always say that in the future we hope to be able to turn it into an independent speller (e.g., using auditory stimuli, like a voice that repeatedly reads aloud the alphabet but where each letter is pronounced either by a female or a male voice and the task is to mentally name male/female).

2.2.2 Asynchronous and Synchronous

Asynchronous BCIs allow users, especially those with significant physical limitations, to communicate with computers and assistive devices instantly, without being limited by previously determined triggers or sequences. These interfaces analyse the user's brain impulses in real-time to detect intentions to begin instructions, enabling a more natural and intuitive connection. Asynchronous BCIs require complex signal processing and machine learning methods to effectively interpret signals as precise commands, while reducing false positives and assuring reliable communication [27].

The main issue with asynchronous BCI technology is that it relies on intricate algorithms to distinguish arranged actions from continuous brain signals. Advanced signal processing is required to accurately extract features from EEG data, as well as robust machine learning models that can learn from and adjust to the user’s individual brain patterns. In order to overcome these difficulties, much research has been done in this field to enhance the accuracy, speed, and user-friendliness of BCIs and extend their use to a more general population [28].

Synchronous BCIs are implemented in an orderly environment, and the user communicates with the device within specific time sequences. BCIs are in charge of timing events and responses, and how the system determines the purpose of the user is competently controlled. This implementation of the system’s operations is helpful in research and recovery environments, which need a high degree of time control over actions [12].

Synchronous BCI is carried out in a particular process, whereby a target or trigger is presented to the user. The system then waits for the user's brain to respond, after which the resulting activity is evaluated during a limited timeline to determine the user interface's aim. The setup stimulus generation waits for the user's response output, and then the system is analysed after a consistent period from which the outcomes guide the sequence. This BCI organization becomes more useful, and the action of the user identifies the interface outcomes. It is beneficial in such activities as spelling systems, where the matrix highlights different letters and characters [9].

2.2.3 Invasive and Non-invasive

Invasive BCIs are a method in neurotechnology that allows direct connection between the human brain and external devices. Thus, even though these systems still require interaction with the human skull and scalp, invasive BCIs have succeeded in obtaining detailed signals by introducing neurosensing devices into the patient's brain and, as a result, ensures adequate practices with apparatus in a connected chain. Since the invasive BCI activity is based on precise and direct connection to the brain's neural signals, this connection technique enables better brain signalling. This enables the improvement of motor functions in individuals with severe physical disabilities and enables a variety of sophisticated methods of communication in addition to sensory input. [9], [29].

It should be noted that invasive BCIs are promising, but they carry some further activities and issues, mainly associated with the surgical installation procedures and long-term biocompatibility. These devices are invasive and must take into account all ethical, safety, and longevity considerations. In addition, the continued and improved development of these technologies will require interdisciplinary investigation, with the expertise from neurology, engineering, and medicine combined to improve the capacity and protection of these systems.

Studies are also looking at incorporating sensory input into BCIs to create a two-way interface that can read brain signals and provide sensory input to the individual [9], [30].

Non-invasive BCIs are of great interest in the neurotechnology field because they make it easier to establish direct contact between the brain and external devices without the need for surgery. Non-invasive BCI-based devices that use methods such as Electroencephalography (EEG), Magnetoencephalography (MEG), and Functional Near-Infrared Spectroscopy (fNIRS) are capable of registering cortical activity from the surface of the scalp. These interfaces have made a significant contribution to the development of applications for assistive technologies, where people with severe physical restrictions have to control prosthetic limbs, computer cursors, and other equipment exclusively through neural commands. Noninvasive BCIs are appealing due to their safety and higher acceptability for more extensive audiences, including patient groups who require rehabilitation and support in communication [27], [31].

Despite the many advantages and opportunities, non-invasive BCIs are encumbered by relatively low signal resolution and precision levels as compared to the invasive alternatives, side-effects of interference from the scalp, skull, and non-neural tissues. The future development of these interfaces will concentrate on further enhancing the existing signal processing technologies and machine learning algorithms to boost the precision and reliability of brain signal interpretation. Notable research efforts are being made to make it easier for the user and simpler to set up, as well as to enhance the system’s capability to identify, accurately interpret, and adjust according to the specific needs and characteristics of each user [32], [33]. Eventually, modern BCI systems should be hands-off, reliable and user-friendly, making it better suited for real-world usage, including at homes and workplaces and accompanied by day-to-day tasks.

2.3 Brain Imaging Techniques

Brain imaging techniques are crucial for BCIs as they can establish the connection between the human brain and external hardware. These methods, therefore, enable the interpretation of neural signs reflecting the user's intentions, which can then be transformed into commands used to manipulate a computer, a prosthetic arm, or any other useful system. The choice of method of brain imaging greatly determines a BCI's framework, features, and use. Indeed, each of these instruments has some benefit as well as a special drawback.

Magnetoencephalography (MEG) and Functional Magnetic Resonance Imaging (fMRI) are usually included in BCIs due to their superior spatial resolution relative to EEG. Since alterations in blood oxygen amounts and circulation brought on by cerebral activity may be utilized to create a practical map of the brain, fMRI allows for a highly accurate image of brain function. Nonetheless, due to their moderate temporal resolution, and the need for significant, expensive gadgets, this approach is currently quite useful for real-time BCIs with use-fMRI. MEG, on the other hand, establishes a proper spatial and temporal resolution since it identifies magnetic fields generated by brain activity. However, it is similarly intricate and costly, limiting its wide use [34].

Near-Infrared Spectroscopy is a non-invasive new brain imaging technology, relying on variations in blood oxygenation in the cortex and measuring the scalp's visible light absorption. NIRS is portable and less restrictive compared to fMRI and MEG and is more convenient for BCI in real-time. NIRS becomes widespread for portable wearable BCI systems, but the technology has low spatial resolution and is very susceptible to superficial scalp signals [35] . At present, EEG is the most widely used non-invasive brain imaging method in BCI due to its excellent temporal resolution, user acceptability, and low cost. EEG measures the brain's voltage using electrodes on the scalp. It is suitable for detecting signals when a cognitive task, movement objective, or sensory processing are elicited. For dynamic BCI applications, the benefit of EEG is its high-speed interpretation of user intention despite low spatial resolution [27].

Table 2.1 Advantages and disadvantages of brain imaging techniques

Brain Imaging Technique	**Advantages**	**Disadvantages**
EEG (Electroencephalography)	-Non-invasive -Portable and affordable -Good temporal resolution -Realtime signal recording	- Limited spatial resolution - Sensitive to artefacts caused by muscular movements and external electrical interference
MEG (Magnetoencephalography)	- Non-invasive -The spatial and temporal resolution are well balanced.	- Expensive - Requires facilities that are specialised - More limited in availability compared to other techniques
fMRI (Functional Magnetic Resonance Imaging)	- Non-invasive -High spatial resolution - Capable of identifying certain brain areas responsible for tasks	- Costly and heavy hardware - Needs an regulated environment - Slow temporal resolution
NIRS (Near-Infrared Spectroscopy)	- Non-invasive - Appropriate for use in wearable devices - Portable and affordable	- Poor spatial resolution compared to other techniques - Restricted depth of penetration (ideal solely for cortical imaging)

As shown in Table 2.1, we used the EEG device in our study because it is portable, affordable and offers good temporal resolution.

2.4 Brain-Computer Interface Paradigms

BCI methods are classified according to the type of brain activity they use: Motor Imagery (MI), Steady-state Visual Evoked Potentials (SSVEPs), and Event-related Potentials (ERPs). ERPs are physiological brain responses to single internal or external sensory or cognitive stimuli. The P300 ERP is commonly used in BCI applications because of its high amplitude, duration, and repeatability [35]. SSVEPs are brain responses to periodic visual stimuli of specific frequencies and are relevant to BCIs due to the fast reaction and minimum traning [37]. MI involves the subjects imagining the movement of different body parts, which elicits characteristic rhythm patterns, which are then recognized by BCIs to control receivers or for assistance in rehabilitation [38]. The subsequent information presents an inclusive description of several of the prevalent BCIs paradigms to support the work plan or refer to scholarly sources.

2.4.1 Motor Imagery-based BCI

MI-based BCIs take advantage of the fact that the brain can generate distinct neural patterns associated with movement imagination or intention without any real performance. This capability is exploited by recording the brain’s electrical activity using EEG sensors during imagining movements [39]. The performance of the primary motor cortex is planning, regulating, and executing voluntary muscle movements. However, even when no real movement occurs, the primary motor cortex exhibits unique patterns of activity. MI BCIs can recognize and interpret these patterns and use them to control external devices or software programs, making it a potential option for people with severe motor impairments to communicate or interact with their peers. MI BCIs process signals using methods such as common spatial patterns (CSP) for feature extraction and classifiers such as support vector machines (SVM), and linear discriminant analysis (LDA) to distinguish between different motor tasks [38], [40].

BCIs have a wide range of uses. In particular, they have demonstrated their promising potential in neurorehabilitation and in enhancing the virtual reality experience. MI have presented an innovative path for users to collaborate with their environments by granting those users with disorders such as a spinal cord injury, stroke, amputees, and others who might have been incapable to handle a robotic limb, walk or even computer work to enhance their flexibility and real-life operation. In addition, the use of MI throughout recovery has presented a lot of possibilities for improving neural plasticity and assisting brain function rectification. Ongoing increases in the field of MI BCIs attempt to enhance their movement (portability) restrictions, usability, and availability. Therefore, the occurrences of this technology represent an important part of the advancement in neurotechnology, human-computer integration, and control frameworks [41].

2.4.2 Steady State Visually Evoked Potential-based BCI

Steady-State Visual Evoked Potential (SSVEP)-based BCIs make use of the brain's natural response to visual stimuli that flicker at particular frequencies. Particularly, when an individual looks at a visual stimulus oscillating at a certain frequency, the brain will generate electrical activity at that frequency and its multiples, which can be quantified via EEG. SSVEP-based BCIs boast the fastest information transfer rates and the shortest user training periods of the BCI modalities and, as a result, are the most viable options for applications requiring quick and dependable user input. An EEG dataset is analysed to identify SSVEP signals by examining frequency components in the EEG that match the frequencies of visual stimuli. This simple approach works because SSVEP has a very strong and easily recognizable nature which is able to retain even in the presence of noise in the EEG. Canonical Correlation Analysis (CCA) and Fast Fourier Transform (FFT) are two commonly used processing methods to increase SSVEP detection [37], [42]. It can be particularly useful for users with severe physical impairments to provide a non-muscular means of communication and control, but requires the capacity to twitch in response to stable frequency vibrating stimuli.

SSVEP BCIs have been utilised for creating spelling devices, controlling wheelchairs, and engaging with virtual and augmented reality environments. SSVEP-based systems offer a significant benefit due to their minimum training needs and consistent performance across many sessions and users. Ongoing research is focused on problems including visual fatigue and the restricted range of flashing frequencies that can be utilised without producing pain or epileptic seizures in vulnerable individuals. Advancements in stimulus design, signal processing techniques, and user interface design are always being sought to improve the usability and efficiency of SSVEP BCIs [43], [44].

2.4.3 P300-Based BCI

P300-based BCIs operate by detecting a distinct event-related potential known as the P300. This neurophysiological response is elicited when an individual identifies a single stimulus within a given set of stimuli. Individuals direct their attention towards a specific stimulus, and the BCI system identifies the corresponding P300 response, enabling communication or control [45], [46]. is potential is due to a positive electrical response in the brain which typically manifests from about 300 milliseconds subsequent to the introduction of a meaning-making stimulus to an individual. Several studies have shown that P300-based BCIs perform efficiently in various applications requiring a user to choose any alternatives present such as virtual keyboard systems and typing devices [45].

2.4.3.1 Structure of BCIs based on P300 Evoked Potential

The following is an outline of the fundamental framework of BCIs that rely on the use of P300 evoked potentials.

The presentation of stimuli: The manner in which stimuli are presented is another critical aspect that significantly influences the efficacy and accuracy of P300-based BCIs. In the case of a speller application, stimuli traditionally refer to characters that appear on a computer screen, initially organized into several rows and columns in a matrix format. The system subsequently highlights individual characters in rows and columns sequentially while the user focuses their attention to the target character. Effective display of stimuli is critical in optimizing user engagement and BCI accuracy. The primary determinants in this case include the duration of stimulus presentation, inter-stimulus interval, and the level of randomness in the selection of rows and column for highlighting. These values must be carefully calibrated to maximize the P300 response and minimize user strain and fatigue.

The process of acquiring EEG signals: The acquisition procedure of EEG signals includes a range of vital steps that are ideally planned to record the exact electrical activity of the brain with a minimum threshold of external noise. The 'placing' of the electrodes on the scalp during the first phase is done using recognised techniques such as the International 10- 20 system.

Amplification is a crucial stage in the process, as the EEG signals typically fall within the microvolt (μV) range and necessitate amplification for precise analysis and interpretation. After amplification, signals are digitized: this moment converts analog signals into a computer form [47].

Obtaining high-quality EEG signals is crucial to ensure the reliability of subsequent analysis and consideration. Notably, the field of EEG technology has made solid progress in wireless recording and dry-electrode systems. It significantly improves the level of comfort and convenience for participants, thus expanding the possibility of using EEG in a clinical and research environment [48].

Signal processing: The vast majority of raw data acquired by the electrodes is contaminated by undesired interference known as artefacts that can be either endogenous, originating from muscle movements (EMG), eye blinks (EOG), or exogenous electrical noise. The artefact removal along with preprocessing methods such as filtering and post-amplification are subsequently used to reveal the actual brain activity [49]. Filtering, artifact removal, and baseline correction can be applied to remove noise sources, artifacts, and unimportant frequency components from raw EEG data. Signal processing algorithms are used to obtain features related to the P300 response [CC]. A prevalent signal processing technique for P300 signals involves averaging multiple ERP recordings obtained from several repetitions of the same stimulus [50].

Feature Extraction: Feature extraction is a critical component of BCIs since it facilitates the translation of a user's intention from brain signals, usually EEG, using important characteristics that distinguish different mental states or responses. The time -domain method includes measuring point features such as wave form amplitude and latency. Frequency-domain methods focused on the power spectral density quantify power distribution over different frequency bands. Other spatial filtering methods, such as Common Spatial Patterns , alleviate the signal-to-noise ratio problem for motor imagery by increasing variance for one logic class while reducing it for the other [49], [51], [52]. Advanced methods include utilising machine learning algorithms like support Deep Learning to automatically detect and extract important characteristics from unprocessed EEG data These techniques are essential for enhancing the precision and dependability of BCIs, allowing users to communicate and control more efficiently [53]. In our study, we used the PCA method.

Classification: EEG classification is the process of examining and classifying patterns of cerebral activity caught by EEG sensors. Algorithms acquire knowledge about patterns and relationships between input variables or features and class labels. This learning is done through supervised learning, with labelled training samples fed to the model. The knowledge obtained is then applied to predict data or novel observations. These algorithms primarily use this learned knowledge to create predictions, or classifications, on previously unobserved data and are applied to novel data [14]. When the BCI system recognizes the target stimulus, it activates the associated activity, such as the selection of a target letter, on the controlled application so that the desired action is taken [54].

Feedback: Users have the ability to get feedback in the form of visual or audible cues, which serve to validate their selections or signal that the system is prepared for the subsequent pick.

Calibration: Calibration precedes the use of a BCI, and it implies the adjustment of the algorithm to the specific user’s characteristics. For the first part of the process, the device should collect and record the user’s brain responses to a set of stimuli, so the classification algorithm becomes trained.. Some BCI systems utilize adaptive algorithms. They regularly modify the classification algorithms used for exacting P300 detection, which rely on varying the user’s brain signals over extended periods to confirm their distinctive and sporadic usage [55].

Familiarisation: The majority of users attend training sessions to become familiar with the BCI system and to develop a conscious control over their brain activity [9].

2.4.3.2 Stimulus Source & Format

The P300 is an endogenous ERP characterised by a latency of 300 to 600 ms, triggered by infrequent and/or meaningful stimuli, contingent upon the individual's attention to these stimuli [56], [57], [58] . P300s are researched using the oddball paradigm [59], [60], [61] , which entails the presentation of a sequence of stimuli, including a rare stimulus scattered among normal stimuli. P300 speller protocols make use of characters, symbols, or pictures or letters of visual stimuli presented on a screen in various different formats. An alternate option has been examined by some researchers to be the seatality of auditory or tactile sensations to support the population with visual impairments or enhance the speller effectiveness in the different environment [62], [63].

The amplitude and latency of the P300 are impacted by various factors [58]. The amplitude of P300 increases as the probability of the target decreases [64]. The P300 amplitude shows a positive correlation with the Inter-Stimulus Interval (ISI), defined as the time interval between the conclusion of one stimulus and the initiation of the subsequent stimulus, as well as with Stimulus Onset Asynchrony (SOA), which refers to the time interval between the onset of two consecutive stimuli [65], [66], [67]. A positive correlation exists between P300 amplitude and the quantity of non-target stimuli that precede a target [68], [69]. Some studies indicate that the Target-to-Target Interval (TTI) is the fundamental factor influencing the variations in P300 amplitude that are ascribed to target probability, inter-stimulus interval (ISI), stimulus onset asynchrony (SOA), and the number of previous non-targets [70], [71].

P300 spellers commonly use a matrix structure for visual stimulus, with characters organised in rows and columns. The Row-Column Speller (RCS) is a prominent illustration where rows and columns flash in succession, prompting the user to concentrate on the desired character for selection. The point where the row and column connect and provide the most pronounced P300 response signifies the selected character, as stated by Farwell and Donchin in 1988 [45]. Another approach utilises single-character display, highlighting characters individually instead of in groups. This method may provide higher accuracy but requires more time for choosing [72]. Auditory spellers may distinguish between target and non-target stimuli by presenting stimuli through various spatial locations or modulated tones [73]. Research has explored using dynamic and engaging stimuli, like moving or interactive elements, and adjusting stimulus parameters, such as colour, size, and frequency, to improve P300 elicitation and decrease user fatigue [74].

Donchin's spellers indicate a significant issue that the TTI varies considerably, adversely impacting P300 amplitudes due to the random flashing of rows and columns. The Donchin method presents high variability in the P300s elicited by target row/column flashes. Despite the development of methods that reduce this issue, it inherently compromises the performance of classification algorithms [23]. Another issue with this type of speller involves perceptual errors, including attention blink [75] and repetition blindness [76]. Rapidly presented stimuli are less easily recognised, resulting in insufficient triggering of P300s [77], [78], which, when triggered, typically exhibit small amplitudes.

A common feature of the ERP-based spelling approaches examined is randomness in the order of presentation of letters, which, as discussed earlier, is typically considered critical for triggering larger P300 ERPs. However, we question whether such randomness is necessary in the Circular method. In fact, Farwell and Donchin mentioned in the results of [45] the possibility of abandoning the oddball paradigm to further improve performance. However, to the best of our knowledge, no research has been done on spellers using a regular (hence periodic) flash sequence.

In the Circular method, instead of highlighting more than one character at a time to produce a BCI speller with periodic stimulation (like the rows and colours of Donchin's speller), we highlighted them one at a time. As this produced identical and longer TTIs, it was expected that the resulting P300s would be bigger and clearer than in other spellers and therefore classification would be better. In addition, as suggested by Farwell and Donchin, this would reveal CNVs that could further help classification.

2.4.3.3 Limitation of P300-based BCI

P300-based BCIs exhibit potential in several applications; yet, they are not without limits, which necessitate ongoing efforts by researchers to overcome. The following are several prevalent constraints associated with P300-based BCIs, along with references to pertinent scholarly investigations addressing these issues:

- P300-based BCIs frequently encounter challenges associated with poor ITR, hence restricting the rate at which users may effectively communicate or engage with the device [79].
- The P300 response exhibits variability among individuals and even within the same individual at different time points, posing challenges in establishing a universally applicable framework [80].
- The achievement of sufficient accuracy in P300-based BCIs generally necessitates the undertaking of time-consuming calibration sessions and substantial user training [81].The achievement of sufficient accuracy in P300-based BCIs generally necessitates the undertaking of time-consuming calibration sessions and substantial user training [81].
- The reliability of P300-based BCIs can be considerably influenced by external conditions, such as noise and distractions [82].The reliability of P300-based BCIs can be considerably influenced by external conditions, such as noise and distractions [82].
- The discomfort associated with electrode placement and the need for cap can impose limitations on the accessibility and user-friendliness of P300-based BCIs [83].The discomfort associated with electrode placement and the need for cap can impose limitations on the accessibility and user-friendliness of P300-based BCIs [83].

- P300-based BCIs are commonly employed for discrete selection purposes and are less well-suited for activities requiring continuous control [84] albeit some BCIs for mouse and robotic control have been built.

2.5 Potential applications of BCI and Literature Review

This section provides a description of the paradigms employed in P300 spellers, along with illustrative examples. We describe the purpose of our proposed paradigm by explaining the process of existing paradigms and their advantages and disadvantages. The methods/paradigms developed throughout the process have solved some problems and sometimes encountered different problems. The problems that the proposed paradigm aims to solve and the problems it faces are presented by comparing it with previous paradigms. In this section, we particularly focused on the P300 spellers. The reason for this is that P300 spellers, which we regard as more efficient, constitute the primary element of our current paradigm. Paradigms such as audio/tactile P300 spellers, SSVEP, MI, and hybrid methods are not included as examples in this section.

Various modifications and enhancements to Donchin's speller have been suggested over time. Variations include the use of flashing pseudo-random patterns of letters rather than traditional rows and columns [54], [85], substituting characters with familiar faces instead of highlighting them [86], [87], employing modifications to letters beyond flashing [88], flashing small squares at the edges of rows or columns instead of entire rows/columns [89], assigning colours to each character instead of utilising flashing and modulation [90], modifying the size and spacing of symbols [91], [92], among others.

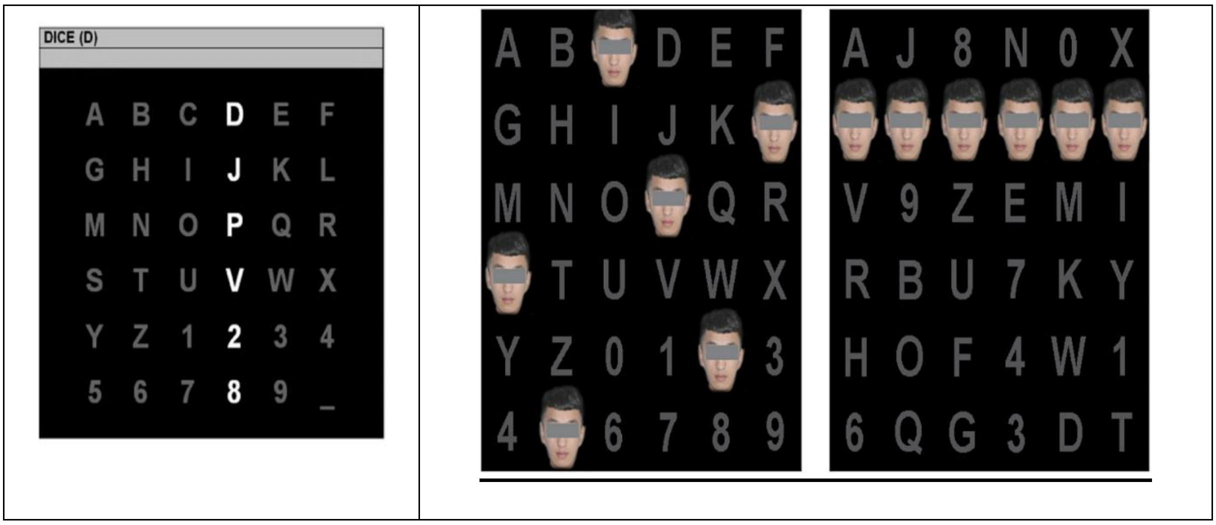


Figure 2-2 Row-coloum paradigms. Classic matrix speller (left) and speller using own face as stimulus (right)

Shown in Figure 2.2(left), the study developed by Krusienski *et al.* [93], the enhancement of the P300 feature space by stepwise linear discriminant analysis (SWLDA) and the inclusion of posterior electrode locations resulted in enhanced classification accuracy, with ideal configurations comprising central-posterior electrodes, 12 and 60 features. The online results confirmed a minimum accuracy rate of 60%, while this rate exceeded 90% in some subjects. Thus, it has shown significant improvements in BCI performance using both methodologies. Lu *et al.* [94] showed two principal techniques to improve P300-speller BCI efficacy. The self-face paradigm , shown in Figure 2.2(right), considerably higher ERP amplitudes in the parietal (340–480 ms, 480–600 ms) and fronto-central (700–800 ms) areas, resulting in improved classification accuracy and a peak ITR of 31.4 bits/min ($P < 0.05$).

Treder and Blankertz [95] investigated the effect of overt and covert attention and proposed innovative spelling designs to improve performance in ERP-based BCIs. They showed that explicit attention results in significantly higher accuracy, larger ERP amplitudes (P1, N1, P2, N2 and P3) and better classification performance than covert attention. The Hex-o-Spell speller in Figure 2.3 (top) showed superior performance compared to the standard

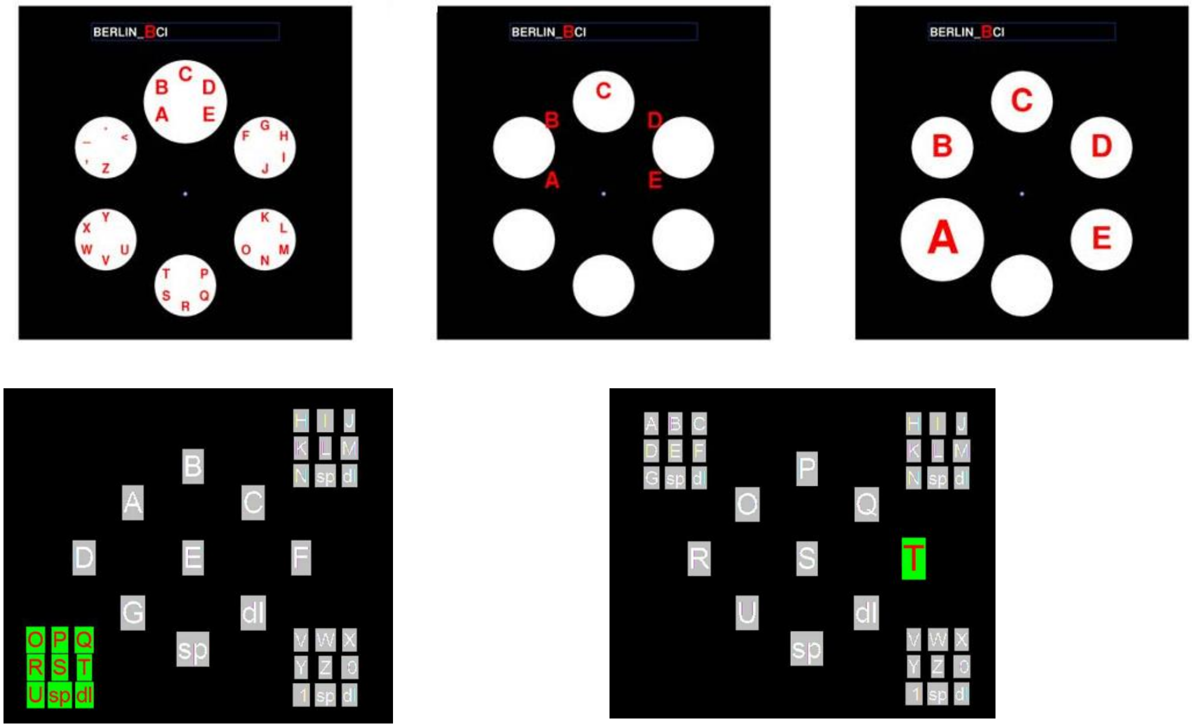


Figure 2-3 The Hex-o-Spell speller (top) and Gaze Independent Block Speller (GIBS) speller (bottom)

matrix speller by effectively reducing peripheral vision constraints, especially in covert attention scenarios. The Gaze Independent Block Speller (GIBS) developed by Pires *et al.* [96] demonstrated an average accuracy of 96.02% and a practical bit rate (PBR) of 16.67 bits/min during online experiments involving healthy participants. This performance surpassed that of the standard row-column (RC) speller, which achieved 85.5% accuracy and an ITR of 14.89 bits/min. The GIBS method, shown in Figure 2.3 (bottom), achieved better results with inter-block switching and demonstrated its applicability for individuals with severe motor impairment.

The GeoSpell for covert attention developed by Aloise *et al.* [97], shown in Figure 2.4 (left), provided a valid ITR (1.86 Symbols/min) and user satisfaction, but showed a slightly lower average accuracy of 77.8% compared to the standard P300 speller, which reached 96.17%. A gaze-independent speller designed by Liu *et al.* [98] used covert visual search tasks

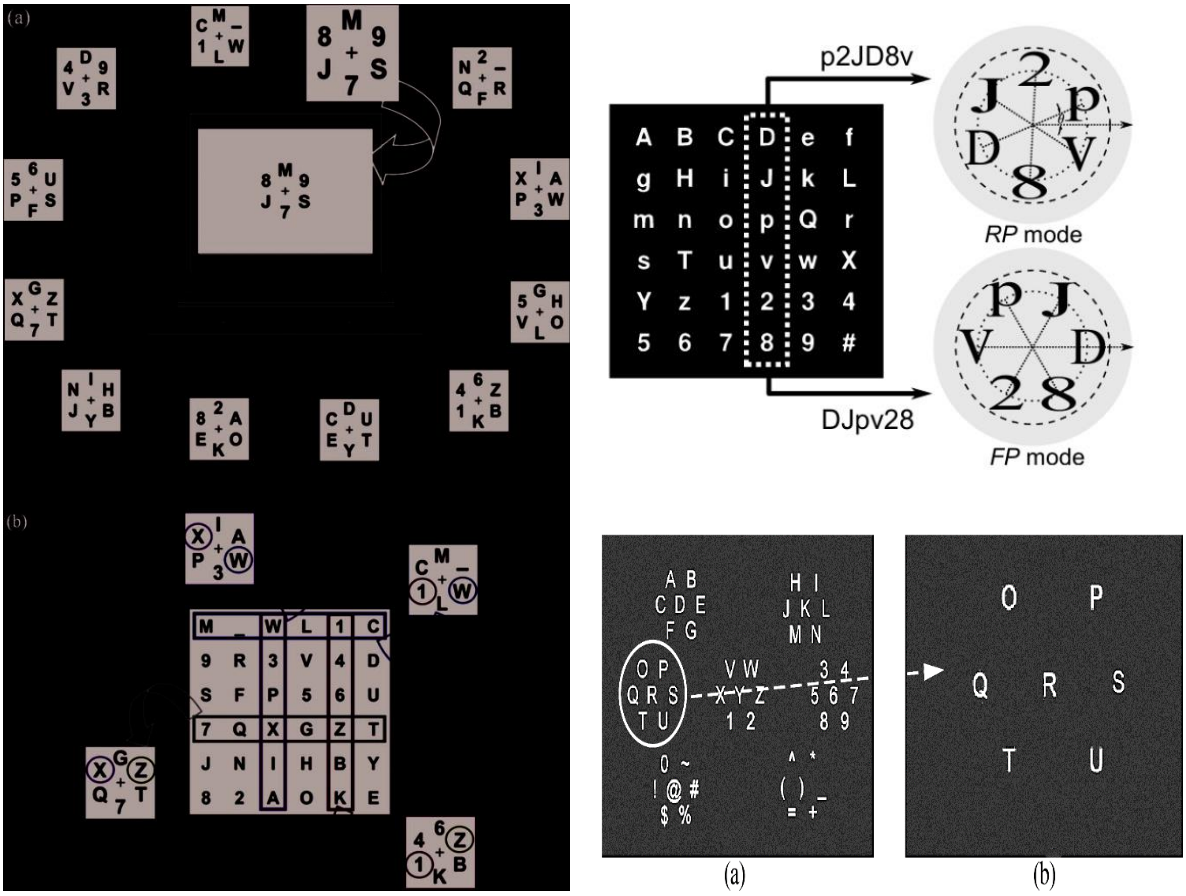


Figure 2-4 Geospell (right), GIBs with covert visual search tasks (right top) and Region-based (RB) (right bottom) spellers

in which users maintained central fixation while identifying targets through covert attentional shifts. The study in Figure 2.4 (right top) evaluated random position (RP) and fixed position (FP) presentation modes, achieving 94.4% and 96.3% accuracy, respectively. The fact that fixed position produced better results suggests that fixed motion should also be investigated. The highest symbol rate was 1.38 per minute and the results confirmed independence from eye movements. A region-based P300 spellerby Reza Fazel-Rezai and Kamyar Abhari [99] divided the display into seven regions and applied a two-level selection process to minimise perceptual errors due to adjacent flashes (see Figure 2.4 (right bottom)). This study shows that target stimulus adjacency negatively affects the accuracy rate. This method reduced the error rate from 36.7% to 18.3%, increased the character choices to 49, and improved P300 amplitudes and spelling speed.

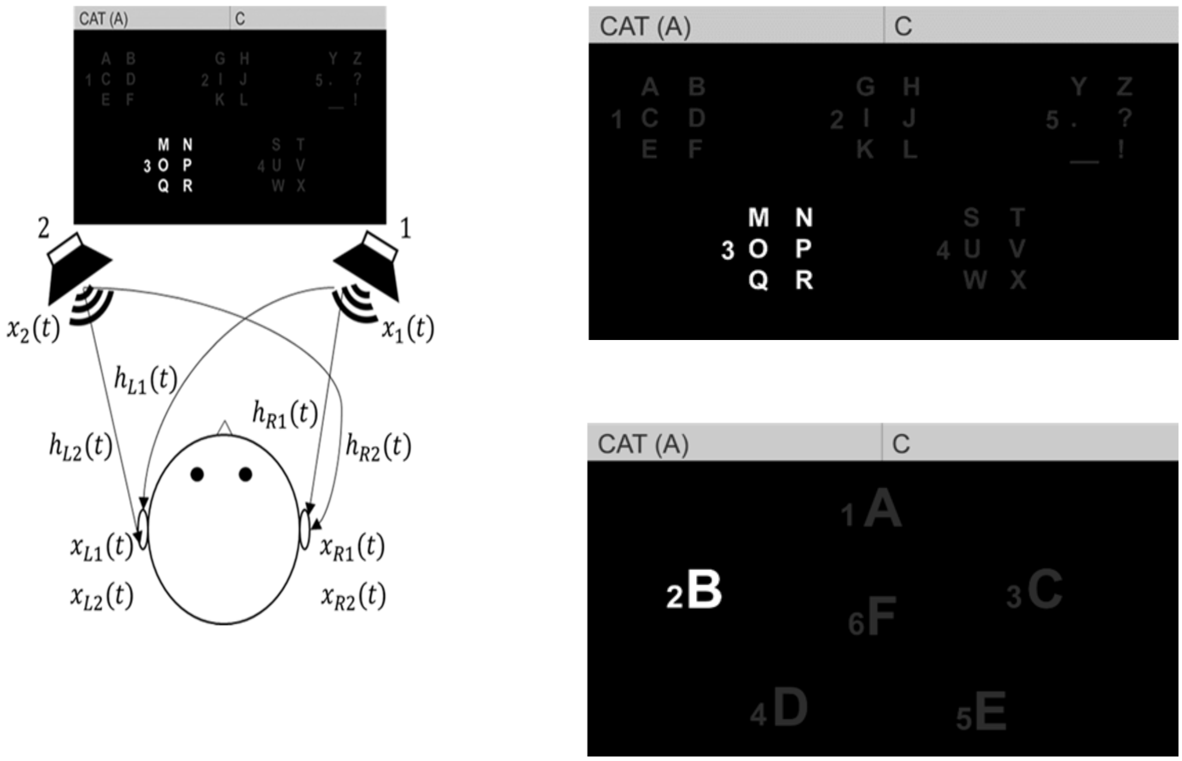


Figure 2-5 Region-based speller based on multisensory (audio) stimuli

Oralhan [100] improved performance over traditional visual or auditory-only paradigms with its first approach combining auditory and visual stimuli for region-based spellers shown in Figure 2.5. The audiovisual P300 speller showed an increase of 15.69% and 66.99% compared to visual and auditory-only spellers, respectively, and achieved a classification accuracy of 90.31%. Furthermore, the information transfer rate increased by 29.11% compared to the visual-only mode. These results indicate that multi-modal stimulation can increase user attention, but the amount of cognitive load needs to be further investigated.

Townsend *et al.* [101] present a novel P300-based Checkerboard Paradigm (CBP) as an alternative to the traditional Row/Column Paradigm (RCP). In the CBP, matrix elements used the checkerboard pattern shown in Figure 2.6 to minimise errors due to spatial contiguity (contiguity-dispersion errors) and to reduce overlapping target stimuli (double flash errors). Using an 8*9 matrix of 18 healthy participants, the results showed significantly higher average

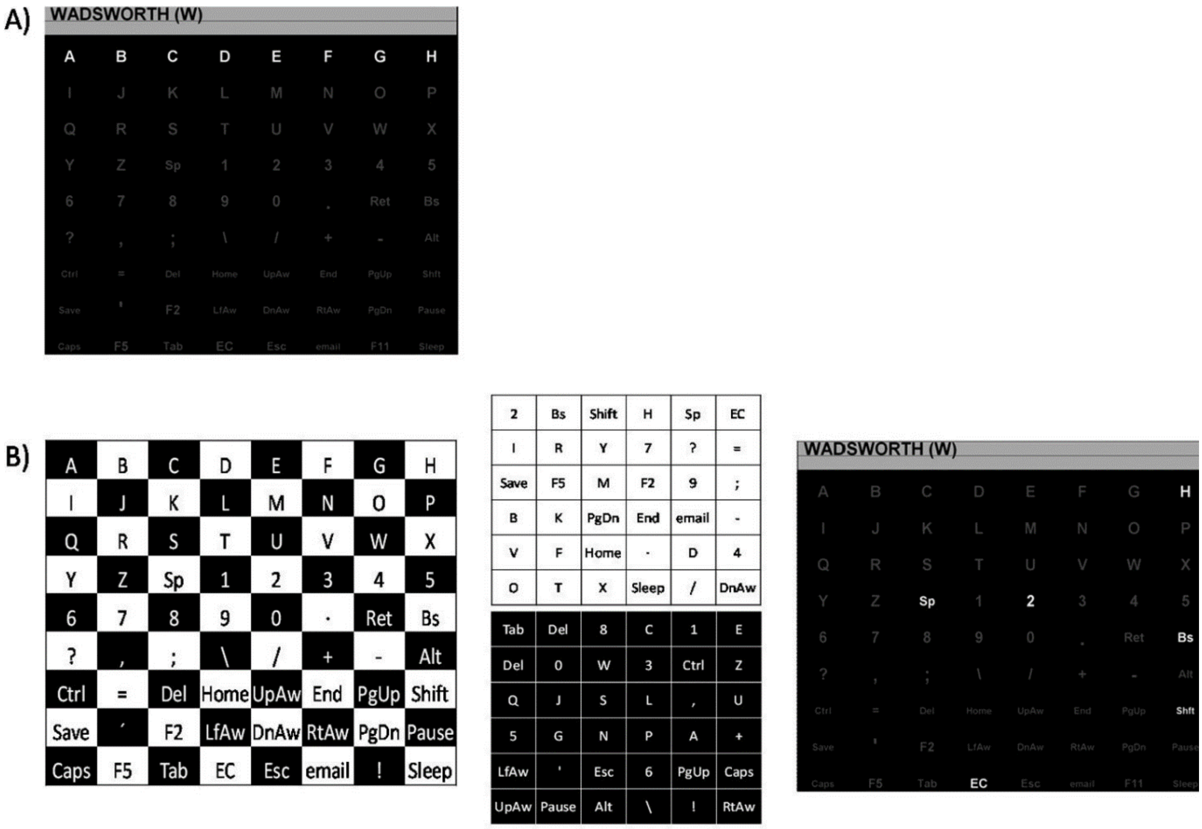


Figure 2-6 Checkboard (CB/CBP) paradigm speller

online accuracy for CBP (92%) compared to RCP (77%) and a higher average bit rate of 23 bit/min compared to 17 bit/min for RCP. The practical bit rate accounting for error correction was also significantly higher for CBP (22.59 bits/min) compared to RCP (16.61 bits/min). Preliminary tests with participants with ALS also showed an average improvement of 24.6% in classification accuracy after switching from RCP to CBP. These results suggest that CBP reduces errors, increases accuracy and improves BCI usability, especially for users with severe motor impairments.

In Shi *et al.*'s [102] study, the Sub-Matrix Based Paradigm (SBP) divided a 6×6 matrix into smaller sub-matrices, reducing errors such as adjacency distraction and double blinking, thereby increasing accuracy and ITR. The method, whose display design is shown in Figure 2.7 (left), achieves 99.7 accuracy and 28.8 bit/min ITR, offering scalability for larger target sets. The 3D Column-Only Paradigm proposed by Korkmaz *et al.* [103] significantly improves

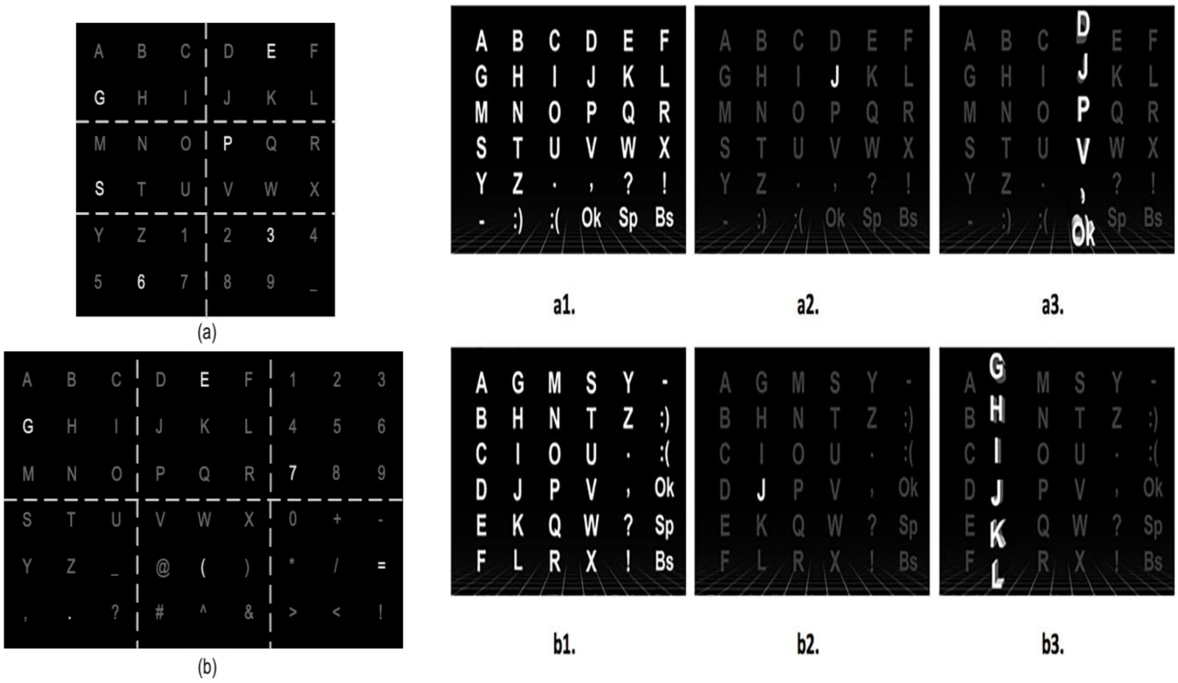


Figure 2-7 Sub-matrix based (SB) (left) and 3d row-column (right) spellers

classification accuracy with fewer electrodes (reducing computational cost) by using dynamic 3D animations and column-only flashes. Focusing on 3D flashing of columns, as shown in Figure 2.7 (right), the system was tested with a two-layer neural network, achieving up to 99.81% accuracy with fifteen flashes and a single-electrode improvement of 9.69% for one flash, demonstrating efficiency and practicality for real-world applications. Participants found the new paradigm more user-friendly, demonstrating its potential for the next generation of BCI systems due to its efficiency and reduced user workload.

Akram *et al.* [104] developed a system that integrates a modified P300-based T9 interface with a random forest classifier for efficient word typing and communication. It allows users to type initial characters through a 3×3 matrix, shown in Figure 2.8 (left), and a custom dictionary to suggest full words, reducing typing time by 51.87%. Experiments with 10 subjects showed that the average typing time per word, which was 3.47 minutes with traditional methods, decreased by 1.67 minutes and increased the speed of information transfer and usability for people with disabilities. Ron-Angevin *et al.* [105] also tested a T9-like speller with the 4×3 matrix in Figure

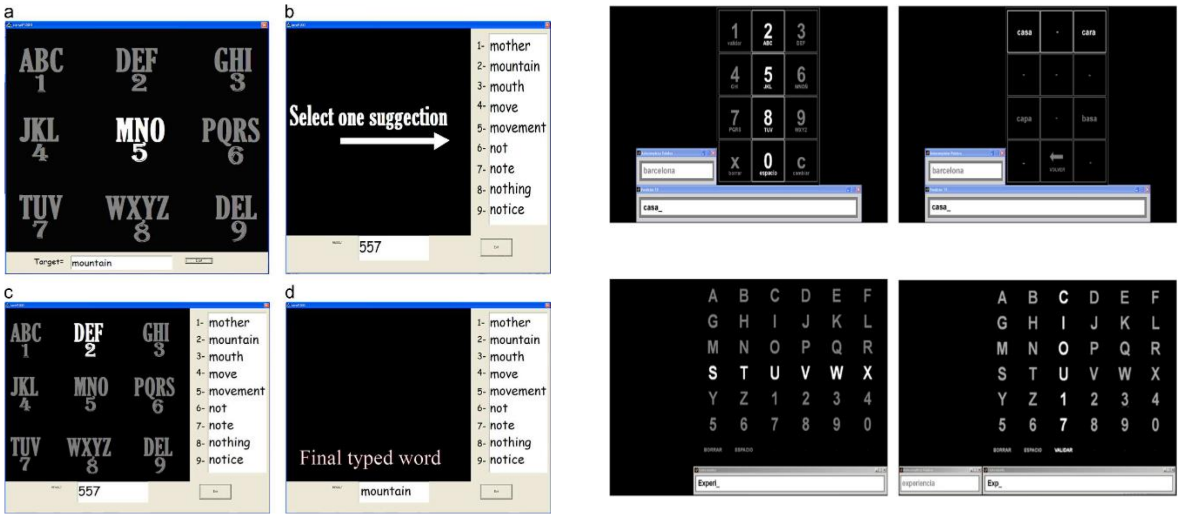


Figure 2-8 T9 spellers based on word possibilities to increase ITR

2.8 (right) with a locked-in ALS patient and 11 healthy participants, enabling the ALS patient to spell words 1.6 times faster than conventional 7×6 spellers while maintaining accuracy. These results highlight the potential for smaller matrices and improved classifiers to improve communication speed and practicality for severely disabled users, but further work with larger populations is recommended.

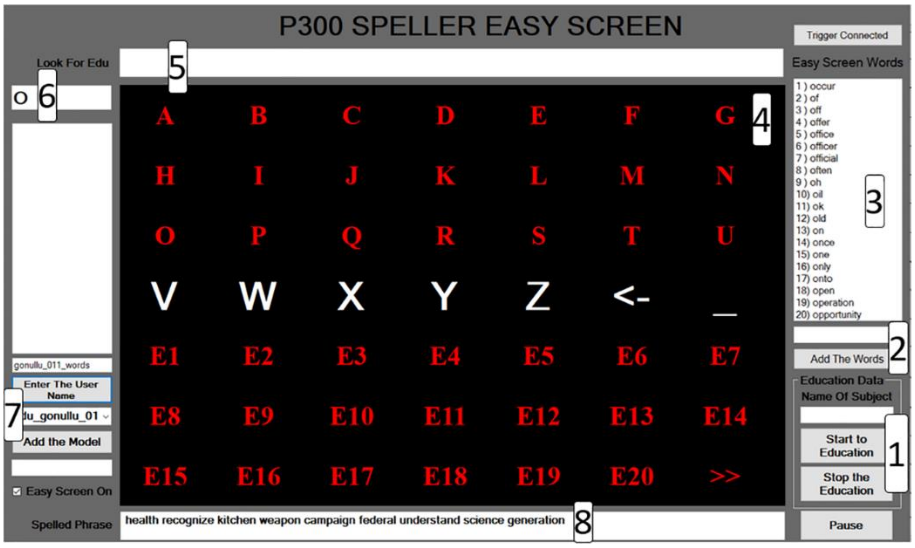


Figure 2-9 RB Easy Screen speller using a 7x7 visual stimulus matrix

Easy Screen P300, developed by Aygün and Kavsaoglu [106], improved word typing speed and accuracy by better detecting P300 ERPs in EEG signals using a 7x7 visual stimulus matrix. As shown in Figure 2.9, the interface includes alphabetic characters as well as 20 shortcut items that allow words to be displayed quickly. The system performed testing with 30 participants, demonstrating an increase in character detection accuracy and output characters per minute relative to traditional P300 spellers. The Easy Screen P300 Speller decreases the average time needed to display a word from 4.53 minutes to 1.31 minutes, enhancing its efficiency as a communication tool, particularly for individuals with disabilities. The integration of the visual stimulus matrix and the word list on a single screen enhances user experience by eliminating the necessity for supplementary interfaces.

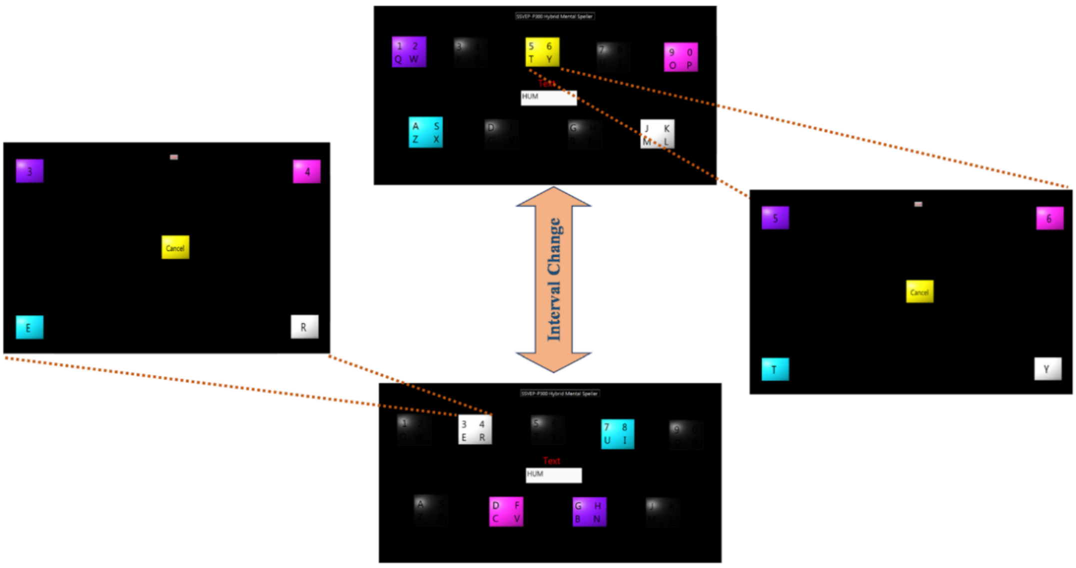


Figure 2-10 The hybrid QWERTY speller

The hybrid QWERTY speller developed by Katyal and Singla [107], which uses a combination of P300 and SSVEP signals and achieves high ITR values, is shown in Figure 2.10. The speller used five flickering frequencies to represent 36 characters and achieved an average classification accuracy of 96.42% with an ITR of 131.0 bits per minute, increasing classification accuracy and ITR compared to conventional P300 and SSVEP spellers. The hybrid approach provided a promising advance for BCI spellers by significantly outperforming in terms of speed and accuracy, offering the potential to expand to more characters while maintaining high efficiency. However, it causes usability difficulties as subjects are exposed to more stimuli and need to concentrate higher.

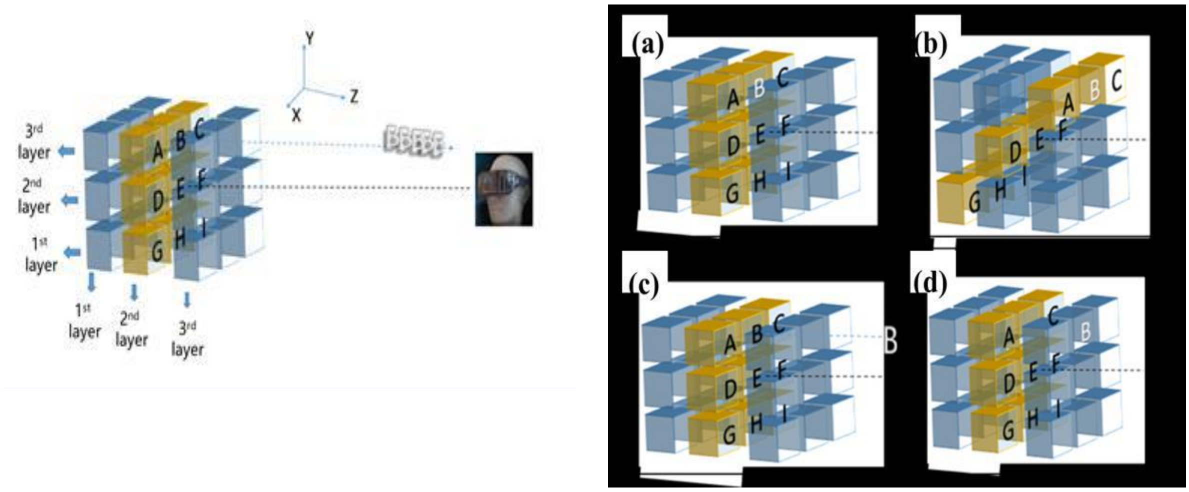


Figure 2-11 Three-dimensional (3D) visual stimuli speller

The study by Du *et al.* [108] comparing the effects of three-dimensional (3D) visual stimuli on P300-speller performance in virtual reality (VR) compared to conventional two-dimensional (2D) paradigms is shown in Figure 2.11. Four presentation paradigms were evaluated, three of which were 3D paradigms, consisting of Different depth information Array Character Flash (DACF), Same depth information Array Character Flight (SACFO) and Same depth information Array Character Jump (SACJ), and one 2D paradigm. The results show that 3D paradigms, especially DACF and SACJ, improve EEG class discriminative features and achieve higher accuracies, with average accuracies exceeding 85% and reaching approximately 95% with more rounds. The results suggest that 3D stimuli improve ERP features and authoring performance, provide a more immersive experience, and advance BCI applications in VR.

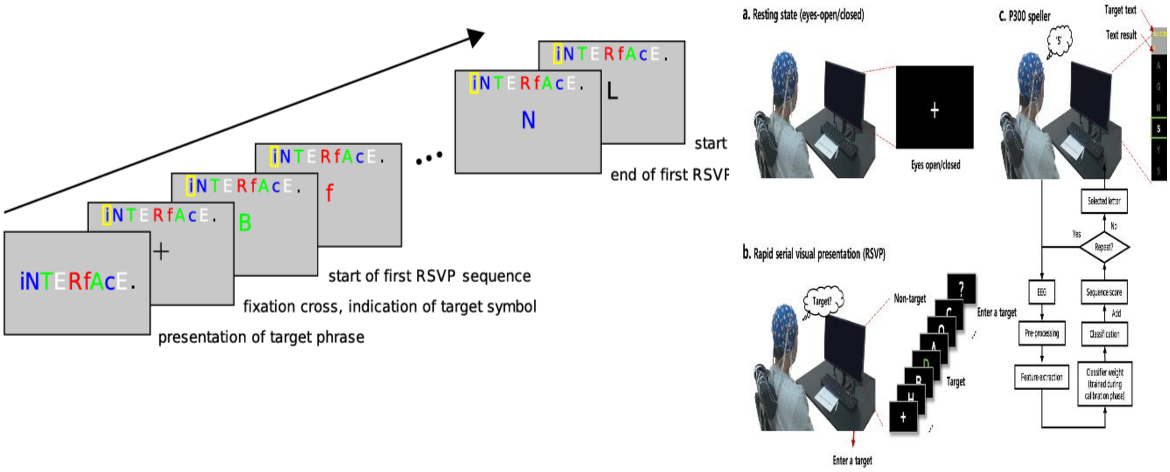


Figure 2-12 Rapid serial visual presentation (RSVP) spellers

Acqualagna and Blankertz [109] developed a Gaze-independent BCI speller using rapid serial visual presentation (RSVP) to facilitate communication for individuals with neurodegenerative diseases. This method enables users to select symbols by concentrating on target letters within a visual stimulus stream, eliminating the necessity for eye movements. Testing three conditions with different stimulus onset asynchronies (SOAs) and colour characteristics, the study achieved an average symbol selection accuracy of 94.8% and a spelling rate of 1.43 symbols per minute in the best condition. The RSVP speller, shown in Figure 2.12 (left), exploits non-spatial visual attention, making it suitable for patients with oculo-motor control disorders.

Won *et al.* [110] compared rapid serial visual presentation (RSVP) and P300 spelling paradigms collected from 55 participants. In the RSVP task, whose interface is shown in Figure 2.12 (right), participants achieved an average target detection accuracy of 91.85% (range: 77.5-100%), with ERPs around 315 ms for target events. For P300 spelling, an average letter detection accuracy of 91.49% (range: 46.43-100%) was observed, reaching 85% accuracy with 9 repetitions, and consistent P300 ERP features were seen around 262 ms during target events.

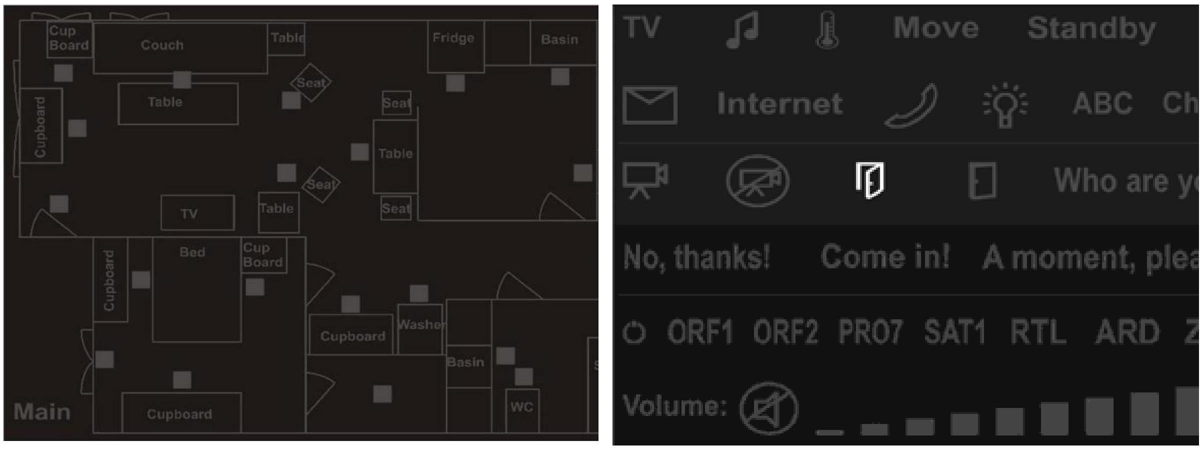


Figure 2-13 Goal-oriented single character spelling

Edlinger *et al.* [111] integrated a P300-based BCI for goal-oriented control with virtual environments for navigation and control tasks (see Figure 2.13). The system was able to train more than 80% of the participants after only five minutes of training. In a single-character study, 55% of the 38 subjects achieved 100% accuracy immediately and 76% made only one error. In a virtual smart home study, subjects controlled various functions with accuracy ranging from 83 to 100%. The information transfer rate (ITR) was satisfactory, reaching up to 84 bits/sec for single character spelling. It has proven to show significant potential for applications such as smart home management and wheelchair control, which require minimal training.

Pires *et al.* [112] compared a novel lateral single character (LSC) P300-based speller, shown in Figure 2.14 (left), with a conventional row-column (RC) speller for use by individuals with severe motor disabilities. The LSC speller, designed to exploit hemispheric asymmetries in visual perception, performed very well with an average ITR of 26.11 bit/min and 89.90% accuracy, compared to 21.91 bit/min and 88.36% accuracy of the RC speller. Involving participants with conditions such as ALS and cerebral palsy, the speller not only improved accuracy and speed, but also reduced the visual discomfort/fatigue common to hybrid and other spellers. Guan *et al.* [113] propose a new P300 speller paradigm called SD-Speller which

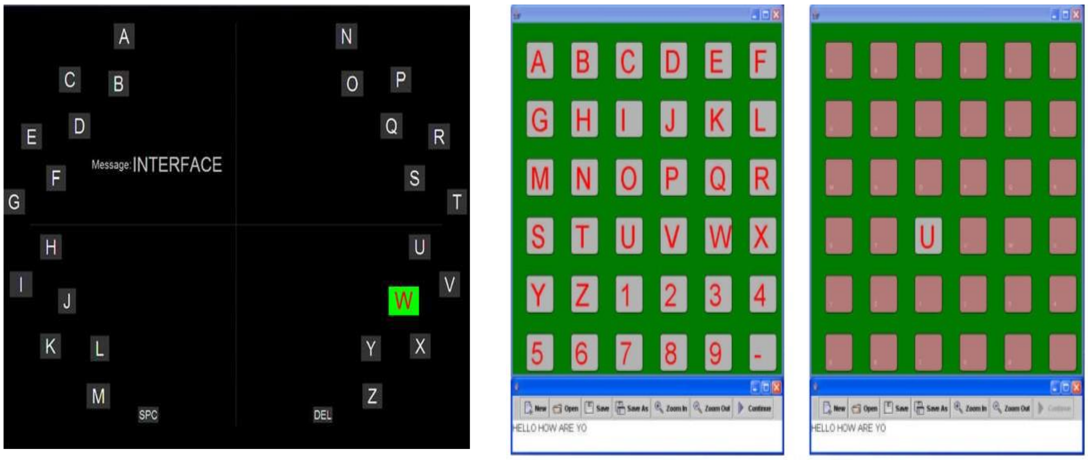


Figure 2-14 Lateral single character (LSC) (left) and Single Display Paradigm (SD)(right) Speller

displays each character randomly instead of intensifying rows and columns of a character matrix like the existing Farwell-Donchin (FD) speller. Online experiments with 6 subjects showed the SD-speller significantly improved character classification accuracy over the FD-speller, reducing error rates by up to 80%. Various signal processing methods were optimized for the FD-speller which reduced error rates by 23%. Comparison experiments found the SD-speller doubled information transfer rate and reduced time needed to achieve certain accuracy levels compared to the FD-speller. Higher P300 signal amplitudes were observed with the SD-speller which could explain the improved performance.

Chapter 3

Research Methodology

The previous chapter provided comprehensive information regarding the fundamental components of BCI, with a particular focus on P300-based BCI systems. The foundational aspects of our method, including its underlying logic and theoretical principles, are outlined. The following chapter provides a comprehensive overview of the practical, hardware, and software processes involved in BCI interfaces, from the initial stage to the final stage.

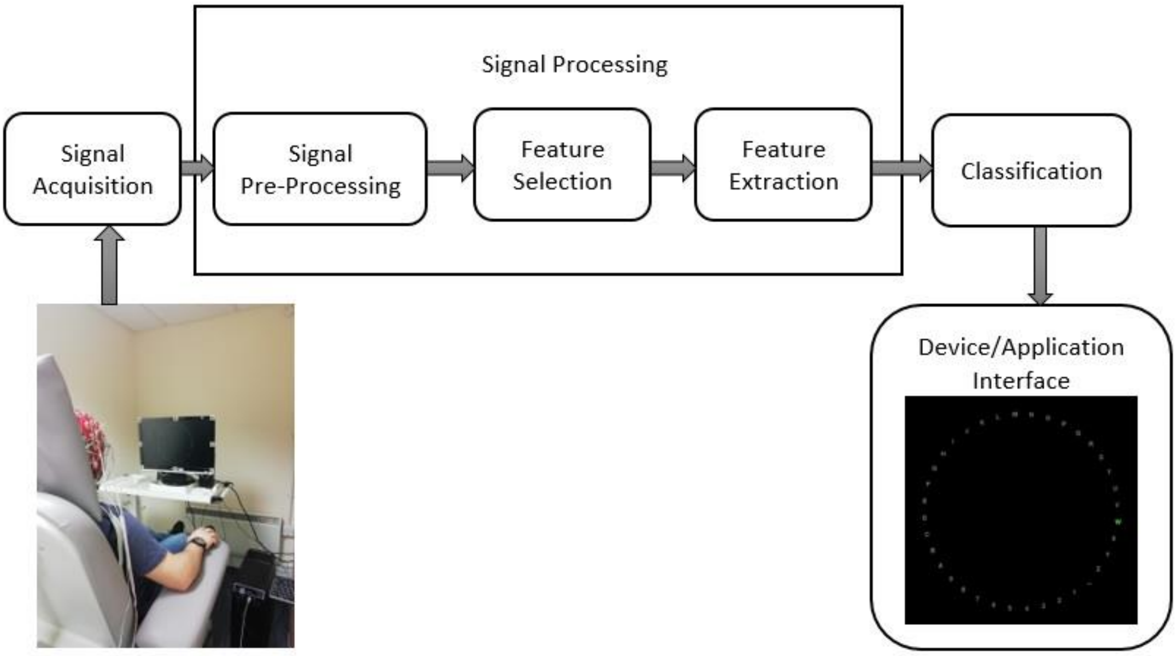


Figure 3-1 Standard BCI processing pipeline including signal acquisition, signal preprocessing, feature selection, feature extraction, classification and interface.

The fundamental tasks and procedures of BCI include signal acquisition, signal processing, feature selection, feature extraction, classification, and evaluation criteria, as illustrated in Figure 15. The theoretical description of the BCI processes is given in this section and the implementation and results are discussed in the following sections.

3.1 Data Acquisition

The first experiment (Exp3seconds) was conducted with 8 subjects with an average age of 29.9 (±3.6) and the second experiment (Exp2seconds) was conducted with 10 subjects with an average age of 31.1 (±5.0). The participants had no physical health issues and had normal or corrected-to-normal vision. One participant in the second experiment participated in part in the first experiment.

Following the provision of detailed instructions, the system was deployed across all participants for subsequent testing. Participants were seated on a comfortable chair approximately 70 cm from an LCD screen measuring 52.5 cm in width and 30 cm in height, with a resolution of 1920×1080 pixels. Brain signal acquisition was conducted using a Biosemi ActiveTwo EEG system equipped with 64 channels. The conductivity and signal quality were improved by using a small amount of conductive gel on the BioSemi 64-channel (10/20 international system) EEG cap electrodes, and the impedance of the electrodes was kept below 20 k.

Table 3.1 Binary classification AUC scores according to downsample rates

	32		64		128		256	
	SVM	**LDA**	**SVM**	**LDA**	**SVM**	**LDA**	**SVM**	**LDA**
Sub1	0.620	0.677	0.616	0.671	0.615	0.671	0.615	0.672
Sub2	0.868	0.896	0.867	0.895	0.867	0.895	0.868	0.895
Sub3	0.637	0.638	0.637	0.646	0.637	0.646	0.637	0.646
Sub4	0.862	0.865	0.862	0.864	0.862	0.864	0.862	0.863
Sub5	0.660	0.740	0.659	0.733	0.659	0.733	0.659	0.733
Sub6	0.884	0.900	0.884	0.899	0.884	0.900	0.884	0.899
Sub7	0.713	0.772	0.713	0.774	0.713	0.774	0.712	0.773
Sub8	0.491	0.496	0.481	0.485	0.477	0.484	0.476	0.484
mean	0.717	0.748	0.715	0.746	0.714	0.746	0.714	0.746

In this thesis, the EEG data originally sampled at a high rate of 2048 samples per second was subjected to a rigorous downsampling process, aimed at reducing the temporal resolution to 32 samples per second to better manage data volume and focus on lower frequency components. Each 1 second epoch normally contains 1 KHz (2048 sampling rate), by reducing this to 32 we reduced the computational cost by changing our dataset from 11124 (309 repetitions*36 epochs)*2048 to 11124*32. Such averaging effectively reduces the dataset size and computational load while also smoothing out high-frequency fluctuations, thereby enhancing the clarity and interpretability of the underlying neurophysiological signals. Downsampling such as this is common in ERP studies where lower frequency dynamics and ERPs (such as the P300) are of primary interest, enabling more efficient data handling and analysis without sacrificing essential signal information. As seen in Table 2, a sampling rate of 32 does not reduce the overall representation ratio and represents the entire data set well because it reduces fluctuations caused by noise.

3.2 EEG Signal Pre-Processing

BCI signal processing is a general term used to describe an extensive array of techniques that are utilized to interpret brain signals to enable the control of external devices or communication systems. The first step involves the acquisition of brain signals, with EEG being common due to its non-invasive nature and ability to capture high temporal information. To enable the quality and interpret-ability of the acquired signals, preprocessing techniques are utilized to enhance the signal. Preprocessing includes, among other techniques, applying spatial filters, removing artefacts, and signal enhancement. In feature extraction, the relevant signal properties are isolated using tools such as time, frequency, and spatial domain analysis to reveal features that correlate activity to a mental state or intention. Finally, the user intention is deciphered through classification, involving either machine learning or statistical approaches to distinguish between different user intentions using the acquired data. The transformation of brain data into a control signal in BCI is a critical multi-step procedure, with possible research always improving each step. BCI signals have come a long way, with research in machine learning algorithms improving classification accuracy and developing new preprocessing techniques to reduce signal noise and artefacts [12], [114].

3.2.1 Referencing

The referencing of the BCI signal is of critical significance with respect to EEG data preprocessing for BCI. The essential goal of it is to increase the quality of the signal, rendering it more interpretable while also due to noise reduction and maximization of the ratio of signal to noise. This is achieved by referring each electrode to a reference electrode or to a reference method, that is used in comparison, through which the potential of the remaining electrodes is conferred. A reference method of types is widely utilised throughout scientific literature. One method, for example, employs a single electrode placed in the neutral area, such as the mastoid or ear lobes or the earlobes which average their recordings. The method of averaging is an average reference that uses the average signal of all electrodes as a singular reference. Laplacian montage computation is a further example where the variance between each electrode and the weighted average of the nearest electrodes is calculated. The type of reference chosen significantly influences the EEG signals recognised and may impact the outcome of BCI applications. There is evidence suggesting that the accurate reference is essential for the correct localisation of electrical brain activity and influences the efficiency of BCIs, particularly needing specific signal attributes like ERPs. In addition, a study by Teplan [115] draws more attention to the importance of considering the impact of reference electrodes and reference techniques on the EEG signal analysis quality. This establishes the requirement for careful selection and usage of automated referencing techniques for standardised BCI systems.

In this EEG study, an electrode was strategically placed in each earlobe, referred to as EXG1 and EXG2, to serve as reference channels. This configuration, known as linked ears reference, is critical for establishing a stable and uniform baseline across the scalp's electrical activity. By referencing each EEG channel to the average of the potentials measured at the left (EXG1) and right (EXG2) ears, we aimed to minimize the influence of common extracerebral noise and improve the specificity of localizing cerebral sources. This referencing method is particularly effective in reducing the effects of lateralized artifacts, such as those induced by muscle tension or eye movements, thereby enhancing the accuracy and reliability of the EEG data interpretation. The choice of a linked ears reference is crucial in studies where comparative lateral brain function is assessed, providing a balanced view of hemispheric differences in neural dynamics.

3.2.2 Frequency Band Filtering

Frequency band filtering is a fundamental technique utilized in signal processing. This method involves the ability to obtain specific frequency components of a given signal, simultaneously diminishing or completely eliminating completely unrequired frequencies. Band filtering is widely used in almost all fields of application, from audio processing to telecommunication and analysis of biomedical signals [116]. Frequency band filtering can be done using a variety of procedures, such as digital filter design, Fourier transformation, wavelet analysis, among others. Some of the Digital filters such as low-pass filter, high-pass filter, bandpass filter, band-stop filter can be utilized in the area of digital signal processing (DSP) to accomplish the frequency band filtering by passing accurate frequency bands and attenuating the frequencies that are beyond the frequency bands [117].

In the preprocessing phase of this EEG analysis, The EEG data were band-pass filtered (Butterworth filter, order 4) at a range of 0.15-30 Hz. This filtering approach is instrumental in isolating the frequency bands most relevant to cognitive and neurophysiological studies, effectively attenuating unwanted high-frequency noise and low-frequency drifts that could obscure meaningful brain activity. The lower cut off of 0.15 Hz is specifically chosen to minimize the impact of slow-wave artifacts, such as those due to perspiration or breathing, while the upper limit of 30 Hz encompasses the delta, theta, alpha, and beta frequency bands, which are critically involved in various brain functions including sleep, relaxation, and cognitive processes. By confining the EEG signals to this frequency range, the filtered data more accurately reflects the underlying neural oscillations relevant to the study's objectives, thereby enhancing the reliability of subsequent analyses and interpretations.

3.3 Artefact Removal

The removal of artefacts is another fundamental step involved in the preprocessing of BCI. Artefacts refer to non-brain activity signals that could significantly compromise and deform the EEG data since they arise from various origins. Indeed, several vital artefacts include eye blinks, muscle movements, including those generating eye movements, ECG heartbeats, external electrical noise, and many more. These artefacts are dangerous because they can obscure the ground truth brain signals being analyzed. Therefore, effective methods of eliminating artefacts are critical for improving the specific accuracy and reliability of BCI systems. Specifically employed methods include ICA, which is a method used to unmix mixed signals into independent sources and wavelet transformation that uses time-frequency analysis to identify artefact components to be eliminated. Furthermore, adaptive filtering, and signal space projection are methods used to suppress the artefacts. The area of artefact removal strategies and methods research remain very hot, as indicated by Urigüen and Garcia-Zapirain [118]. While these authors stress the importance of artefact processing of BCIs, others such as Fatourechi *et al.* [119] draw attention to the continued challenge of balancing artefact removal and preservation of essential brain signal components. This further underscores the importance of the preprocessing phase of implementing BCI technologies.

3.3.1 Independent Component Analysis (ICA)

Independent Component Analysis is a reliable computational technique used in BCI systems to remove artefacts due to its capability to decompose complex multivariate statistical signals into independent components. ICA has proven highly successful in artefact decomposition and removal from EEG signals, such as eye blinks, head movements, and electrical noises. In essence, it decomposes the recorded signals into naturally independent sources based on statistical independence. As mentioned earlier, ICA theory assumes that EEG signals are linear combinations of independent source signals to be estimated from the recorded independent signals. Following the above assertion, ICA can differentiate between the signals of interest, the noise, and artefacts. Eliminating the separated non-interest signals has significantly enhanced the EEG signal and, as such, enhanced BCI applications by achieving a notable and more excellent efficiency. The study by Makeig *et al.* [49] has provided sufficient evidence to about the appropriateness of ICA in EEG data analysis by applying it to analyse artefacts and detect their role in EEG. Delorme and Makeig [120] have performed an effective analysis of ICA and provided detailed procedures in utilising ICA. Their observation was based on the improved signal interpretations and enhanced BCI data analysis.

3.3.2 Ocular Artifact Removal

The ocular artefact removal technique developed by Croft and Barry [121] is a regression-based method that initially captures physiological noise during a short calibration period, then deriving channel-specific regression coefficients that measure the extent of contamination of each EEG channel by these noise signals. These coefficients are used to subtract the estimated contribution of ocular activity from the EEG, significantly reducing blink and saccade artefacts while preserving true brain activity. It is simpler to implement and computationally faster than more advanced approaches such as ICA, provided the calibration is accurate. Because of these advantages, which make it a popular choice for both research and clinical EEG applications, and its satisfactory performance in our methodology, we preferred it to ICA.

EEG signals were obtained for each subject divided into 1000 ms epochs starting with each stimulus pre-presentation. We applied an artefact rejection procedure to these epochs, which involved calculating the first Q1(T) and third Q3(T) quarters of voltages at each time step across all epochs. The following procedure was then applied to remove periods where the signal was outside the range of samples in a period:

$$r = [Q_1(t) - (1.5Q_3(t) - Q_1(t)), Q_1(t) + (1.5Q_3(t) + Q_1(t))] \tag{3.1}$$

This method was applied to all channels (19 channels, parietal and occipital lobes) to maximize the use of valid information.

3.4 Feature Selection

The selection of features in BCI process is one of the most critical aspects during their development. The primary purpose of the procedure is to select the most relevant features from the EEG signals. This is aimed at increasing the classification accuracy, and ultimately, the performance of the system. In this procedure, the feature space is reduced to a reduced group of features that carry the most information about the relevant work. This results in a more efficient and accurate system for the BCI since it simplifies will computation, complexity and possibly increases the classification speed and accuracy. Particularly, efficient feature selection prevents overfitting, and this enhances the model generalization and deepens the researchers' understanding of the characteristics of the BCI event under consideration. BCIs incorporate various feature selection techniques using statistical and machine learning approaches such as mutual information, Fisher's discriminant ratio, and wrapper methods which assess subgroups feature subsets based on their value in a specific outcome prediction. Lan *et al.* [122]. have demonstrated the importance of feature selection in an s-BCI. Their work indicates the potential of the feature selection process in boosting classifier performance by selecting only relevant features. Lotte *et al.* [123] examined the feature selection in the BCI field and stressed the importance of critical feature selection in improving the BCI application reliability and efficiency. In addition to standard statistical approaches, the current approaches to BCI feature selection include deep learning-based methods. These methods enable the automatic feature extraction and selection of relevant features using hierarchical learning models. They show the power of capturing intricate or non-linear relationships in high-dimensional data and can perform well compared to conventional methods. However, their challenges remain in terms of model feature interpretability, and model computation complexity. Arvaneh *et al.* [124]. explored the use of constraint-based.

3.4.1 Channel Selection

Channel selection is directly related to classification success; thus, identifying the optimal channel set is essential. Therefore, a number of channel sets listed below were tested and the most suitable set was determined. Channel selection employs various methods, including Manual, Embedded, Filtering, Wrapper, and Hybrid approaches [125]. In certain studies involving manual channel selection, sufficient results were observed [126], [127].

First, we performed a statistical analysis on the 64-channel BioSemi data using the correlation matrix method to reduce the number of channels used. In order to investigate an experimental method, we first determined the midline of the brain as the centre line. The electrodes [O1, O2, Oz, POz, Pz, CPz, Cz, Fz], which are all on or close to the central line, were chosen as references to determine which other channels to include. The Pearson correlation coefficient was applied to identify the most correlated data among 64 channels collected from the Biosemi EEG device and mentioned above 8 channels. For each of the 8 channels, the 20 channels with the highest correlation were identified separately. This resulted in a list of 160 (8 channels*20 highest correlated channels) candidates.

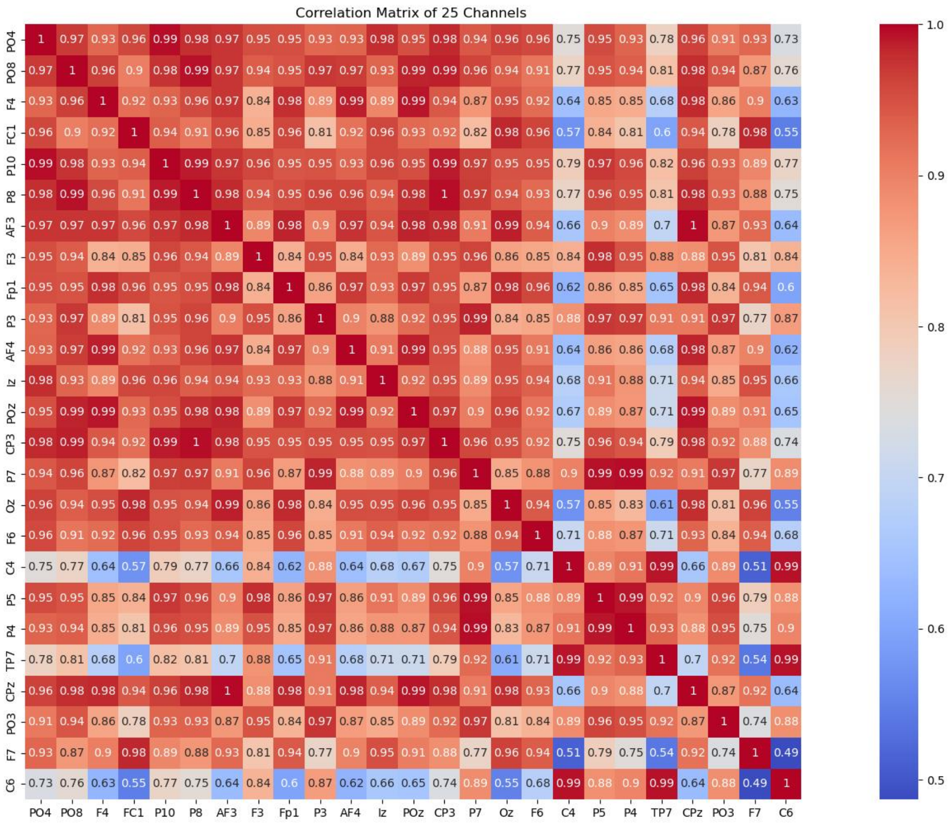


Figure 3-2 Correlation Matrix of Target Stimulus of 25 Channels

From these, the 25 channels with the highest frequency in the list were finally selected. Specifically, we focused on a feature that was generated by averaging only the target stimulus. In Figure 3.2 we report correlations and we can see the selected 25 channels and their statistical similarity with each other, and we thought that we could use it for possible channel matching and feature selection. Since the choice of 25 channels was a predetermined number, it could have been further reduced by removing irrelevant channels. Based on the results obtained from preliminary analyses, we decided to use direct channel selection instead of this method.

ERP-based spellers mainly utilise P300 components; therefore, for classification, we focused on 19 specific channels located in the central, parietal, and occipital regions: Cz, CPz, Pz, POz, Oz, P1, P2, P3, P4, P5, P6, P7, P8, PO3, PO4, PO7, PO8, O1, and O2. Table 3 shows the AUC scores of both SVM and LDA binary classification for 4 different channel sets. The 19 manually selected channels give the best result in binary classifications by a small margin. This success is more evident in the character selection classification. Although 3 channels

Table 3.2 AUC scores of channel selection and classification methods

	19ch		25ch		64ch		3ch (Fz,Cz,Pz)	
	SVM	**LDA**	**SVM**	**LDA**	**SVM**	**LDA**	**SVM**	**LDA**
Sub1	0.620	0.677	0.646	0.678	0.648	0.690	0.665	0.711
Sub2	0.868	0.896	0.852	0.919	0.851	0.919	0.853	0.922
Sub3	0.637	0.638	0.637	0.632	0.644	0.639	0.659	0.657
Sub4	0.862	0.865	0.878	0.849	0.888	0.845	0.877	0.854
Sub5	0.660	0.740	0.732	0.735	0.753	0.741	0.698	0.719
Sub6	0.884	0.900	0.851	0.849	0.840	0.834	0.826	0.843
Sub7	0.713	0.772	0.707	0.726	0.700	0.722	0.705	0.749
Sub8	0.491	0.496	0.549	0.513	0.554	0.516	0.568	0.510
mean	0.717	0.748	0.731	0.738	0.735	0.738	0.731	0.746

(Fz, Cz, Pz) can provide both sufficient binary classification results and reduce the computational cost more, it was not preferred because it would be more affected by possible signal noise in character classification.

As seen in Table 3.2, SVM classification obtained lower accuracy rates than LDA classification in preliminary tests. As a result, LDA was selected as the preferred classification technique for the subsequent stages of the research. The LDA algorithm demonstrates superior performance in binary classification tasks while maintaining a modest computational load. According to the data shown in Table 3.2 and 3.3, it can be observed that the Circular technique exhibits superior performance to Donchin's speller in AUC scores. However, it is imperative to note that the current strategy for character categorization has not been finally optimised, thus necessitating additional study into alternative classification approaches.

3.4.2 Time Window Selection

A sliding time-window was tried to achieve faster classification and reduce computational costs. The ranges were determined based on the data obtained from the ERP average of the target signals.

Table 3.3 Protocol Time Windows and Epoch Durations AUC score - 3 seconds experiment

Epoch Time (ms)	Circular AUC	Donchin AUC
0 – 1000	0.75	0.67
160 - 780	0.73	0.63
270 - 700	0.73	0.68
310 - 780	0.72	0.65
470 - 780	0.69	0.63
550 - 700	0.67	0.59

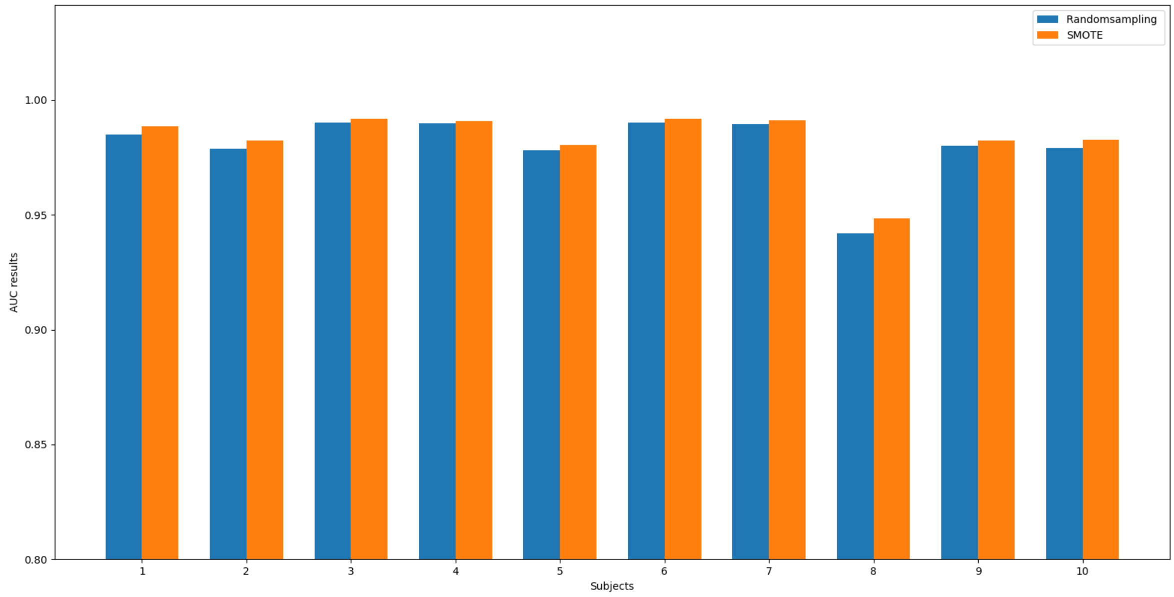
Each 1000ms epoch is segmented into shorter epochs to study where the most important ERPs might be located. Table 3.3 shows the AUC performance of the Circular method at various time windows. Despite the fact that limiting the time frame decreases the computational expense and enhances the speed of our system, using smaller epochs was not employed in the final classifications due to its negative impact on the classification success rate.

3.5 Feature Extraction

The feature extraction process in BCIs is one of the critical stages of the signal processing pipeline. As mentioned earlier, its main goal is to obtain relevant information from the raw brain signals that could be related to specific cognitive processes or reveal user intentions. In other words, this process converts the high-dimensional noise EEG data to a more manageable set of features, which accurately represent the underlying brain activity. A set of common BCI feature extraction techniques include time-domain analysis, frequency-domain analysis, and spatial filtering [128]. When used in BCI research, these techniques are implemented to emphasize specific characteristics of the EEG data, such as power spectral densities or ERPs. In most cases, more advanced techniques, such as wavelet transform and machine learning algorithms, have been adopted to capture both temporal and spectral information simultaneously, thus presenting a more holistic view of the EEG signal. Moreover, the choice of feature extraction technique has a considerable impact on the BCI system integration, as it influences the system's ability to distinguish between different cognitive tasks or user commands. Through the work of researchers such as Kundu and Ari [129] and Bashashati *et al.* [119] substantial progress has been made in this field. These studies have contributed critical insights into the efficiency of different feature extraction methods in the context of BCI and suggested potential sites of improvement for BCI performance. These data demonstrate the ongoing evolution of BCI systems that continue to be optimized to provide a more accurate and efficient means of user interaction.

3.5.1 Resampling

Synthetic Minority Oversampling Technique (SMOTE) is one of the most common techniques in machine learning for tackling class imbalance situation of a dataset, especially in classification tasks where the minority class detector is under-represented. The SMOTE algorithm generates synthetic samples using the linear interpolation between existing minority class instances and their nearest neighbours, which increases instances for the minority class and helps to avoid overfitting from duplication [131]. SMOTE is a method which creates new synthetic data points instead of merely duplicating existing points as in random oversampling, which helps with the generalization of the model and introduces better classification performance for imbalanced datasets [132]. It has been shown effective in a range of areas that feature class imbalance as a significant hurdle, such as fraud detection, medical diagnosis, and bioinformatics [133]. Nonetheless, SMOTE is not without its drawbacks, including susceptibility to noise and the generation of overlapping regions between classes, which requires careful consideration in its application and may be complemented with other techniques, such as ensemble methods or more sophisticated oversampling strategies [134].



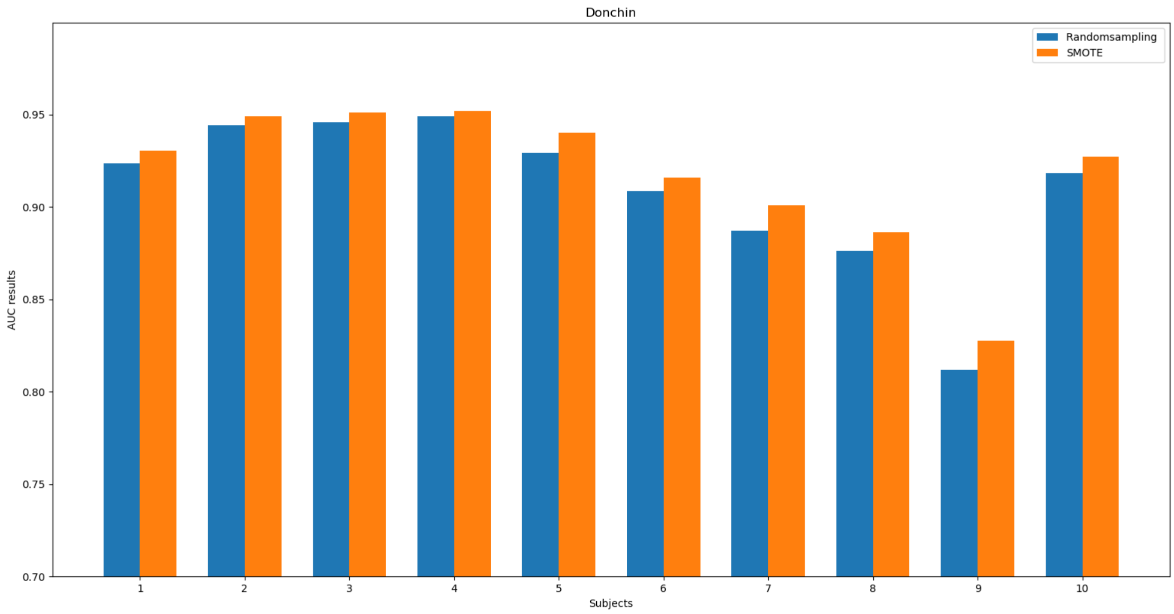


Figure 3-3 Imbalanced Data Processing. AUC scores of the Resampling and SMOTE methods of the 2-second experiment

Resampling via duplication is used in BCI research to mitigate class imbalance in datasets, which is prevalent in ERP analysis, including P300 detection. This technique consists of duplicating samples from the minority class to guarantee an unbiased representation during model training, preventing a classifier class note[307] from leaning toward the majority class. Although duplication-based resampling improves the sensitivity towards underrepresented classes, it is prone to overfitting, because it reuses the same samples in multiple training epochs, which reduces the model's generalization ability on unseen data. Studies utilizing this paradigm for BCI systems, specifically to counter imbalanced data events and to enhance classification accuracy of minority-class events, report higher accuracy in the presence of imbalanced data, which is a common occurrence in ERP driven signals ([135], [136]). Nevertheless, advanced resampling methods, including synthetic oversampling or adaptive augmentation, are being advocated to counter the overfitting danger and achieve more robust systems.

One of the most important possible problems in BCI speller systems is that the number of target stimuli is low, but the number of non-target stimuli can be tens of times higher. The Donchin method presents a ratio of 1 to 5, whereas the Circular method exhibits a ratio of 1 to 35 (Target / Non-Target), indicating a significant challenge in classification. To solve this problem, we could take 2 approaches; either reduce the non-target data or increase the target data. The decision was made to increase the Target data, as reducing it could lead to potential classification issues caused by the small amount of data available.

There are also 2 methods for increasing the target data; SMOTE and resampling respectively. Figure 3.3 shows that the AUC scores of SMOTE and resampling methods are close. In order not to manipulate the classification method, duplication of the experiment's original samples was preferred to artificial sampling in the SMOTE method. The classification success was improved without causing overfitting.

3.5.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is essential in BCI systems, particularly in feature extraction. Specifically, PCA is used to eliminate dimensions in EEG data, and therefore it simplifies the complexity of the signal without much loss of the data information. This is achieved by converting the original variables, which may be somehow correlated, into another

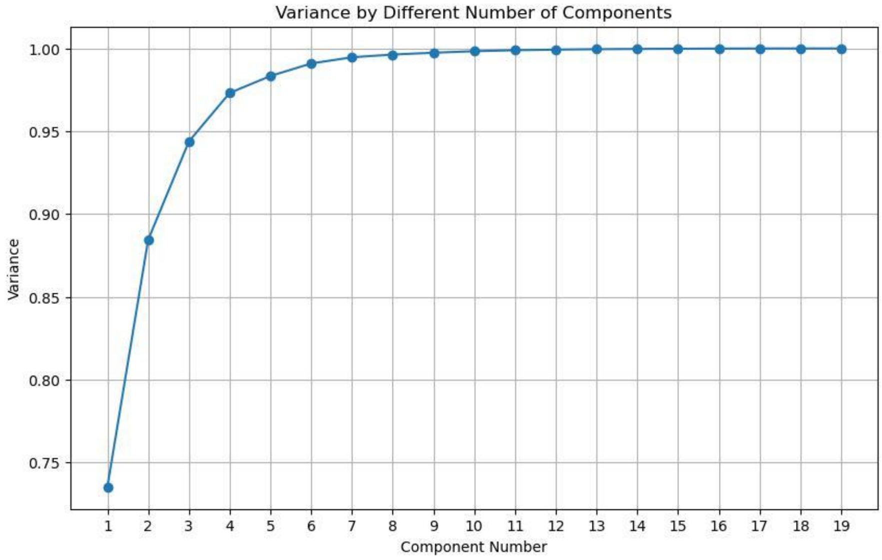


Figure 3-4 Circular 1-19 PCA components AUC results

new set of variables called principal components. The arrangement of the new components is such that the few initial components retain almost all the variations observed in the original data. As a result, BCI systems use such basic elements instead of the raw EEG; thus, this allows the system to reduce the noise and enhance the exact pattern relevant for discrimination and characterization features. Additionally, PCA also reduces the computational burden, thus making real-time BCI systems more practical and effective.

The study by Bashashati *et al.* [119] provides an excellent review of PCA concerning other signal processing methods in BCIs. This study emphasized the improvement in feature acquisition brought about by PCA in BCI and the overall improvement in the BCI system. The importance of distinct recognition of different commands or mental stimuli is crucial in BCIs for actual effective communication and control. This was recognised by McLoughlin *et al.* [130] describe how PCA identifies relevant features in data to make BCI systems more effective and adaptive.

In this comprehensive EEG analysis, we initially implemented PCA on a dataset comprising 64 EEG channels to evaluate the effectiveness of varying the number of components from 1 to 19 in terms of variance captured. The objective of this method was to determine the smallest possible number of components that may be representative of our data, which is captured by 19 channels, through the analysis of variances. This exploratory stage was crucial for determining the optimal complexity of our model, balancing between information retention and computational efficiency. The results are reported in Figure 3.4. These indicate that the first 5 components captured a substantial portion of the variance within the data in Circular. Although additional components gradually increased the variance explained, the marginal gains were not significant enough to justify a higher model complexity, leading us to select 5 principal components that captured the majority of the variance (approximately 98%). This decision was grounded in the desire to maintain a parsimonious model that avoids overfitting while still capturing the essential dynamics of the EEG data.

Subsequently, we applied PCA to a refined subset of 19 EEG channels, again retaining only the first 5 components. This second phase was targeted at a more focused dataset, where the primary objective was to extract meaningful features that are most representative of the underlying neural processes. PCA determination was performed on the train segment of the data separated as train-test in the classification phase to avoid overfitting. By applying the same dimensionality reduction approach, we ensured consistency in our data treatment, facilitating a coherent interpretation of the neural signatures across different subsets of channels. The reduction to five principal components in this smaller set further emphasized the robustness of these components in encapsulating key information across varied configurations of EEG channel arrays, thereby validating our analytical approach in the context of neurophysiological research. This methodology not only enhances the interpretability of the EEG data but also streamlines the analytical pipeline for subsequent cognitive and clinical investigations.

3.6 Classification

The classification of BCI systems is a critical step that includes taking the elements derived from EEG signals and analyzing them to ascertain the user's intentions. This process uses different machine learning and statistical algorithms to classify the characteristics into pre-determined categories that correspond to specific commands or mental states. Linear discriminant analysis (LDA), support vector machines (SVM), neural networks (NN), and other deep learning models are some of the algorithms that are used in EEG data analysis due to their effectiveness in handling the complex and multidimensional nature of this kind of data. For BCI applications, classifier selection and calibration are critical to achieving optimal accuracy and reliability, which ultimately determines the performance of the system and the user comfort and happiness. Recent studies have focused on improving the classification technique through the implementation of adaptive algorithms that can accommodate user-specific variability to improve the usability and effectiveness of the BCI. These studies aimed to demonstrate the importance of the algorithm selection, feature compatibility, and system adaptability in optimizing the BCI performance. For example, studies by Lotte *et al.* [123] and Lantz *et al.* [137], have made significant contributions to logic-based algorithms, which shows the continuous improvements in BCI technology that aim to make the devices more adaptive and user-friendly.

3.6.1 Linear Discriminant Analysis (LDA)

This classification method is frequently used in BCI systems due to its simplicity, efficacy, and high computing performance. LDA is based on the basic concept which consists in finding a linear combination of features that separates two or more classes of objects or events. In the case of BCIs, LDA is used to separate various mental states of the user or the intentions of a user by projecting complex EEG signal features into a space where these classes are the easiest distinguished. The rationale behind this is to maximize the ratio of between-class variance to within-class variance in a given data set in order to maximize the distinction between classes. The application of LDA in BCIs is made much more attractive due to its simplicity and strong performance in cases when the basic assumptions of normality and equality of covariance of the classes are relatively followed. LDA works well in this case study due to its capability of finding the linear boundary that maximizes the separation between target and non-target responses within the feature space. When the number of dimensions of the EEG data is very high, LDA components will project the data in such a way that the variance between classes will be maximized in comparison to the variance within each class as described in Equation 3.1.

$$J(w) = \frac{w^t s_b w}{w^t s_w w} \tag{3.1}$$

The study of Krusienski *et al.* [138] has shown that using LDA combined with the right feature extraction algorithms enables an improved accuracy of the P300-based BCIs. This makes the method a reliable tool for transforming EEG data into accurate commands or selections. Additionally, the study made by Blankertz *et al.* [139] highlights the importance of preprocessing and feature extraction in increasing the performance of LDA classification. This shows the interdependence of these processes in maximizing the potential of P300-based BCI systems. The efficiency of this method regarding P300-based BCIs is great, especially when a strong preprocessing step enhances the signal-to-noise ratio of EEG signals.

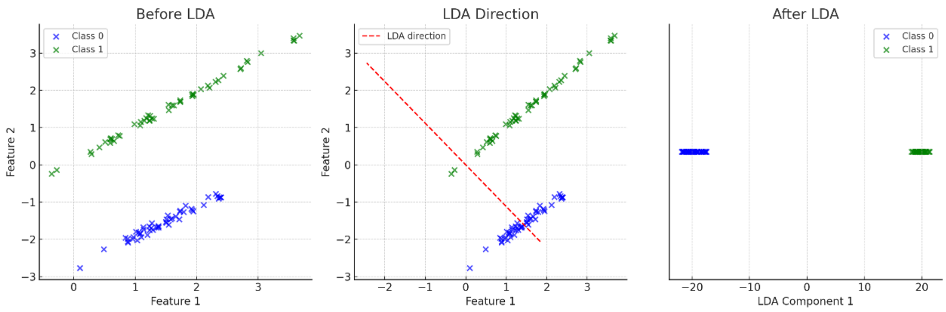


Figure 3-5 Linear combination of features that separates or characterizes two or more classes

The leading classification method for P300-based BCI spellers is LDA [140]. In the preliminary binary classification test results of our study, LDA was partially better than SVM. The test method and results are described in detail in the following sections. Overall, as can be seen in Figure 3.5, it is divided into 2 groups (target/non-target). Since the few target stimuli caused difficulties in both LDA and other classification methods, additional methods (resampling) were tried to increase the classification accuracy without causing overfitting.

3.6.2 Support Vector Machine (SVM)

Support Vector Machine (SVM), is a machinery learning classification technique that offers a reliable and efficient method to analyze EEG signals. SVM operation is primarily defined by the essential concept of choosing the best hyperplane that can efficiently separate the suitable data region, enclosed by distinct classes in the element space. This aspect makes SVM particularly appropriate for BCIs as a precise determination of mental stages or commands is crucial in most applications. Due to its multidimensionality, efficient results with little data and robustness to noise, SVM can be particularly useful in BCIs. SVM is facilitated with kernel function that transforms data to a higher dimension; thus, the data clues can be divided. SVMs can excellently maintain complexity due to these elements and can identify behaviors that bear dual rational connections.

Various studies have been undertaken to explore the methodology of SVM in BCIs, indicating suitable accomplishments in numerous paradigms, encompassing both MI and P300 speller and SSVEP. SVMs have been used in Lotte *et al.*'s study [123] to classify MI and P300 speller-based BCIs. Studies have shown that SVM has been effective in various BCI designs which are attributed to their potential to break overfitting block and get fair weights for distinctive categories. Rakotomamonjy and Guigue [141] have also done a study to show SVM efficiency in an increase in classification for the P300 speller BCI. SVM has also been proven to tackle stacking belief and regularised backend uses in various features of our signals, although few efforts have been accumulated around their use in EEG indicators. SVMs have be underscored with deep focus by Gerson et al [142] that one should always use SVMs with proper features extractions and preprocessors to get close to the determinants results. Schölkopf and Smola [143] have given a comprehensive review of SVM in machine learning. SVM's ability to accurately classify data, even with non-linear signals, and its flexibility to be used with different BCI types, signals and methods, has led to a significant increase in user preference.

3.7 Performance Metrics

A wide variety of performance criteria is used to measure the efficacy and efficiency of BCIs in the decoding and translation of brain signals into actions. Accuracy, information transfer rate, and latency are some crucial ones among them. Accuracy is pivotal for ensuring the possibility and efficiency of reliable communication between the system and the user. It is measured as the portion of correctly detected intentions or command attempts [27]. Information transfer rate, usually measured in bits per minute, is the combination of all such possibilities. In essence, ITR quantifies how much information a user can communicate to the device by the product of the user's probability of transmitting information and the system's speed and accuracy to recognize commands and intentions. Lower ITR means that users will be unable to communicate rapidly or efficiently [144]. The latency denotes the duration it takes the system to respond to the user's action or intention. It is crucial for the real-time application because it has a vital impact on user satisfaction when there are time-sensitive tasks. The shorter the period, the better, as lengthy durations would irritate users and hinder their capacity to control the system [93].

Additionally, the consideration of user-centered criteria, such as usability, comfort, and cognitive load is essential for guarantee the continuing acceptance and efficiency of BCI technology. Usability is the ease with which users may interact with the system and its level of intuitiveness. Comfort is the physical and psychological benefits with which the user may wear or use the tool for extended periods of time. Cognitive load is the amount of mental effort needed by the operator to handle the BCI. Lower cognitive load is preferable to eliminate operator fatigue and ensure the engagement of BCI over the long term [145]. The aforementioned measures demonstrate the importance of developing BCIs that combine computational effectiveness with usability in order to ensure a seamless integration of the technology into users' daily lives and routines. Thus, the current BCI performance measures research is implemented to enhance not only the technical criteria but also to create the user experience for the wider adoption of the technology.

3.7.1 Confusion Matrix

The confusion matrix is an essential measure of the performance of BCI systems. It gives a detailed summary of the classification accuracy by comparing the expected commands or intentions with the actual user intentions. In BCI, the matrix is highly utilized since it is essential in ensuring the system's functioning capability, as it can robustly distinguish between different mental states or commands. The conceptual framework, which requires binary classification as in the Circular method, has four primary elements: true positives, true negatives, false positives and false negatives. According to Tharwat, [146] , true positives and true negatives indicate the number of correct recognized targets and non-targets, respectively. Additionally, false positives and false negatives are the errors that occur when actions are wrongly classified as intentions or unrealized commands. The confusion matrix also allows for the calculation of other metrics, such as precision, as the ratio of true positives over true positives plus false positives, recall, that is the ratio of true positive over true positives and false negatives, and the F1 score, which is the harmonic mean of precision and recall. The F1 score is particularly important as it provides a combined measure to assess the balance between precision and recall [147].

While the basic elements of the confusion matrix are vital in understanding the model, the matrix can also help in identifying unique challenges of a BCI system such as the ability to differentiate between comparable cognitive cues or more subtle user intentions. Analysis of the matrix is beneficial to identify commands are more prone to misinterpretation, giving directions for further system refinement [148]. For instance, numerous false positive cases for a specific command may indicate the need for more robust feature extraction or band negativity for this class. However, the confusion matrix also provides a detailed summary of classification performance, making it essential for comparing different algorithms, feature sets, classifiers. Thus, these tools help in advancing BCI research by revealing areas of strength and opportunities [149].

3.7.2 Mutual Information & Information Transfer Rate (ITR)

The most commonly used measure to evaluate BCI systems is the ITR, which is a essential parameter that defines how effective it is to transmit information from one entity to another using BCI. Information Transfer Rate is the quantity of information transferred within a certain time frame. It is comprised of two main factors: the percentage of the intention displayed accurately in the reading of the BCI and the percentage of the intention demonstrated used as an order [27]. Among such a wide range of areas, there are situations where fast and accurate communication is required, the same assistive devices designed specifically for people with severe motor impairments.

The computation of the ITR factors several quantities, indicating the number of unique instructions the BCI can identify, the accuracy of command identification, and the amount of time the user requires producing a command signal including inevitable system delays [144]. A BCI system with a higher ITR will be more efficient and able to communicate with a user more rapidly and accurately. Nevertheless, it is difficult to achieve a high ITR because of the tradeoffs involved in speed, accuracy, and number of instructions. For instance, increasing the number of detectable instructions may decrease the overall precision or require extended signal generation times. As a result, the ITR is affected. Optimal ITR can be achieved by carefully balancing these factors to meet the unique requirements and skills of each user.

Beyond measuring the performance, the importance of the ITR also refers to designing a framework to advance and improve BCI technology. It is important to note that developers and researchers focus on enhancing the ITR to design interfaces that are more effective and easier to use. The end goal is better communication and control for BCI-reliant patients. Within the framework, recent research studies are devoted to developing new signal-processing algorithms, machine learning, and training the users. The purpose is to improve the accuracy and overall effectiveness of BCIs, and, consequently, ITR and usability [149].

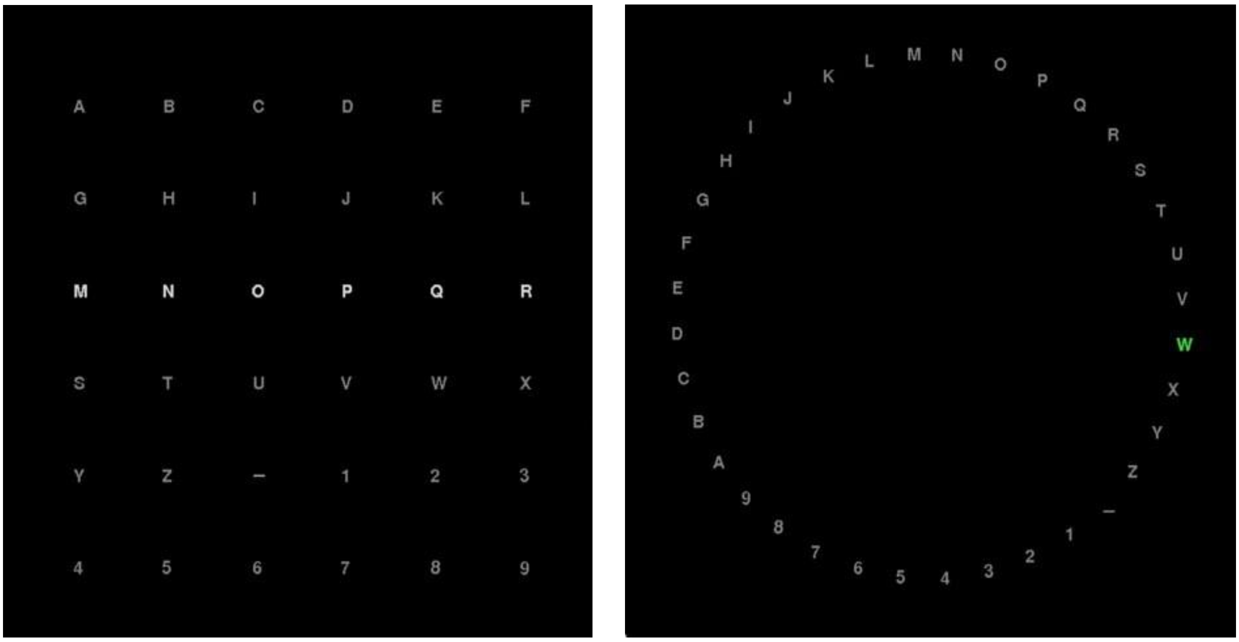
3.8 Experimental Protocols

The P300 ERP refers to the alteration in amplitude that is observed within the time window of approximately 300ms to 700ms subsequent to the subject's attention being directed towards the target stimulus [150]. The phenomenon under consideration is noted to arise from a range of sensory responses, including but not limited to visual, tactile, and auditory stimuli [9], [79]. The endogenous component is generated through internal cognitive events [80].

The Oddball paradigm is a frequently employed approach for studying the P300 component. The operational mechanism of the paradigm is predicated upon the differentiation between stimuli directed at irregular intervals towards targets and non-targets. First and foremost, target stimuli are discerned from other stimuli within the Oddball paradigm. The stimuli exhibit periodicity, while the target stimuli within each period are presented randomly.

The circular method involves the sequential stimulation of flashing stimuli in accordance with specific instructions. In contrast to the traditional Oddball paradigm, the targets in this study are not presented in a random manner, but rather in a sequential order. Previous research has indicated that when there is a lack of variability in the flashing targets, the P300 amplitude does not manifest adequately [54], [55]. In the proposed methodology, the targets are presented in a sequential flashing manner, leading to a limited ability to elicit a significant P300 amplitude. This is primarily due to the predictable nature of the target presentation and the absence of any deliberate effort to track the frequency of flashes. In contrast to the repetitive tasks outlined in the study, it was found that cognitive tasks elicited a robust P300 signal in response to exogenous auditory, visual, and sensory stimuli. Increasing the level of attention within the protocol has the potential to induce a greater magnitude of changes within the system. By employing this approach, it becomes possible to adjust the temporal gap between the operational framework of the system and the stimuli.

Two distinct systems have been devised for the purpose of comparing the Donchin paradigm, a classical Oddball paradigm and the Circular paradigm employed in the present chapter. Two experiments were conducted within our system. The Circular and Donchin paradigms are two experimental designs used in cognitive research. The Circular paradigm involves the presentation of 36 circular stimuli, which include both alphabets and numbers ranging from 0 to 9. On the other hand, the Donchin paradigm is characterised by a matrix structure consisting of a 6 by 6 grid. The script employed in this context shares the same set of characters as the Circular script, yet it deviates from the circular form and instead adopts a square organisation of the stimuli. The circular sequential paradigm comprises stimuli arranged at a 10-degree angle along a hypothetical circle located at the centre of the screen. The system, comprised of grey stimuli against a black backdrop, elicits a colour change in active stimuli, rendering them either green or red. Nevertheless, the system can be categorised into two distinct groups based on the order in which the stimuli are presented: sequential and random. Our experiments were conducted using a sequential training approach.



(a) (b)

Figure 3-6 Interface of the proposed method and classic method (a) Donchin's matrix speller and (b) circular sequential speller.

As shown in Figure 3.6, the colour of the background is black and the letters begin as grey. The study developed by Salvaris *et al.* [151] for mouse control, which includes 8 directions, is the basis of this design. In both paradigms, subjects engage in cognitive processes that involve directing their attention towards changes in colour in certain targets. In the Donchin protocol, a modification in targets is observed when the target stimulus transitions from a grey with RGB=(100,100,100) color to white pure white with RGB=(255,255,255). Conversely, in the Circular procedure, the target stimulus undergoes random alternations between green with RGB=(0,255,0) and red with RGB=(255,0,0) colours. In the Donchin protocol, the subjects are tasked with counting the number of target flashes. Conversely, in the Circular protocol, the subjects are required to identify the colour of the target flash and to remember the colour of the last flash. In the experiments, half of the participants first tested the Circular protocol followed by the Donchin protocol, while the other half tested the Donchin protocol first and then the

Circular protocol. Hence, the two protocols were counterbalance, effectively mitigating the potential negative impact of fatigue and attention on the assessment of performance.

The experimental procedure commences with an initial practise session, during which the participant familiarises themselves with the protocols and examines their functioning. The commencement of each session is characterised by the appearance of a dark screen, followed by the presentation of stimuli. During the course of practise sessions, it is seen that no targets are presented, and instead, the system merely exhibits flashing cycles. Following the demonstration session, the participant is presented with the task instructions displayed on the screen. Subsequently, a brief interval of 2 seconds is provided before the commencement of the initial protocol, consisting of 20 blocks. After the completion of each block, the protocol remains in a state of pause, awaiting the input from the subject regarding the number of times the target flashes in the case of Donchin's experiment, and the final colour of the target in the case of Circular's experiment. This input is expected to be provided by the subject using the mouse scroll wheel. This is a colour selection consisting of Red and Green. During the experimental sessions consisting of 20 randomly selected targets, it was possible to use all 36 characters as targets. However, it is anticipated that this limitation will be addressed in future investigations.

The experimental design comprises a total of 20 blocks, with each block asking the user to focus on a distinct target character. The experiment initially starts with the demonstration stage. In the beginning, the experimental procedure is once more explained to the participant, followed by one simulation of the real repetitions of the experiment. Initially it flashes blue so that the subject recognises the target character and focuses on how many times it flashes or which colour it flashes according to the task. Examples of questions asked at the end of a block include "Colour of last target flash?" and "Target flash number?" The participant is instructed to direct their attention towards the target stimulus by inquiring about the number of flashes and the final colour exhibited by the target stimulus. Enhanced P300 amplitudes can be achieved when the subject is alert and attentive to the experiment. Each block is comprised of a series of repetitions, with the number of repetitions falling within the range of 13 to 17. Each repetition signifies the occurrence of all characters flashing at least once.

In both spellers, the character participants were instructed to focus on during a segment of the experiment was highlighted in blue with RGB=(0,0,255) for two seconds prior to the the start of the flashing. The characters were initially selected in a pseudo-random order and applied in the same order in each experiment/participant. In the Circular method (*Y, 4, 6, E, D, H, 5, _, 3, C, X, L, O, W, _, 9, H, Z, A, Q*) and the Donchin method (*Z, U, _, T, 9, W, K, 6, S, Z, J, 7, Y, M, E, B, B, I, 3, W*) the characters are shown in order. Despite inherent randomness, it is seen that some characters are repeated. In this way, we had the opportunity to compare character-based classification results and test whether the method works stably. If the same character shows very variable classification results, it can be concluded that the system is strongly influenced by the user's current mood. This indicates that the system is not stable and shows classification difficulties. As will be seen in the following sections, it is seen that the same characters in the Circular method obtain similar results on average.

Chapter 4

Sequential Speller with a 3-Second Revolution

In this chapter, the design and stimulus-presentation duration of the Donchin and Circular spellers are firstly explained. In one repetition of the flashing cycle, that in this chapter lasts 3 seconds, Donchin's speller highlights 12 stimuli (6 rows and 6 columns) and while the Circular speller highlights 36 stimuli/characters. The grand average ERP amplitudes of the target and nontarget stimuli produced by the protocols were compared. Following the discovery that the Circular method produced higher ERPs than Donchin's method, a statistical comparison of the ERP mean values for target and non-target stimuli across the 19 channels was conducted separately. Initially, general information was obtained by presenting the subject AUC scores in a detailed table. Subsequently, they were analysed separately on a subject-based and character-based basis. The overall accuracy of the subjects and the AUCs of the analysed characters were evaluated for their potential to be alterative to existing studies. In the classification phase, `predict_proba` in the `sklearn.lda.LDA` library was used to generate probability scores for each *epoch* separately. In each repetition, 12 proba scores were generated for Donchin and 36 for Circular. We grouped the repetitions to reduce the noise effect and increase the classification performance. The factors contributing to the inferior performance of the Circular method compared to the Donchin method during the classification phase, despite the significantly bigger ERPs generated by the proposed method, were examined.

4.1 Introduction

The BCI system primarily serves as a communication conduit for individuals experiencing motor disabilities, including spinal cord injuries and amyotrophic lateral sclerosis (ALS), and challenges faced by the elderly. Additionally, its application extends beyond healthcare, encompassing multimedia devices, gaming systems, and military technologies [12].

Diverse stimuli can induce specific waveforms of evoked potentials, among which the P300 event-related potential stands out for its unique response to particular stimuli. Characterized as an evoked potential, the P300 is distinguished by its positive peak and its typical emergence around 300 milliseconds after stimulus presentation. This phenomenon was first documented by Sutton *et al.* [59]. The elicitation of the P300 event-related potential necessitates participants' focused attention on a series of randomly presented stimuli, where task-relevant stimuli are rare compared to the more frequent task-irrelevant ones. In our research, we employed non-invasive evoked EEG signals to develop a speller, leveraging the P300 potential for its operational mechanism.

4.2 Methodology

The Oddball paradigm is a widely utilized protocol in BCI technology for eliciting P300-based event-related potentials. However, this method faces challenges related to speed and performance efficiency, impacting its overall functionality. Initially, our research did not achieve the same level of accuracy and information transfer rates as the standard Oddball paradigm used in the Doncin speller. However, it did yield several enhancements. The improvement observed can primarily be attributed to the innovative geometric arrangement of the stimuli and the specific visual stimuli used within our experimental protocol. Unlike the Oddball paradigm, our methodology emphasizes a strategic sequence in stimulus presentation, aiming to optimize subject engagement and concentration levels. By adopting a systematic approach to the timing and sequence of stimuli, we enhance the ability for participants to discern the target stimulus amidst distractors, thereby augmenting the efficacy of P300 signal detection.

In the study conducted with the 8 participants, participants used both a Donchin speller and the new Circular speller. With the former one repetition was executed over the course of 12 epochs, while in the latter one repetition was carried out over 36 epochs. In the experiment

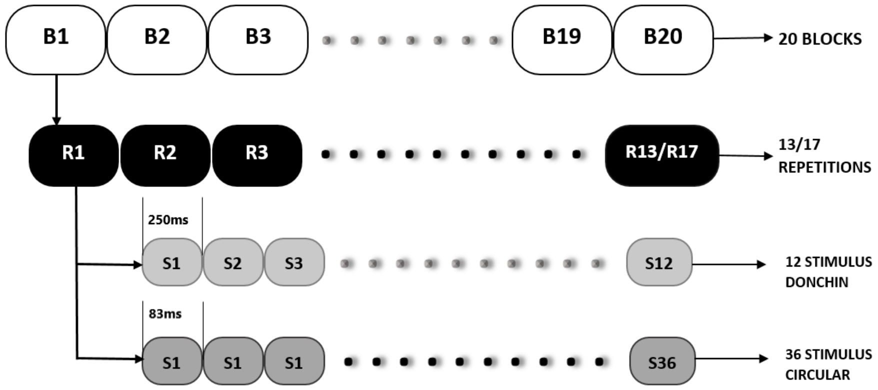


Figure 4-1 Timeline of the experimental protocols used in this study.

reported in this chapter, in the Circular speller all stimuli within one repetition were presented in a rapid succession within a time frame of 3 seconds. In this manner, it can be observed that the duration of each flash in the Circular paradigm (ISI=SOA=3/36 seconds=83.3ms) is comparatively shorter than the duration of each epoch in the Donchin paradigm (ISI = SOA = 3/12seconds = 250ms).

Figure 4.1 shows the timeline of the whole cycle. Although the duration of the Circular stimuli is shorter, since it shows stimuli sequentially, it is easier for the subjects to detect the stimulus and the P300 amplitude produced is higher. Nevertheless, the system was primarily engineered with the objective of achieving the same cycle time in both speller. While the average number of repeat occurrences remained consistent, it was hypothesised that the new approach would exhibit greater efficacy when assessed using ITR-based measurement.

According to the findings presented in Figures 4.2, 4.3 and 4.4, a notable and largely statistically significant positive ERP in the parietal and occipital lobes of the brain can be observed in target epochs (which is not present in non-targets) which is most likely a P300 ERP. Initially, a total of 64 channels were chosen for the purpose of classification. However, later only 19 channels were retained as using 64 channels diminished generalisation and had a substantial computing burden. The observed ERPs in the parietal and occipital lobes of the brain suggest that EEG channels and samples could be used directly as features for classification. However, there exist many approaches to feature extraction that attain improved outcomes while using a reduced number of channels/features. The unbalance in both datasets was balanced as described in Section 3.5.2 and the target/non-target data were equalised. Then, 5 components were extracted from the 19 channel data using PCA as described in Section 3.5.1. For classification, scores were generated using `predict_proba` in the `sklearn.lda.LDA` library, and the highest values of these scores were used to select target characters.

4.3 Results

In this section, we analyse and compare the average ERPs for the 3-second Dochin and Circular protocols performed with 8 participants. Then, we interpret the subject/character AUC scores, and finally, the character classification results are presented and discussed.

Figure 4.2 presents the ERP grand averages for target and non-target stimuli across channels Fz, Cz, and Pz for both Donchin's and our Circular speller, in Experiments 3s. For improved visualisation of finer elements, a higher sampling rate of 128Hz was employed in the figure, as opposed to the 32Hz used for classification.

Figure 4.2 illustrates that within the Circular method, the target stimuli elicit a higher amplitude response in comparison to the non-target stimuli. This amplitude must be significantly different in order to discriminate between target stimuli and non-target stimuli. The Figure 4.2, showing the ERP fluctuations in the 1 second between the start and end of the epoch, shows that the ERPs produced by our proposed method for targets are significantly different from the average of the non-targets. The Donchin approach is characterised by the occurrence of the target stimulus within a brief time frame in an indeterminate time span from a previous target. This means that the row and the column of the target stimulus can flash

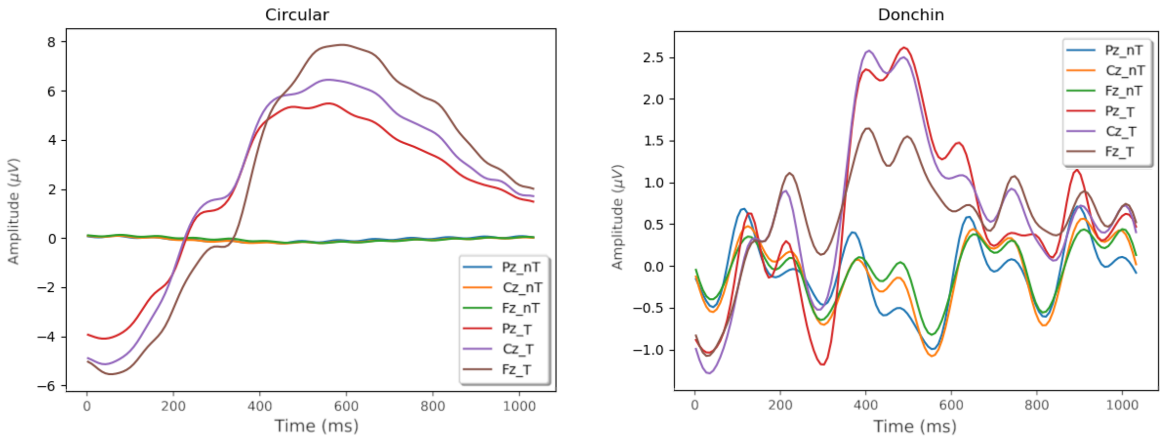


Figure 4-2 Circular and Donchin grand average ERPs

consecutively or with very little temporal delay, which hinders the generation of a distinct P300 signal in response to the target stimulus, resulting in less favourable classification outcomes. As can be seen in Figure 4.2, in the Donchin method, the P300 ERP is deformed by the usual ripples at the inter-stimulus presentation frequency in the 1000ms epochs due to the succession of target stimuli, possibly influencing the classification rate.

Figures 4.3 and 4.4 present ERP waveforms recorded from 19 EEG channels: central (Cz, CPz, Pz, POz, Oz), parietal-occipital (PO3, PO7, PO4, PO8), occipital (O1, O2) and parietal (P1, P3, P5, P7, P2, P4, P6, P8). This representation of ERP waveforms allows a comprehensive analysis of spatial (electrode-specific) and temporal (time-dependent) neural dynamics in different brain regions. The graph of each channel, for targets (solid line) and non-targets (dashed line), shows the electrical activity of the brain in response to these two stimulus types. The x-axis represents time in up to 1200ms after stimulus onset, while the y-axis shows ERP amplitude in microvolts (µV), capturing the positive and negative deviations that characterise the ERP. Notable ERP components such as the P300 (a positive deflection typically occurring between 300 ms and 600 ms post-stimulus) are evident in target responses for several channels, particularly in parietal and central regions (e.g. Pz, CPz). Larger ERP amplitudes for target stimuli in the time windows highlighted by grey shaded regions are statistically

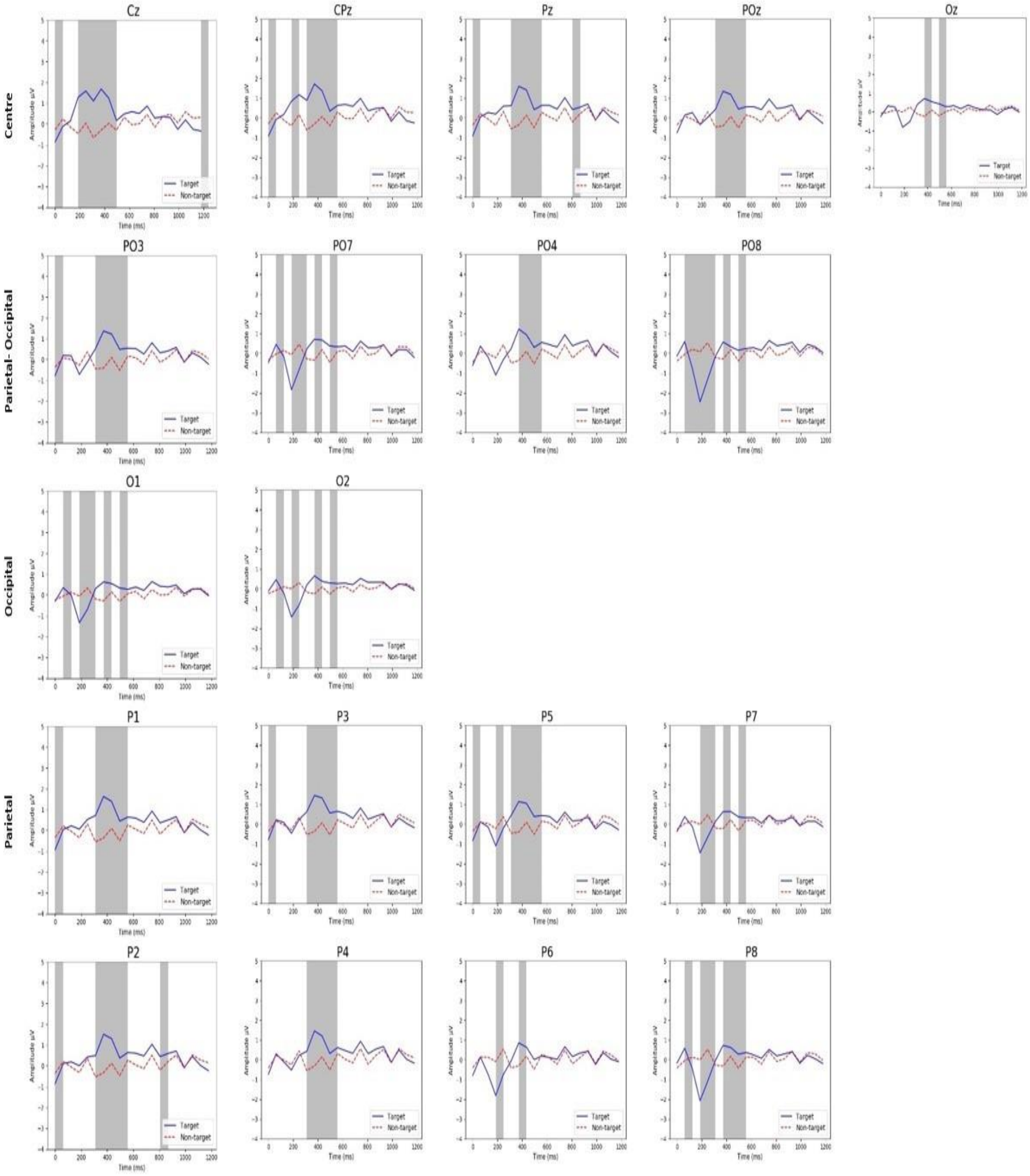


Figure 4-3 ERP grand-averages of the targets (blue lines) and non-targets (red lines) for 19 EEG channels for the Donchin speller in Experiment 3 seconds. Shaded areas in each plot represent statistically significant differences.

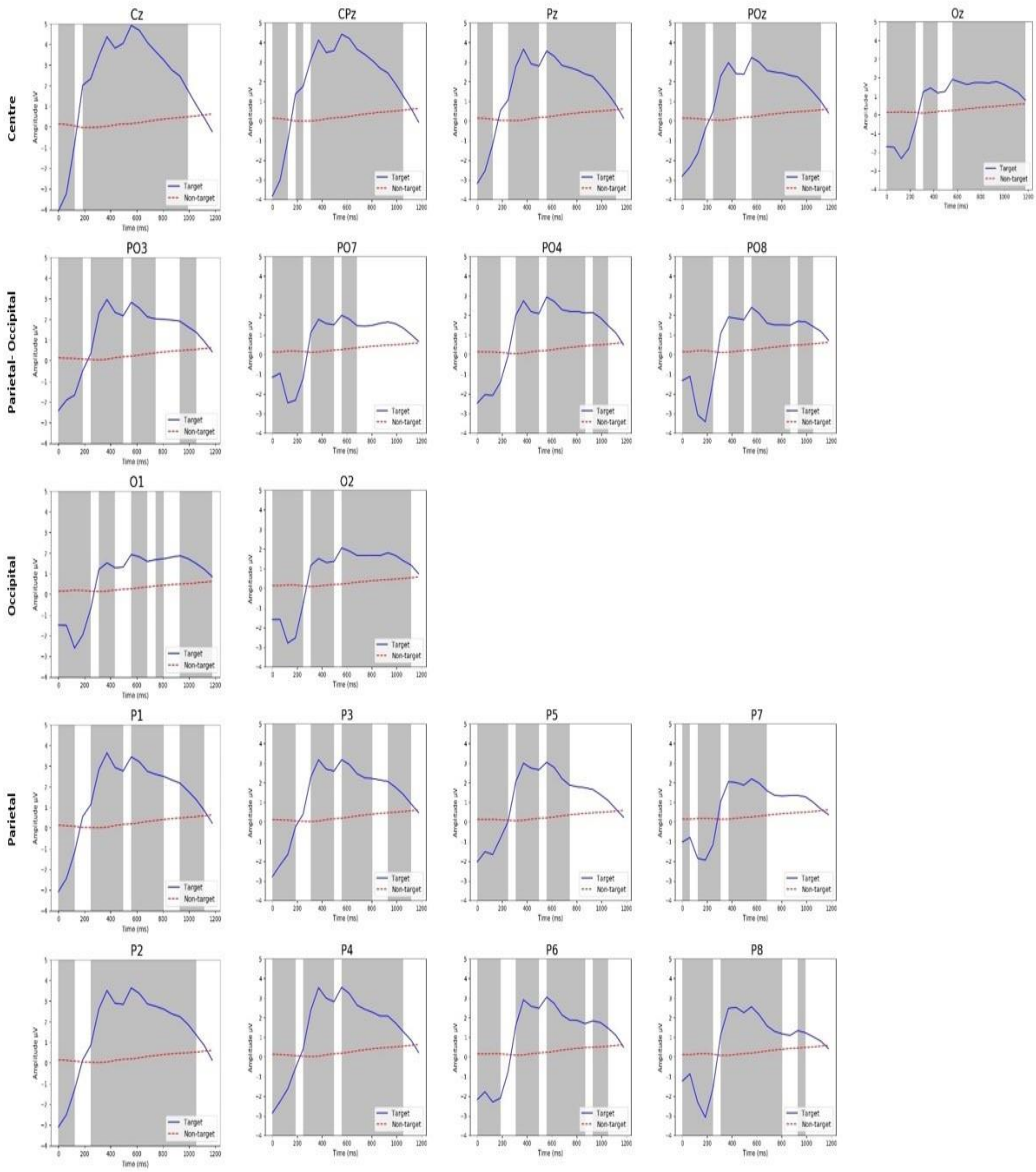
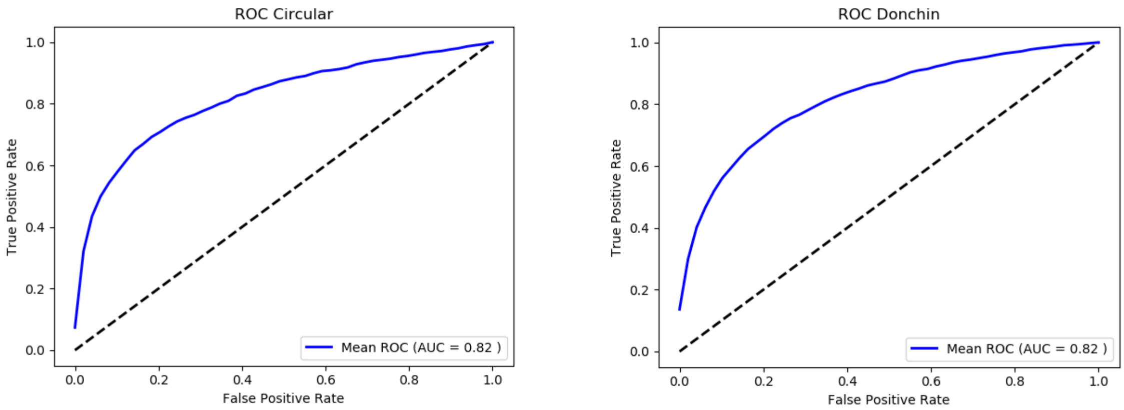


Figure 4-4 ERP grand-averages of the targets (blue lines) and non-targets (red lines) for 19 EEG channels for the Circular speller in Experiment 3 seconds. Shaded areas in each plot represent statistically significant differences.

significant (Wilcoxon ranked test, pvalue<0.05) difference between target and non-target stimuli. In the Donchin method (Figure 4.3), analysing channels in occipital regions (e.g. O1, O2) showed more modest ERP differences reflecting visual/cognitive recognition. Parietal-occipital channels (e.g. PO3, PO4) and parietal channels (e.g. P3, P4) showed marked differences between conditions in terms of their involvement in task-related cognitive processes.

As shown in Figure 4.4, for the Circular method, central and parietal channels (e.g. Cz, CPz, Pz) present strong positive deflections for target stimuli compared to non-targets, especially within grey highlighted windows, highlighting their involvement in decision-making and attentional processes. Parietal-occipital channels (e.g. PO3, PO4) show moderate amplitude responses to the cognitive task, while occipital channels (e.g. O1, O2) exhibit smaller amplitude differences in cognitive processing. Parietal channels (e.g. P3, P4) showed strong amplitude changes, further supporting their involvement in higher-order cognitive functions such as target detection and categorisation.

We utilised the Area Under the Curve (AUC) score to assess the performance of our target/non-target classifiers. The AUC is the area beneath the Receiver Operating Characteristic (ROC) curve. The ROC curve is the result of plotting the true positive rate vs the false positive rate obtained by a classifier for all possible values of the classifier's threshold. Therefore, the accuracy of identifying targets and non-targets is assessed by AUC. The binary classification accuracy is insufficient and provides little information due to the imbalance between the number of non-target stimuli and the number of target stimuli. Examining the AUC parameter and ROC graph yields more significant outcomes. Figure 4.5 demonstrates that the Circular technique (with a 3s revolution time) is no more effective in differentiating between target and non-target than the Matrix speller. A long TTI most likely resulted in a more pronounced P300 signal, but there weren't AUC differences between the two techniques. The Wilcoxon Signed Rank Test was utilised to statistically analyse the measurement results, yielding a p-value greater than 0.05.



(a) (b)

Figure 4-5 Receiver operating characteristic (ROC) curves - 3 seconds experiment (a) Circular's speller ROC curve, (b) Donchin's speller ROC curve

At this point, there exists an imbalance between the target and non-target stimuli in the Circular method, with a ratio of 1 to 35. The issue of imbalanced data was addressed by duplicating the target stimuli in both the Circular technique and the Donchin approach. In both experimental trials, a subset of fatigued individuals exhibited diminished levels of concentration during the course of the experiment, thus leading to categorization outcomes that fell well below the average. Tables 4.1 and 4.2 show the AUC scores of each subject for the 20 blocks (characters) spelled with each method. According to the average AUCs (both AUC=0.82) presented in Figures 4.6 and 4.7, all subjects except for subject 8 in the Circular method and all subjects except for subject 7 in the Donchin method achieved acceptable results. The observed poor results in subject 8 (Circular) and subject 7 (Donchin) were found to be related to the lower/inadequate level of concentration. Considering that these outliers were only a tiny fraction of the participants and that fatigue was not noted among the other participants, it can be concluded that these outliers do not indicate any problems with the proposed methodology.

Table 4.1 Circular Subject AUC scores for each character - 3 seconds experiment

Circular Blocks AUC

	Y	4	6	E	D	H	5	_	3	C	X	L	O	W	_	9	H	Z	A	Q
Sub1	0.82	0.88	0.88	0.88	0.76	0.74	0.86	0.81	0.71	0.86	0.79	0.73	0.8	0.89	0.78	0.85	0.76	0.82	0.8	0.77
Sub2	0.99	0.84	0.9	0.96	0.96	0.91	0.95	0.92	0.91	0.91	0.9	0.9	0.95	0.97	0.92	0.97	0.94	0.89	0.97	0.92
Sub3	0.61	0.86	0.83	0.75	0.71	0.85	0.87	0.75	0.72	0.74	0.64	0.65	0.77	0.86	0.71	0.8	0.7	0.58	0.76	0.8
Sub4	0.81	0.8	0.89	0.9	0.84	0.8	0.91	0.73	0.97	0.92	0.93	0.97	0.98	0.95	0.94	0.92	0.91	0.98	0.95	0.98
Sub5	0.89	0.94	0.95	0.94	0.93	0.95	0.91	0.88	0.97	0.85	0.95	0.94	0.91	0.89	0.9	0.86	0.88	0.93	0.85	0.89
Sub6	0.97	0.99	0.99	0.97	0.98	0.96	0.99	0.99	1	0.92	0.98	0.98	0.94	0.95	0.98	0.99	0.99	0.98	0.97	0.94
Sub7	0.92	0.92	0.74	0.87	0.86	0.7	0.82	0.9	0.84	0.76	0.77	0.75	0.69	0.77	0.71	0.75	0.72	0.66	0.8	0.73
Sub8	0.47	0.53	0.42	0.58	0.51	0.44	0.59	0.47	0.51	0.48	0.59	0.29	0.4	0.58	0.47	0.51	0.4	0.54	0.53	0.57

Table 4.2 Donchin Subject AUC scores for each character - 3 seconds experiment

Donchin Blocks AUC

	Y	4	6	E	D	H	5	_	3	C	X	L	O	W	_	9	H	Z	A	Q
Sub1	0.88	0.84	0.81	0.85	0.82	0.75	0.85	0.78	0.74	0.75	0.79	0.83	0.77	0.87	0.79	0.78	0.8	0.74	0.83	0.77
Sub2	0.93	0.86	0.54	0.89	0.88	0.82	0.86	0.76	0.86	0.86	0.86	0.73	0.7	0.64	0.9	0.88	0.82	0.86	0.8	0.78
Sub3	0.93	0.95	0.85	0.96	0.93	0.95	0.92	0.89	0.93	0.91	0.89	0.92	0.83	0.87	0.89	0.94	0.96	0.83	0.91	0.84
Sub4	0.71	0.8	0.75	0.77	0.83	0.79	0.92	0.74	0.8	0.77	0.74	0.77	0.76	0.82	0.75	0.73	0.74	0.77	0.82	0.78
Sub5	0.9	0.85	0.74	0.83	0.79	0.83	0.83	0.85	0.86	0.84	0.81	0.79	0.79	0.84	0.82	0.92	0.83	0.85	0.87	0.81
Sub6	0.86	0.89	0.87	0.92	0.84	0.9	0.94	0.92	0.92	0.93	0.92	0.92	0.87	0.92	0.97	0.91	0.93	0.93	0.93	0.66
Sub7	0.6	0.61	0.61	0.66	0.68	0.61	0.71	0.86	0.76	0.77	0.73	0.7	0.67	0.73	0.64	0.69	0.64	0.65	0.79	0.71
Sub8	0.89	0.74	0.79	0.83	0.87	0.85	0.81	0.88	0.88	0.86	0.85	0.81	0.79	0.81	0.79	0.93	0.89	0.91	0.88	0.91

The heatmap in Table 4.1 shows the AUC scores of eight subjects across 20 blocks/characters in the Circular Blocks methodology. Higher AUC values, shown in red, indicate better model performance, while lower values, shown in blue, indicate poorer performance. The results reflect a generally robust performance, although there is some variability between subjects, with some subjects such as subject 6 achieving consistently high AUC scores (above 0.9 for most blocks) as opposed to subjects such as subject 8 achieving low AUC scores. In the heatmap in Table 4.2, subjects such as subject 3 and 6 exhibit consistently high AUC scores in most blocks, indicating strong and reliable model performance. Subjects 2 and 4 also show occasional low scores in certain blocks, indicating variability in performance depending on block characteristics. This variability between subjects and blocks is explored in more detail in the following steps in order to take into account individual differences and block-specific characteristics in model optimisation. The overall distribution suggests that although the methodology is effective for many subjects, further improvements may be required to increase generalisability and consistency of performance.

Upon analysing the AUC scores of the subjects in Figure 4.6, it was observed that subject 8 exhibited random performance in the Circular technique. In Figure 4.7, subject 7 showed low success in the Donchin method. During the post-experiment discussions, it was concluded that the acquired results were attributed to the subjects' mental and physical fatigue rather than the instructions or procedures of the experiment. The outliers in the Donchin method are in a larger spectrum compared to the Circular method, which shows that the Circular method gives better results.

In the Circular approach (Figure 4.6), subject 6 achieved the highest median AUC 0.99 and very narrow interquartile range (IQR), indicating very consistent performance with no outliers. Subjects 3 and 5 also performed very well with median AUCs of around 0.94 and 0.93, respectively, but the IQRs is a little wider. This suggests a moderate degree of volatility. Subject 8 results are the worst — median AUC around 0.55, and IQR between 0.48 and 0.62,

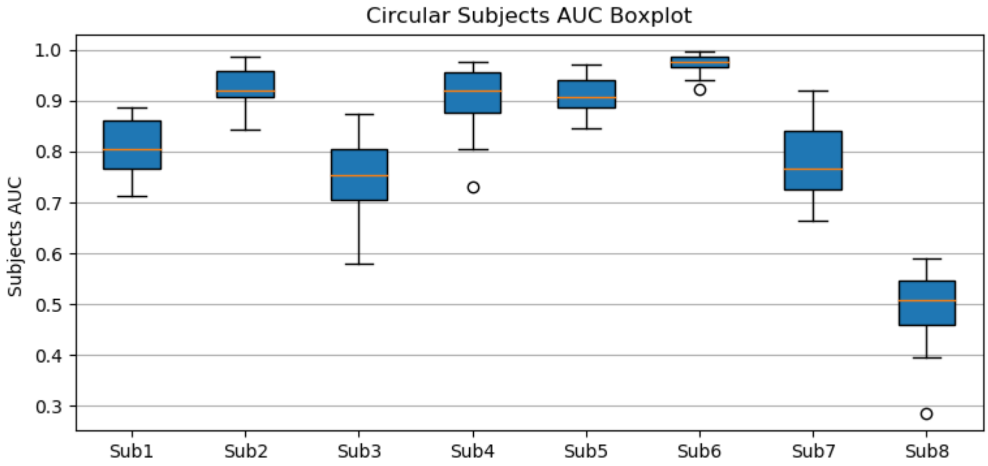


Figure 4-6 Circular Subject mean AUC score boxplot - 3 seconds experiment

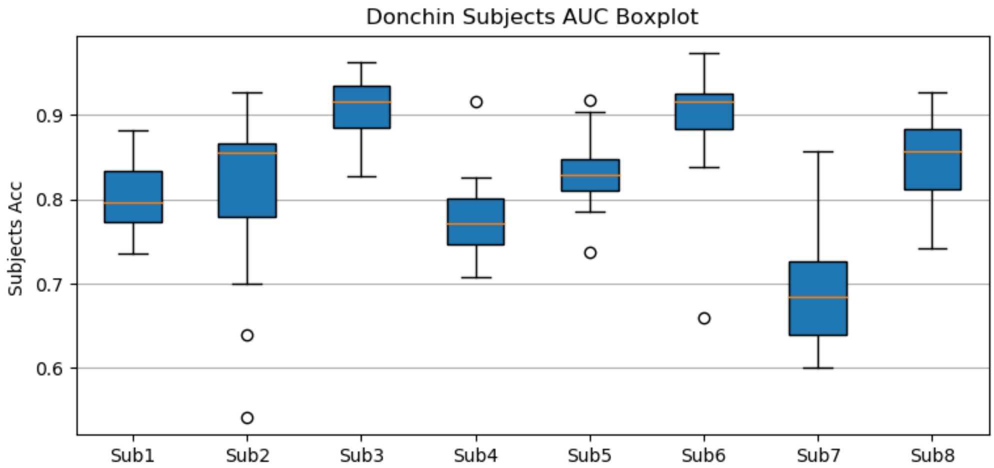


Figure 4-7 Donchin Subject mean AUC score boxplot - 3 seconds experiment

with one outlier below 0.4. Subject 7 does is the worst for the Donchin's speller (Figure 4.7) with a median around 0.7, and give an outlier. Also with Donchin, subject 6 excels, with a median of nearly 0.93, and a narrow IQR indicating a good overall performance. Subject 3 performs comparably well with a median around 0.92, but with a little more spread. This shows that Sub8 in the Circular method and Sub7 in the Donchin method achieve a poor result with lower averages and higher volatility. There are also outliers, a few of which are around 0.6. Subject 6s in both methodologies show great performance.

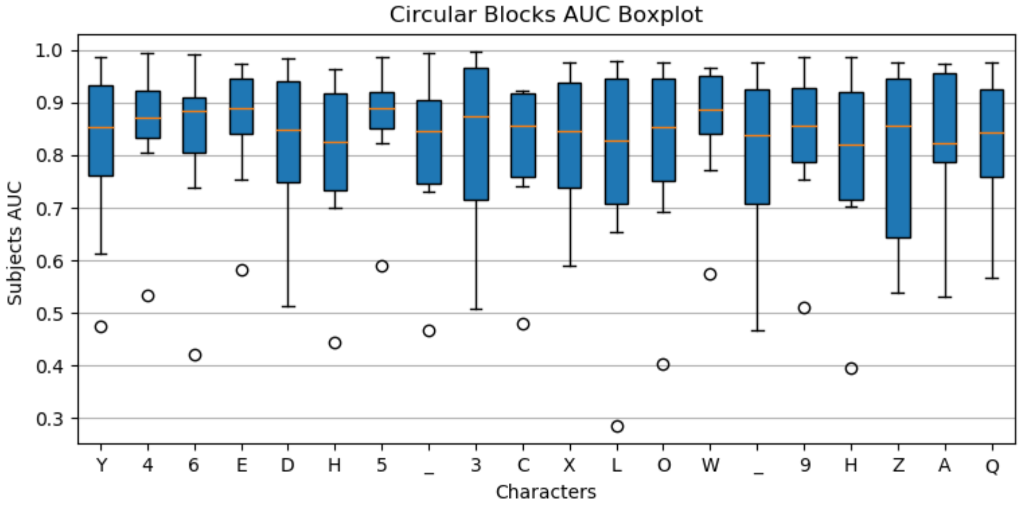


Figure 4-8 Circular - Mean AUC scores boxplot of each character - 3 seconds experiment

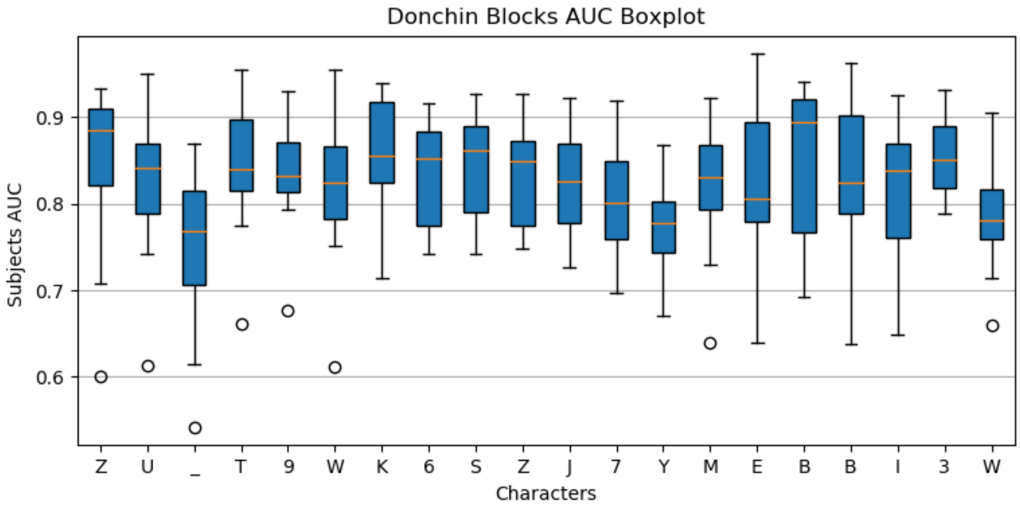


Figure 4-9 Donchin - Mean AUC scores boxplot of each character - 3 seconds experiment

The present study additionally examines the character-by-character AUCs for the two spelling methodologies. Figures 4.8 and 4.9 illustrate the variability of such AUC scores. As depicted in the picture, the Circular technique demonstrates a higher accuracy rate and more stability in the character based AUCs. The Circular protocol effectiveness in recognising target and non-target stimuli is believed to be minimally influenced by variations in character shape and position. However, the wide spectrum of outliers negatively affects the final character-based LDA/group classification results. The high AUC results did not work as well as desired in character selection due to outliers.

Finally, various methods were used for character classification and the results are listed in Table 4.3. The EEG data of 19 channels were applied to PCA after the filtering and artefact removal processes mentioned in section 3. Five components were identified through the PCA method, capturing approximately 98% of the variance. In each repetition we had 1 to 35 target/non-target epochs for circular and 1 to 5 target/non-target epochs for Donchin, and a dataset consisting of 5 components of each epoch. To overcome this imbalance, the Resampling method described in section 3.5.2 was applied and the target stimuli were duplicated until they were equal to the non-targets. For each epoch, probability scores were generated using *'proba'* from the `sklearn.lda`.LDA library. Character classification was made by applying the following formula:

$$c_{b,i} = \underset{c \in \{1,\ldots,36\}}{arg \max}(\overline{ProbA_{b,\iota}}(c)) \tag{4.1}$$

We assume there are 20 blocks in total. Each block be labelled by $\boldsymbol{b} \in \{1,2,\ldots,20\}$. Each block $\boldsymbol{b}$ contains $\boldsymbol{i}$ repetitions. This number can vary between 13 and 17. Each repetition consists of 36 characters, labelled $c \in \{1,2,\ldots,36\}$.

In the Table 4.3, 'Repetitions' indicates how many repetitions of trials were grouped before classification, i.e. for 'Repetition 3' the classification is the average of three stimulus presentations. It shows the success of character categorization and the ITR in the current experiment based on the number of repeats and highest prediction scores. The results indicate that the accuracy rate tends to rise with an increase in the number of repeats, as expected. There is a notable rise observed when shifting from 1 to 2 repetitions. A linear improvement in the results is observed and an acceptable success rate is reached after 6 repetitions. According to the average accuracy and ITR average, the Donchin method is generally performed better.

Table 4.3 Accuracy and ITR as a function of the number of trials averaged before making a selection for the circular sequential speller and Donchin's speller - 3 seconds experiment

		Repetitions												
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Circular	**Accuracy (%)**	0.30	0.43	0.54	0.59	0.50	0.70	0.71	0.71	0.74	0.77	0.79	0.81	0.82
	ITR (bits/min)	13.96	12.60	12.10	10.45	6.42	9.17	8.04	7.03	6.69	6.42	6.09	5.82	5.49
Donchin	**Accuracy (%)**	0.35	0.51	0.66	0.73	0.83	0.84	0.87	0.95	0.93	0.97	0.97	0.97	0.97
	ITR	18.04	16.57	16.67	14.72	14.56	12.38	11.27	11.57	9.88	9.64	8.77	8.04	7.42

In the Circular paradigm, accuracy starts at about 30% with 1 repetition and increases to 82% with 13 repetitions, while the corresponding ITR starts at about 13.96 bits/minute and decreases to 5.49 bits/minute by the 13th repetition. In contrast, the Donchin paradigm starts with 35% accuracy with 1 repetition, climbs to 97% by repetition 10, but its ITR also drops from 18.04 bit/min at 1 repetition to roughly 7.42 bit/min by repetition 13. In particular, Donchin tends to provide higher accuracy and also shows a higher initial ITR compared to Circular (e.g. 16.57-16.67 bits/min around 2-3 repetitions), but both paradigms show a trend where more repetitions provide more accuracy but ITR decreases.

4.4 Discussion

In this chapter, we designed an interface to the existing random flashing matrix as an alternative to a P300-based BCI paradigm with a repetition duration of 3 seconds and each repetition consisting of sequential flashes of 36 characters. Previous research has shown that sequential systems can also be used with spellers, although limited to 8 directions. The results of this study provide a comparative analysis of Circular and Donchin spellers, focusing on ERP grand averages, classification performance and cognitive processing dynamics. Based on these data, the performance of the Circular method, which is a P300-based BCI system, is analysed.

4.4.1 ERP Averages and Cognitive Tasks

ERP grand averages showed different patterns between the Circular and Donchin methods. In the circular speller, we observe that target stimuli elicit higher amplitude responses than non-target stimuli in areas associated with decision-making and attentional processes, such as the central (Cz) and parietal (Pz) areas. However, the Donchin speller exhibited fluctuations in the P300 signal due to overlapping target flashes and fluctuations between target stimuli.

As can be seen in Figures 4.2 and 4.4, an expected/sequential target produces a more distinct P300 amplitude for the user than a random/unexpected target. When we analyse the ERP patterns, we see that the circular speller is able to produce a more stable and distinct P300 signal, which is essential for effective character classification. The importance of ERPs is also seen in previous studies emphasising the importance of temporal interval in stimulus presentation. However, the 3-second repetition time in the Circular method may have caused fatigue, which may have negatively affected the potential of the participants' ability to sustain their attention. Therefore, shorter repetition times should be tested.

4.4.2 AUC and Classification Analysis

AUCs were used to measure the classification success of subjects across methods. It can be seen that both methods achieved an average AUC of 0.82. The Circular method seems to have less variability and fewer outliers. Subject 8 in the Circular speller and subject 7 in the Donchin speller had lower AUCs. This is thought to be due to mental and physical fatigue during the experiment. This also indicates the need for different strategies to mitigate fatigue-related performance decrements.

When we analysed the heatmaps and graphs, subjects such as subject 6 generally achieved high AUCs (median ~0.99) and narrow IQRs, demonstrating the robustness of the Circular method. When we analysed the Donchin method, it showed more variability due to wider IQRs and more prominent outliers, especially for some subjects such as subject 7. These results also point to the potential for the Circular speller to perform more reliably across different users.

The accuracy and ITR results in Table 4.3, which indicate the effect of repetitions, show that both methods benefit from increasing repetitions. Between 1 and 2 repetitions a significant increase in accuracy is observed. The Donchin method generally achieved higher accuracy and ITR, particularly with more repetitions. However, the Circular method showed comparable performance after six repetitions. Thus, it demonstrated the potential to achieve similar results with an optimised protocol.

4.4.3 Repetitions Impact on Accuracy and ITR

The analysis of accuracy and ITR as a function of repetitions shows that both methods benefit from increasing repetitions. Between 1 and 2 repetitions a significant increase in accuracy is observed. The Donchin method generally achieved higher accuracy and ITR, especially with more repetitions. However, the Circular method showed comparable performance after six repetitions. Thus demonstrating the potential to achieve similar results with a more optimised protocol.

The balance between accuracy and repetition time is a critical consideration for practical BCI applications as it affects ITR. The ITR performance of the Circular method with more repetitions may limit its real-time usability. However, its stability and robustness make it a promising alternative for applications requiring high reliability.

4.4.4 Fatigue and Individual Performance

Especially for subjects with outliers such as subject 8 (Circular) and subject 7 (Donchin), fatigue is an important factor affecting performance.Verbal feedback after the experiment indicates that reduced concentration due to mental and physical fatigue resulted in lower AUC and character classification. This result highlights the importance of designing experiments and protocols (e.g. shorter repetition time) that minimise cognitive load and fatigue. Stimulus presentation parameters such as TTI, ISI and repetition time can be increased or decreased depending on the individual performance of the subjects.

4.4.5 BCI Design and Limitations

Although the circular speller has shown several advantages, its long repetition time (3 seconds) may not be ideal for all candidates. Shorter repetition times or adaptive timing techniques could be investigated to increase its usability in real-time applications. In addition, the study had a relatively small sample size (8 participants) and some participants did not perform optimally, which negatively affected the results. This limits the generalisability of the results. Future research should include larger and more diverse groups of participants to confirm the results.

The study also highlighted the need for advanced pre-processing techniques to handle outliers and variability in ERP signals. Techniques such as adaptive filtering, machine learning-based artefact removal and individualised calibration can further improve classification performance.

In contrast to matrix studies, our speller was able to produce high P300 amplitudes by asking what colour the stimulus was rather than how many times it flashed. We argue that the high amplitude of the target stimulus is not primarily due to the stimulus colour/question procedure, but mainly due to the procedure of exposure of the sequential system to the target by the subject. The Circular speller produces statistically distinct and stable P300 signals, making it a promising alternative to traditional matrix-based approaches. The participant and character AUCs and the ERPs produced indicate that it can be used for applications requiring high stability, such as assistive communication devices for individuals with severe motor disorders. However, we need to reorganise the balance between experiment duration and participant concentration level. To achieve more user-friendly designs by improving user experience and performance, outliers should also be minimised.

4.5 Conclusion

This study presented a first comprehensive comparison of Circular and Donchin spellers, highlighting the strengths and limitations of each approach. The Circular method showed greater stability and robustness, while the Donchin method achieved higher accuracy and ITR with increasing repetitions. Since the amplitude and AUC scores obtained by our proposed method showed that it can produce more successful results in a short repetition, we repeated our experiment with a 2-second repetition and report results in the next chapter. The findings emphasise the importance of balancing accuracy, repetition time and user fatigue in BCI design. Future research should focus on optimising these trade-offs and addressing individual variability to advance the development of practical and reliable BCIs.

Chapter 5

Sequential Speller with 2 seconds revolution

Farwell and Donchin’s original BCI speller utilised visual stimulus presentation and the oddball effect, eliciting a P300 ERP response from the brain to a rare stimulus of interest. Most BCI spellers continue to rely on this principle and the original design proposed by Donchin. Several issues impact oddball spellers, which have been gradually addressed since the work of Farwell and Donchin, resulting in significant yet incremental performance improvements.

This study builds on previous research regarding a BCI for mouse cursor control, utilising a periodic stimulation protocol. We begin to explore whether a periodic presentation pattern could serve as a viable alternative to oddball-based BCI spellers. This study applies the concept of periodic stimulation to a BCI speller, wherein 36 letters are arranged in a circular format and highlighted in a sequential manner. The performance is compared to that of Farewell and Donchin’s speller at two different stimulation rates.

Following a similar order as in Chapter 4, first the ERPs are presented, then the subject- and character-based AUCs are analysed in tables and figures, and finally the character classification results are discussed. The results indicate that our speller generates notably large and distinct P300s, as well as comparably clear ERPs, consistent with the hypotheses proposed by Farwell and Donchin. At the higher stimulation rate, this results in a markedly improved classification accuracy and an approximately doubled information transfer rate compared to Donchin's speller.

5.1 Introduction

Target stimuli can be elicied t among the characters because they produce more detectable P300 signals than non-targets. Since the seminal work by Farwell and Donchin [45] (more on this below) based on visual Event Related Potentials (ERPs), a huge variety of BCI spellers have been introduced over the last 30+ years, including many based on SSVEPs, different perceptual modalities (auditory and tactile), and hybrid systems (e.g., relying on ERPs and SSVEPs, or on multimodality, e.g., visual and auditory) [152], [153], [154], [155], [156], [157], [158], [159]. Here we focus on BCI spellers based on ERPs. Most ERP based spellers rely on P300 elicited via the oddball paradigm [59], [60], [61] where one has to identify a rare and unpredictable target stimulus among non-target stimuli. The first speller of this kind was proposed in [45] and is known as the *matrix speller* [1]. There the letters of the alphabet were organiser in a matrix, the rows and columns of which are flashed/highlighted one at a time but in random order, and participants need to focus on the letter they want to spell and mentally count the number of times the row or column containing such letter are flashed. Target stimuli can be elicited among the characters because they produce more detectable P300 signals than non-targets.

Naturally over the years a number of variations and improvements of it have been proposed, one issue with it being the variable amplitude associated with P300s elicited by the protocol [160] and perceptual errors such as repetition blindness, attentional blink and near targets [77], [78]. Some examples of variations include flashing pseudorandom patterns of letters instead of rows and columns [85], the use of familiar faces [86], [87], the use of different changes to letters other than flashing [88] the use of colour [90], etc.Naturally over the years a number of variations and improvements of it have been proposed, one issue with it being the variable amplitude associated with P300s elicited by the protocol [160] and perceptual errors such as repetition blindness, attentional blink and near targets [77], [78]. Some examples of variations include flashing pseudorandom patterns of letters instead of rows and columns [85], the use of familiar faces [86], [87], the use of different changes to letters other than flashing [88], the use of colour [90], etc.

In [45] it was argued that their matrix speller would present an advantage over a *pure odd-ball speller* which would just present (or highlight) the letters of the alphabet one at a time in random order: it required participants to wait on average a shorter period (a smaller number of non-target stimuli) between flashes of the character a participant wanted to spell (the target stimulus), while with a pure odd-ball speller participants would have on average to wait until all other characters in the alphabet (non-target stimuli) have flashed. However, later research indicated that this is actually a viable approach.

The reason is that in most spellers the best P300 recognition accuracy would be obtained by temporally spacing the stimuli in such a way that their ERPs minimally overlap. However, this would lead to poor Information Transfer Rates (ITRs) [161], [162] because each selection would take a significant amount of time. To counter this, often spellers use shorter Inter-Stimulus Intervals (ISIs) and compensate for the reduced accuracy by averaging ERPs over multiple repetitions of stimulus presentation. In general, there is a tradeoff between deformations/amplitude reductions of the P300 (resulting in lower accuracy) and selection time, often the optimal ITR being associated with very short ISIs and a few repetitions of stimulus presentations. With such a strategy even a pure odd-ball speller might do well.

For instance, in [113] Guan *et al.* presented a matrix speller (with the usual 6 × 6 organisation) where characters flashed one at the time with an ISI of 60ms. The stimuli sequences were random but avoided neibouring characters flashing immediately after one another. Based on reported results and the presentation time of 2160ms for the 36 characters, we can compute ITRs, the best being 49.3 bits/min (obtained with 1 repetition), which is significantly higher than the 12 bits/min obtained with the original matrix speller [45].

However, a later comparison between this same paradigm and a region-based speller obtained significantly lowers ITRs for the former, the best being 26.1 bits/min (obtained with 3 repetitions) [163].

Guan *et al.* [113] approach was modified and tested in a recent study [164], where a 4× 10 matrix of characters was used. Here, however, characters where flashed/highlighted for 100ms, but flashing a new one every 30ms. So, there were up to than four stimuli on the screen at any given time. In addition, this protocol was compared with one where stereo visual stimuli and so characters were perceived both as flashing and moving cubes in 3–D space. In either protocol, all characters were highlighted within 30×40 = 1200ms. While accuracies and ITRs where graphically reported in [164], there appears to be an inconsistency between such data. Based our best estimates of accuracies and the presentation time of 1200ms, ITRs should be approximately 69 bits/min for Guan’s protocol and 91 bits/min for the proposed 3–D cubes version. While these are slightly lower than the reported ones, they are still quite impressive.

5.2 Methodology

The Oddball method is one of the widely used brain computer interface protocols for P300-based ERPs. However, speed and performance issues occur that adversely affects the operation of this method. Our method has been observed to have a greater accuracy and information transfer rate as an alternative to the existing Oddball method. The key factor that contributes to this performance improvement is the task sequence and visual stimuli of the protocol. The key point of the method is that, unlike the Oddball method, the stimulus sequence is in a certain order and the subjects can be better focused. In this way, the stimuli are shown in a certain order and at same intervals, and the subject can more easily distinguish the target between the stimuli. Method allows us to create 36 sets of codes since we can define multiple targets.

Unlike Chapter 4, we reduced the Repetition time from 3 seconds to 2 seconds. Therefore, the epoch time for the Circular method was 55.56ms (2000/36) and the epoch time for the Donchin method was 166.67ms (2000/12). Similar methods were used for data acquisition, signal processing and classification.

5.3 Results

In this section, the results of 2-second Dochin and Circular experiments conducted with 10 participants are presented and discussed.

The Circular speller (Figur 5.1) shows an obvious P300 ERP for targets at both presentation speeds, which correlates with the identification and silent naming of the target character's colour, as outlined in the Circular speller protocol. However, is not preceded by the typical early, pre-attentive ERPs observed in Donchin's speller grand average, but rather by a significant negative component. This is likely the concluding phase of a Contingent Negative Variation (CNV) [165], [166] as suggested by Farwell and Donchin [45], or potentially a Readiness Potential (RP) [167], [168]. Both are characterised as slow, negative-going potentials that arise in anticipation of an event or action. Studies have identified CNVs in contexts involving fixed foreperiods prior to stimulus presentation and in purely cognitive tasks [166], [169]. The readiness potential (RP) is typically linked to the preparation of motor actions [170], [171], [172]; however, recent findings indicate its association with the initiation of voluntary cognitive tasks [173].

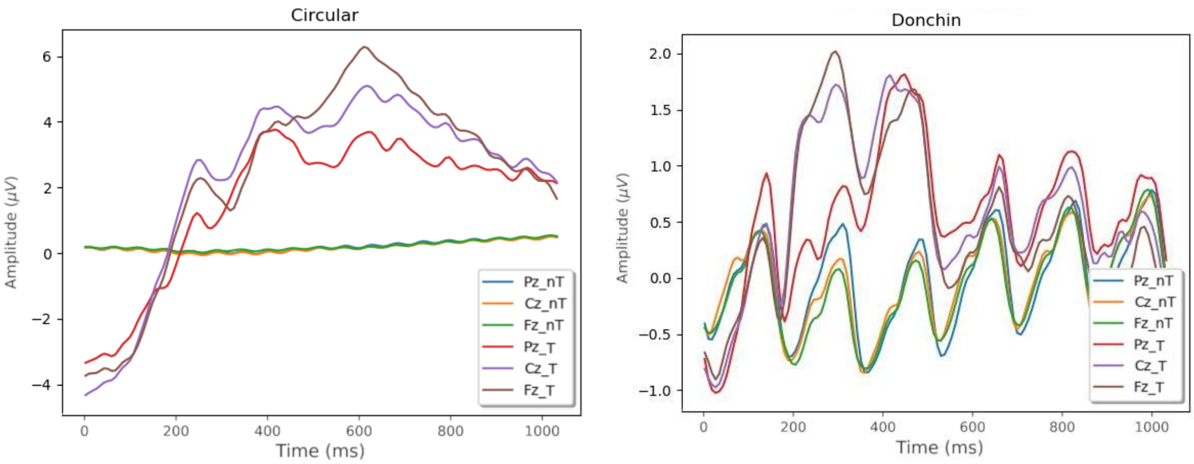


Figure 5-1 Circular and Donchin grand average ERPs - 2 seconds experiment

Figures 5.2 and 5.3 present the grand averages of the ERPs generated by the Donchin and Circular spellers in Experiment 2s, across all channels analysed, captured over 2s epochs to facilitate the examination of CNVs. In the plots, shaded regions indicate statistically significant differences, as determined by the Wilcoxon Signed Rank Test, with p-values below 0.05. The Wilcoxon test was applied to each sample within an epoch, comparing the voltages at that specific sample in the individual averages for targets against the individual averages for non-targets collected from the 10 participants in the experiment. A sampling rate of 32Hz was employed, consistent with that utilised for feature extraction and classification.

Figure 5.2 shows that, in Donchin's speller, statistically significant differences between target and non-target epochs primarily occur within the time interval of 300ms to 550ms following stimulus onset, aligning with the P300 time window for the relevant electrodes. Figure 5.3 shows that, in contrast to Donchin's speller, the Circular speller exhibits substantial differences in ERP amplitudes between target and non-target stimuli. These differences are statistically significant for a considerable portion of the initial 1000 ms of the epochs, indicating their presence in the majority of individual average ERPs, and are evident across most channels. In all 19 channels examined, statistically significant differences in the CNV preceding the P300 and a 500ms preparation period at the end of the epoch were observed. This indicates that, for the Circular speller, anticipatory potentials are present and assist in the discrimination of targets from non-targets, as predicted by Farwell and Donchin.

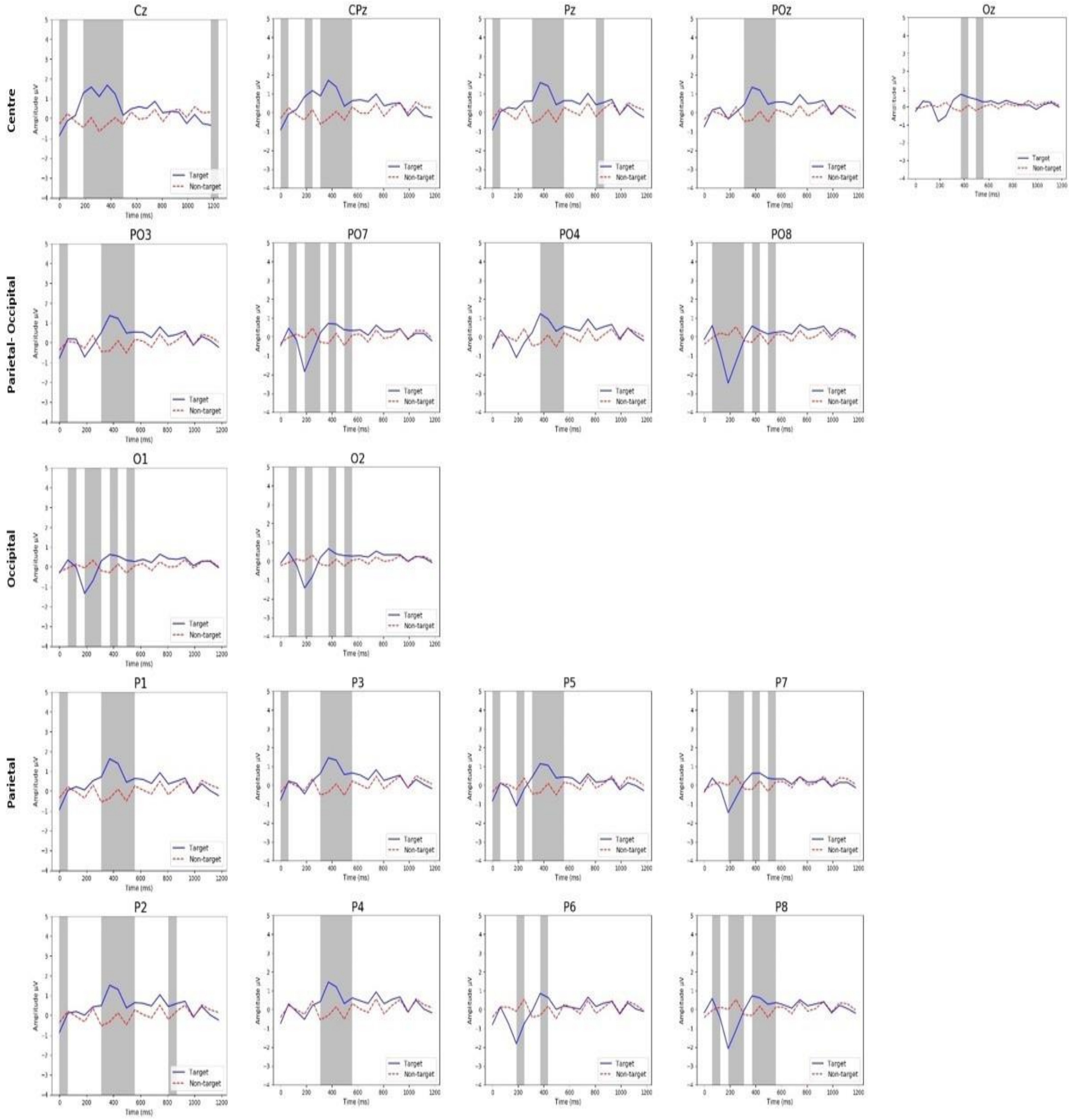


Figure 5-2 ERP grand-averages of the targets (blue lines) and non-targets (red lines) for 19 EEG channels for the Donchin speller in Experiment 2s. Shaded areas in each plot represent statistically significant differences.

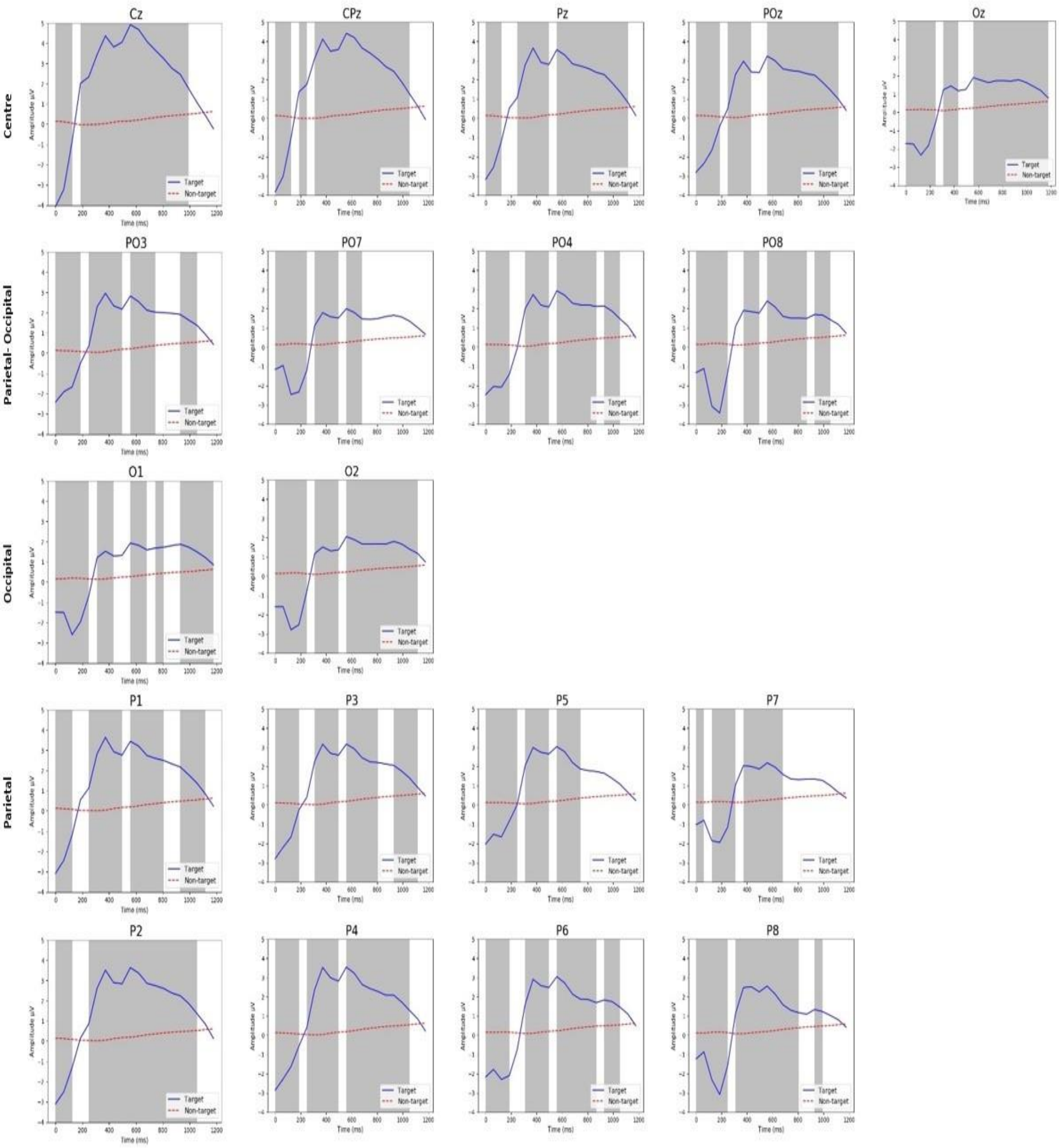
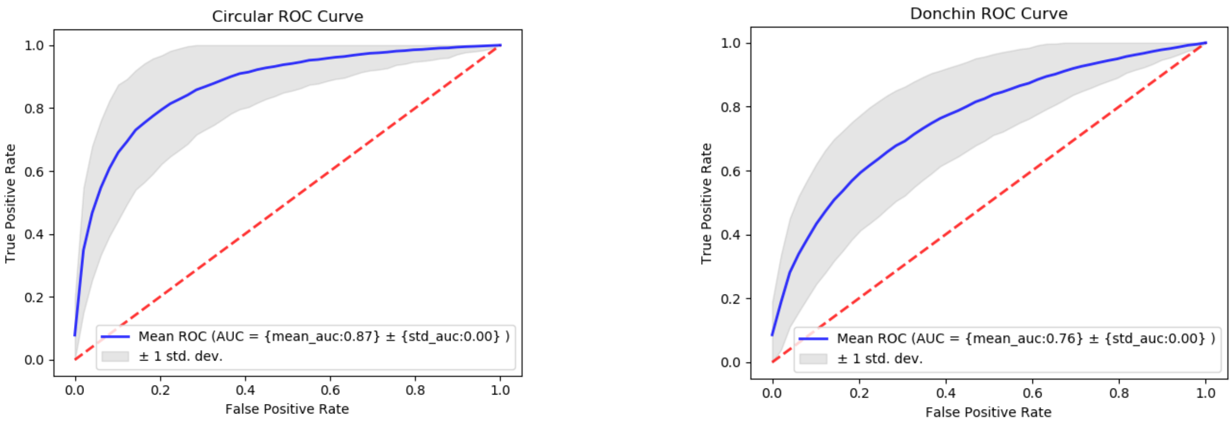


Figure 5-3 ERP grand-averages of the targets (blue lines) and non-targets (red lines) for 19 EEG channels for the Circular speller in Experiment 2s. Shaded areas in each plot represent statistically significant differences.

As shown in Figure 5.2 when the amplitude of the P300 occurs, a significant change is observed in parietal and occipital lobes of the brain. Firstly, all 64 channels were selected for classification. However, this method was not used because of its lower accuracy and high computational cost. The change in the parietal and occipital lobes of the brain is a sign that the channels in this region are suitable for feature selection. However, there are several methods to achieve better results using fewer features. PCA is a statistical approach that is used to reduce data dimensionality while maintaining as much information as feasible. It entails converting a set of variables into a new set of uncorrelated variables known as principal components, which explain the most variance in the data. Initially, PCA was applied using all 64 channels and the feature set consisting of 5 components was extracted. Although this method produced satisfactory results, PCA was applied with 19 channels consisting of the more active parietal and occipital lobes of the brain, as we mentioned above, for better classification and the number of components was reduced to 5.

However, since SVM classification was observed to reach lower accuracy rates than LDA classification, LDA was chosen as the classification technique in the next stage. LDA produces better results for binary classification with low computational cost. Table 5.1 and 5.2 shows that the Circular method performs much better binary classification in LDA classification. While the P300 signal typically occurs between 300 and 600 milliseconds, more favourable outcomes are achieved when the complete epoch is incorporated in Table 5.1. Nevertheless, because this is not an accurate and adequate approach for character classification, further research into classification methods is required.

Area Under the Curve (AUC) score was used to measure the accuracy of our classifier based on the target. AUC is the ratio of the true-positive number to the false-positive number. In other words, it represents the area under the Receiver Operating Characteristic (ROC) curve. It produces more relevant results against imbalanced classes because it considers both the true positive rate and the false positive rate at the same time. Binary classification isn’t an adequate measure, as the number of non-target characters is 35 times the number of target stimuli. Therefore, looking at the AUC parameter and the ROC graph produces more meaningful results. In Figure 5.4, it is seen that the Circular method is more successful in



(a) (b)

Figure 5-4 Receiver operating characteristic (ROC) curves and AUCs - 2 seconds experiment (a) Circular's speller ROC curve, (b) Donchin's speller ROC curve

target/nontarget separation. These results were obtained by obtaining the more pronounced P300 signal via the longer TTI as mentioned above.

There is a Target/Non-target stimulus imbalance at this stage, such as 1 to 35 in the Circular approach. Target stimuli (minority class) were duplicated and the number of target-non-target stimuli equalized to adjust the imbalanced data set. The imbalanced data problem was solved by resampling/duplicating the target stimuli in both the Circular method and the Donchin method. In both experiments, some tired participants did not focus fully on the experiment, resulting in below-average classification results. The results shown in Table 5.2 occurred because participant 8 did not achieve a sufficient level of focus in both experiments. Since these outliers did not occur in a large number of subjects and the participant was observed to be tired, they do not indicate a problem with our proposed method.

Table 5.1 Circular Subject AUC scores for each character - 2 seconds experiment

Circular Blocks AUC

	Y	4	6	E	D	H	5	_	3	C	X	L	O	W	_	9	H	Z	A	Q
Sub1	0.88	0.95	0.92	0.95	0.86	0.95	0.8	0.81	0.92	0.86	0.88	0.79	0.93	0.91	0.87	0.93	0.93	0.94	0.87	0.96
Sub2	0.85	0.83	0.79	0.86	0.92	0.83	0.9	0.89	0.84	0.9	0.94	0.83	0.85	0.91	0.82	0.93	0.95	0.93	0.94	0.84
Sub3	0.93	0.94	0.95	0.91	0.94	0.92	0.83	0.84	0.94	0.89	0.94	0.82	0.79	0.94	0.9	0.96	0.94	0.92	0.92	0.89
Sub4	1	0.97	0.97	0.97	0.99	0.99	0.97	0.94	0.94	0.99	0.97	0.98	0.98	0.98	0.9	0.97	0.98	0.98	0.96	0.89
Sub5	0.92	0.82	0.81	0.93	0.86	0.92	0.85	0.84	0.87	0.85	0.76	0.81	0.8	0.84	0.79	0.89	0.89	0.89	0.87	0.78
Sub6	0.96	0.95	0.89	0.93	0.96	0.96	0.9	0.97	0.94	0.93	0.95	0.87	0.91	0.89	0.95	0.95	0.92	0.92	0.97	0.97
Sub7	0.84	0.84	0.89	0.92	0.96	0.93	0.94	0.83	0.95	0.95	0.88	0.94	0.85	0.92	0.89	0.87	0.96	0.96	0.97	0.94
Sub8	0.6	0.74	0.84	0.82	0.69	0.75	0.77	0.74	0.65	0.7	0.59	0.79	0.76	0.74	0.7	0.69	0.58	0.54	0.61	0.69
Sub9	0.89	0.81	0.83	0.8	0.71	0.93	0.81	0.8	0.76	0.85	0.84	0.87	0.82	0.85	0.76	0.9	0.64	0.89	0.87	0.91
Sub10	0.93	0.87	0.77	0.84	0.85	0.86	0.85	0.77	0.94	0.85	0.9	0.82	0.83	0.94	0.78	0.9	0.92	0.89	0.93	0.9

Table 5.2 Donchin Subject AUC scores for each character - 2 seconds experiment

Donchin Blocks AUC

	Y	4	6	E	D	H	5	_	3	C	X	L	O	W	_	9	H	Z	A	Q
Sub1	0.81	0.73	0.65	0.88	0.76	0.81	0.83	0.85	0.84	0.73	0.76	0.8	0.79	0.79	0.65	0.77	0.74	0.83	0.82	0.85
Sub2	0.9	0.91	0.77	0.85	0.9	0.91	0.86	0.84	0.83	0.85	0.86	0.73	0.88	0.88	0.81	0.85	0.86	0.88	0.89	0.8
Sub3	0.81	0.73	0.71	0.73	0.82	0.68	0.69	0.73	0.76	0.82	0.79	0.74	0.7	0.8	0.77	0.65	0.78	0.75	0.74	0.78
Sub4	0.83	0.9	0.79	0.91	0.91	0.89	0.95	0.92	0.89	0.91	0.9	0.89	0.92	0.89	0.96	0.82	0.91	0.9	0.97	0.91
Sub5	0.8	0.72	0.85	0.74	0.81	0.82	0.8	0.7	0.87	0.79	0.74	0.73	0.84	0.81	0.72	0.81	0.82	0.69	0.8	0.8
Sub6	0.93	0.81	0.79	0.84	0.86	0.82	0.77	0.71	0.84	0.84	0.87	0.77	0.82	0.81	0.84	0.85	0.76	0.73	0.8	0.8
Sub7	0.71	0.8	0.61	0.75	0.64	0.71	0.69	0.68	0.71	0.75	0.57	0.74	0.67	0.65	0.74	0.67	0.77	0.77	0.62	0.7
Sub8	0.73	0.66	0.65	0.68	0.55	0.75	0.74	0.74	0.66	0.7	0.64	0.68	0.61	0.61	0.58	0.74	0.53	0.7	0.58	0.63
Sub9	0.58	0.6	0.55	0.52	0.48	0.66	0.52	0.58	0.63	0.52	0.63	0.57	0.51	0.64	0.5	0.62	0.69	0.47	0.58	0.6
Sub10	0.87	0.84	0.79	0.89	0.78	0.87	0.86	0.76	0.8	0.79	0.88	0.86	0.75	0.84	0.88	0.79	0.71	0.76	0.76	0.85

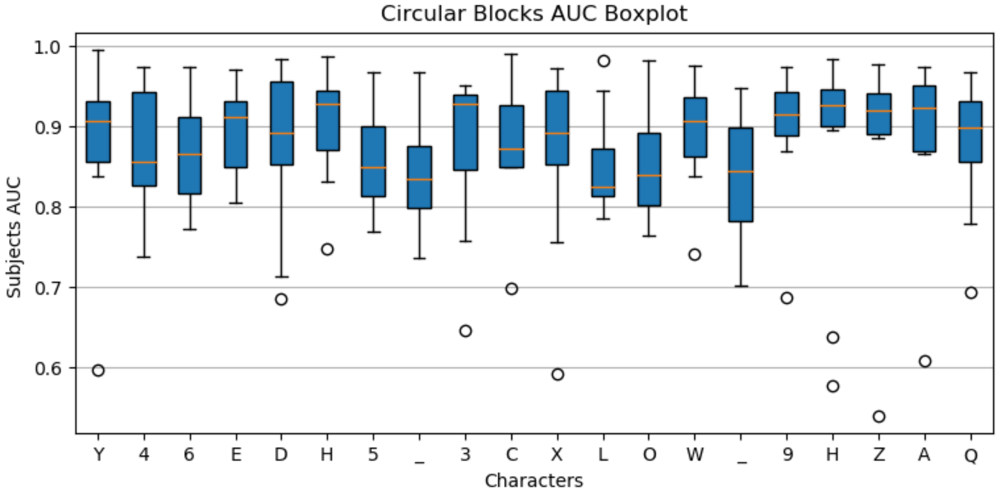


Figure 5-5 Circular - Mean AUC scores boxplot of each character - 2 seconds experiment

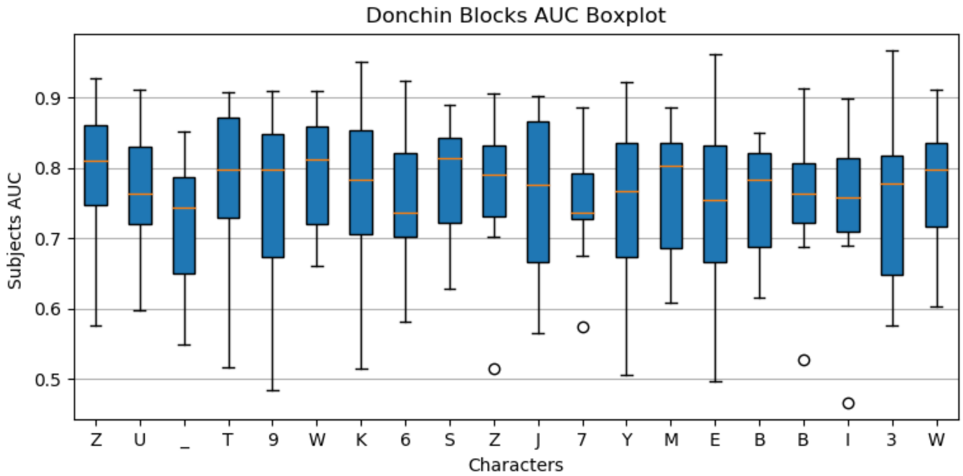


Figure 5-6 Donchin - Mean AUC scores boxplot of each character - 2 seconds experiment

The Circular method, the character classification of the circular effect is also investigated. Figure 5.5 shows whether the location and order of the characters cause problems in classification. As can be seen in the figure, in the Circular method, the characters are classified with a more stable and higher accuracy rate. In Donchin method, since it is not known when and how often the stimulus will flash, it is seen that it causes fluctuations in the character classification results. It is observed that the proposed method can successfully distinguish the target/non-target stimulus without being affected by the shape, position and order of the characters.

Table 5.3 Accuracy and ITR as a function of the number of trials averaged before making a selection for the Circular sequential speller and Donchin's speller.

		Repetitions												
		1	2	3	4	5	6	7	8	9	10	11	12	13
Circula	Accuracy (%)	44.56	58.44	68.02	72.46	79.11	81.25	84.74	84.14	85.50	87.50	86.00	90.50	89.50
	ITR (bits/min)	40.05	30.88	26.26	21.81	20.15	17.56	16.16	13.97	12.76	11.96	10.55	10.57	9.57
Donchi	Accuracy (%)	31.36	47.32	57.14	64.31	69.61	76.75	78.68	82.00	83.33	85.50	86.00	85.00	86.50
	ITR	22.56	22.05	19.86	17.99	16.35	15.98	14.27	13.38	12.22	11.49	10.55	9.48	9.02

Table 5.3 shows the success of character classification according to the number of repetition and maximum estimation scores of the present study. For example, Rep4, the target stimulus location was determined by averaging the indices indicated by the highest proba-LDA score obtained from 4 repetitions. The results obtained indicate that as the number of repetitions in the repetition increases, the accuracy rate in general increases. It is observed that a significant increase occurred when passing from 1 to 2 repetitions. It is seen that there is a linear increase in the results and a satisfactory success rate is achieved after 6 repetitions. The average ITR results, which are used to measure the data transmission rate, show that the Circular method is more successful, although it has a negative impact on the mean of Subject 8.

The data transfer rate was calculated using the equation below:

$$\text{ITR} = \left(\log_2 N + P \cdot \log_2 P + (1-P) \cdot \log_2\left(\frac{1-P}{N-1}\right)\right) \Big/ \left(\frac{T}{60}\right),$$

where N is the number of classes, P is the accuracy of the classifier and T is the selection time in seconds.

Although each repetition fluctuates greatly within itself, the overall results show an increasing success rate. Although there were outliers in each iteration that would adversely affect the classification, on average, the Circular method performed more successful classification at all stages.

According to these results, the classification success and speed of data transmission of the developed system is at a competitive level. It has proven to provide 45% classification accuracy in one repetition and successful communication with 40.05 bits/min ITR.

The test results indicate that the Circular method produces better results, it should be determined whether it is statistically different with the fire Donchin method. Wilcoxon Signed Rank Test was used to measure this difference statistically and the p-value of the measurement result is below 0.05.

5.4 Discussion

This study tests the hypothesis proposed by Farwell and Donchin [45] that periodic highlighting of stimuli in a BCI speller may elicit slow preparatory potentials, such as CNVs, alongside P300 ERPs, potentially enhancing classification performance. We didn't strictly follow to Farewell and Donchin’s recommendation to sequentially flash the rows and columns of a matrix speller due to the challenges associated with this paradigm, as discussed in previous chapters, which subsequent research on RSVP and SD spelling methods aimed to resolve.

We didn't strictly follow to Farewell and Donchin’s recommendation to sequentially flash the rows and columns of a matrix speller due to the challenges associated with this paradigm, as discussed in Chapter 3, which subsequent research on RSVP and SD spelling methods aimed to resolve. We implemented the circular shape of the letters, drawing from previous research on a sequential BCI mouse [151] and containing a few similarities to the LSC speller [112], which featured four neighbouring letters as opposed to the two in our design. We presented the letters sequentially, contrasting with [112], where letters were displayed randomly, with the only periodicity being the alternation of flashes between the left and right sides of the screen.

Circular method also utilised colour, particularly in the modification of the letters, which distinguishes it from [45]. In contrast to earlier speller protocols that utilised colour solely to enhance stimulus salience (e.g., [90]) while the cognitive task involved counting the highlights of the target, our novel approach integrates a mental task that necessitates attention to the colour of the highlighted target characters, which were randomly presented in green or red. This may appear to be a minor distinction; however, in [151], when stimulation was periodic, the cognitive task of counting target flashes did not produce any P300 ERPs, whereas the task of mentally naming the colour of targets resulted in the largest P300s.

In the colour naming task, Circular speeller successfully elicited significant CNVs and P300s when targets were present, confirming our initial predictions in [45]. The P300s elicited by the Circular speller were found to be larger and more distinct compared to those elicited by Donchin's speller. This indicates that the high TTI employed in Circular paradigm, along with the mental task, sufficiently compensates for the lack of randomness and surprise in the timing of the flashes. The unexpected finding was that accuracies and ITRs for the Circular speller were higher at the faster presentation rate compared to the slower rate, contradicting conventional wisdom regarding P300.

A notable degree of smoothness is evident in the grand average ERPs of the Circular speller for Experiment 3s. This observation indicates that, across various trials or participants, the mental task may not have consistently occurred at the same interval following target presentations. This inconsistency could lead to variability in the ERPs of participants or a temporal shifting in individual averages. This results in smoother and lower-resolution grand averages, as discussed in [174]. The effect is significantly less pronounced in the Circular speller's grand average for Experiment 2s, indicating that jitter or temporal shifts are less evident.

The observations align with the identified presence of CNVs or RPs in the Circular speller, consistent with Farwell and Donchin's prediction and the existing literature on temporal preparedness and the foreperiod effect. These are examined in experiments where a warning stimulus precedes a target stimulus that necessitates a response [175], [176], [177], [178]. The warning stimulus improves participant preparation, leading to reduced reaction times and increased accuracy. When the temporal difference between warning and target stimuli (the foreperiod) remains constant, an increase in the foreperiod correlates with longer reaction times to the target stimulus and decreased accuracy. Participants find it easier to estimate elapsed time for shorter foreperiods compared to longer ones. The shorter foreperiod results in reduced variance in the allocation of attentional resources in preparation for the task.

In the Circular speller and its BCI mouse counterpart, the regular interval between consecutive target flashes allows the previous target flash to function as a warning stimulus for the subsequent target, with the temporal distance between them serving as a constant foreperiod. Consequently, as discussed, we should expect increased variability in the timing of mental tasks, similar to response times observed in preparedness studies, as well as in the associated ERPs, particularly with extended foreperiods, such as in Experiment 3s. This could be an explanation for the enhanced smoothing observed in the grand averages for Experiment 3s compared to those in Experiment 2s.

The Circular speller ERPs for channels Fz, Cz, and Pz are taller, wider, and significantly delayed with regard to pointer control, but they have comparably clear and distinct P300s for targets when compared to those we described for the circular pointer control protocol in [151]. More precisely, the P300 spans roughly 450 ms in pointer control against 650 ms in the speller, (2) the peak amplitude is 3–4μV for pointer control versus 4–8μV for the speller, and (3) the P300 peaks at approximately 400 ms for pointer control versus approximately 600 ms for the speller. Additionally, we observe the same "flat-line" grand averages for non-targets, with only a slight ripple brought on by the stimuli's flashing, which in the pointer control ERPs is at 8Hz because a 125ms ISI was used.

A significant difference is that in the target ERPs for pointer control, the standard early exogenous components are present, whereas the CNV or RP are absent. This is likely attributable to the pointer control BCI having a TTI of 800ms, whereas the speller utilised TTIs of 2s and 3s. Upon completion of the mental task related to target presentation, associated by the corresponding ERPs, there was not enough time for the EEG to return to a resting state, thus precluding the observation of any significant CNV, which is characterised as a slow cortical potential.

As discussed in Section 5.3, the Circular speller produces larger ERPs for targets compared to Donchin’s speller; however, at the slower presentation rate, both spellers exhibit the same AUC. This result appears counterintuitive; however, it can be explained as follows: (1) As discussed in Sections 3.1.2 and 4.2, the Circular speller expects timing jitter in the execution of the mental task linked to a target flash, leading to corresponding jitter in the ERPs; (2) consequently, a classifier must be capable of identifying jittered versions of the P300 and CNV ERPs associated with targets; however, (3) this presents challenges, as epochs near targets, particularly those related to non-targets immediately before and after a target, will contain slightly shifted versions of these ERPs (the shift being 83.3 ms, or less than 3 samples). This makes non-targets almost indistinguishable from jittered versions of the targets.

In Experiment 2, smaller P300 amplitudes were observed for both Donchin’s speller and the Circular speller, which corresponds with the expected results based on the reduced TTI. In Donchin's speller, this results in a reduced ROC and a lower AUC compared to Experiment 3s. Conversely, the Circular speller exhibits the opposite effect. The observed phenomenon can be attributed to the foreperiod effect previously discussed. In Experiment 2s, the shorter foreperiod leads to reduced mental task jitter and, subsequently, decreased ERP jitter when compared to Experiment 3s. This reduction facilitates the classifier's ability to distinguish between targets and non-targets more effectively.

The results for the Circular speller appear to rise more slowly than Donchin's when we closely examine the accuracy data shown in Table 5.3. This phenomenon is attributed to the mental task jitter in the Circular speller previously discussed. Although reduced at an increased presentation rate, it remains evident. Averaging scores across multiple repetitions can mitigate EEG noise; however, it does not eliminate the jitter linked to the mental task. Consequently, the Circular speller's accuracy increases at a slower pace than Donchin's, and it is probable that it will saturate below 100% as the number of repetitions increases. Both the rearrangement of stimuli and the further reduction of the TTI may address the issue, as discussed in the subsequent section.

5.5 Conclusions

This study presents a novel EEG speller that, through a periodic stimulation paradigm, induces both P300 event-related potentials and slow cortical potentials. Farwell and Donchin initially proposed the potential viability of such a speller in their important 1988 study [45]. Nonetheless, no published studies seem to have performed and evaluated this concept, as the majority of research has concentrated on incremental modifications of the original row-column oddball speller.

This study analyses whether a periodic presentation procedure could serve as a feasible alternative to oddball-based BCI spellers. We chose a circular arrangement of letters, a single-display approach for their highlighting, and we highlighted them in colour, following successful experience with the development of a BCI mouse [151]. Stimuli were presented in succession with brief inter-stimulus intervals of 83 ms and 55 ms. We believe that a significant factor in the effectiveness of the strategy was our modification of the mental work from typical target-flash counting to the silent naming of the colours of target flashes.

The results indicated that our sequential speller generates not only surprisingly substantial and distinct P300s but also comparably clear CNVs, as proposed by Farwell and Donchin. At the slower stimulation rate, these didn't produce substantial improvements in accuracy and information transfer rate compared to Donchin's speller. At an ISI of 55 ms, the Circular speller exhibited better classification accuracy and an ITR that was 2 to 3 times greater than that of both the Donchin spellers and the slower Circular speller.

Significantly more work is required in future study. Initially, we should to evaluate a variant of the Donchin speller in which rows and columns are periodically highlighted in colour, requiring users to mentally identify the colour of the targets. Based on our findings with the Circular speller, this approach is expected to provide better results compared to the original Farwell and Donchin speller assessed in this study. Secondly, considering the performance improvement noted in the 2s experiment compared to the 3s experiment, together with prior research on a BCI mouse where all stimuli were highlighted within 800ms, it is possible that faster presentation durations could further enhance the performance of the Circular speller. Thirdly, to tackle the accuracy-saturation issue referenced at the conclusion of the preceding section, drawing from the methodology in [112], it may be feasible to spatially arrange the stimuli (e.g., in two concentric circles) to optimise the distance between successive flashes (e.g., highlighting the characters in the inner circle asynchronously with those in the outer circle), thereby reducing near target responses. Fourthly, we can use extended epochs that would encompass a greater portion of the CNV, potentially enhancing classification efficacy. Fifthly, we ought to investigate more advanced feature extraction and categorisation techniques. Ultimately, following additional offline improvement efforts to enhance the speller, we should start online testing.

Chapter 6

Achievements, Conclusions and Future Work

6.1 Achievements

In early 1969, Donchin [31] proposed the first single-trail analysis of event-related potentials based on the difference between the ERP and the average evoked potential. Signal processing and classification methods in P300-based BCI methods have advanced since the 1970s, alongside the development of different interface designs. It was thought that this method could be applied on the Speller with the P300-based Mouse developed by Alvaris *et al.* [151].

The investigation focused on the design of the 36 characters/stimuli in order to generate a distinct P300 signal in the subject while minimising interference with other stimuli due to crowding and adjacency of stimuli (which affects most other spellers). As an alternative to randomization, a sequential stimulus system was devised to avoid confusion between stimuli. The choice of shape and colour was decided on the basis of examples in the literature. Initial results, although open to improvement, indicate the possibility of an alternative to the existing RC speller paradigm.

Despite this being a completely new and untested paradigm, , the Circular method outperformed Donchin method, providing a 45% improvement in single-trial character classification accuracy (31% vs 45% task accuracy), and 74% improvement in ITR (from 23 vs 40 bits/minute) . Both paradigms converged to over 90% character-classification accuracy as the number of repetitions increased.

While the 3-seconds experiment shows that Donchin performs better than Circular, the 2-seconds experiment shows that, unlike Donchin's speller, our proposed method benefits from a faster stimulus presentation and thus can produce higher ITRs. We believe that the good results of the Circular method are partly attributable to the speller allowing subjects to reduce their attention levels immediately following the mental task, as they know when the next mental task is due. While with the longer (3s) stimulus duration this “rest period” increases and so in principle the participants would fatigue less. However, longer waiting times between target stimulus presentation reduce the ability of participants to accurately predict the time of the next mental task, including jitter and reducing classification accuracy. Also, of course, with longer inter-target presentation times, there is an associated reduction in ITR.

During the signal acquisition process, data were collected by using Biosemi 64 channel wired EEG device. Although this system produces high quality data, it causes discomfort in users in long-term use because it restricts mobility. This and fatigue/focusing problems are important issues that directly affect classification success in BCI systems. Although wireless dry EEG devices provide an alternative for mobility, it is still difficult to obtain good quality/low noise data. Invasive techniques offer both mobility and high-quality data, but, their limited adoption is due to the necessity of a surgical procedure.

EEG data were collected with a 2048Hz sampling frequency and 64 channels. Although this sampling frequently and the use of all channels provide good data for detailed research, they increase the computational cost considerably. Therefore, we had to downsample our data to the smallest sampling rate that still ensured the relevant ERPs were still represented well. We found that a sampling rate of 32Hz was sufficient. Subsequently, we carefully selected 19 channels, specifically the occipital and parietal lobes, fromthe initial 64 channels of EEG data, following the guidance provided in the literature. In addition to reducing computational costs, minimising the influence of non-relevant brain areas with P300 signals helped us inprove classification performance. Still with the aim of attaining optimal performance, while minimising data usage, we applied the technique of PCA, finding that our data can be appropriately represented by 5 components. All this resulted in reducing the input features from 64∗2,048=131,072 to 32∗5=160 features per second.

There is always a significant imbalance between target and non-target stimuli in the data gathered from BCI spellers, and with Circular in particular. Accurately classifying targets in a system with 1 target stimulus among 36 stimuli is highly challenging. Without modification, standard classification techniques either resulted in low accuracy or overfitting. In order to train our system, we had two options: either to reduce the number of non-target stimuli or to increase the number of target stimuli by resampling and to equalise them with non-target stimuli. Due to the limited number of trials, we decided to increase the number of target stimulus epochs through resampling, as the option of reducing non-target stimuli would reduce system performance.

6.2 Future Work

The study in this thesis provides an alternative to the approach of randomly flashing stimuli in BCI paradigms with its corresponding issues, such as adjacency, crowding and fatigue. The positive results obtained in this thesis have been discussed previously. In this section, based on the lessons learnt and the weaknesses identified in the thesis, the work that needs to be done in the future is indicated.

The online experiment phase was unable to proceed due to Covid restrictions and financing limitations. Given that BCI systems are especially designed for individuals with motor-neuron diseases and are meant to be used in daily activities, in the future it is imperative to conduct online experiments with the Circular speller. Firstly, the experiments should be conducted online using a similar participant group to the one used in the thesis (university students), and feedback should be collected. Any necessary modifications or improvements should be implemented based on these first online studies. Following these improvements, the next stage should be to conduct experiments specifically including motor-neuron patients, who are the primary target users. The results of these online studies will allow for a more accurate evaluation of the cognitive processes accuracy rate and the test results of individuals and groups with varying physical abilities.

During the experiment, the subject was left alone in the room to make the subject feel more comfortable and there was no direct communication. Although the desired goal (feeling of comfort) was generally achieved with this experimental environment, some subjects did not show sufficient concentration because they were tired (they participated in the experiment after working hours). Since this was not recognised and intervened during the experiment, it caused some subjects to produce unusually bad results. Throughout future experiments, we may need monitor the subjects for any potential issues, lapses in focus, need for rest, or more requests.

Currently, there is a continuous development of artificial intelligence, classification algorithms, and novel methods. In this thesis, we were able to test a limited number of signal processing, feature selection/extraction and classification methods. Methods that are currently available but not tested in our thesis and newly developed methods should be studied in future research to determine if they produce better results.

Upon analysing Chapters 4 and 5 collectively, it was noted that the shorter stimulus time produced better results. It is possible that even lower stimulus times, such as 1 second, might result in further improved classification results and higher ITRs. Of course, it is also possible that the optimum time is in between 2 and 3 seconds. Finally, it is not unlikely that the optimal time varies person by person. Therefore, future research should experiments using both shorter and longer stimulus durationsboth at the level of groups and person-by-person.

Hybrid character selection/classification methods should be tested in the future to increase the success rate of classification. For instance, the process of spelling can be executed more efficiently combining the Circular design with the T9 approach. Other combinations could also be fruitful.

In our proposed method, the stimuli were arranged in a circular pattern. To increase the distance between the stimuli, they could also be arranged in a square pattern. Also different geometric shapes could be tried as stimulus layout (e.g. rectangle, hexagon, star, zigzag,.. etc.). The stimuli progress sequentially from A to Z, and then from 0 to 9. This order can also be arranged so that the index number increases by 2, first the odd-numbered indexes, then the even-numbered indexes. Thus, it can be determined whether the P300 signal is easier to discriminate.

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Appendix A

1. Experiment Consent Form

CONSENT FORM

Title of the Project: Brain Computer Interface P300-based Speller with Sequential Stimulation

Researchers: Ahmet Can Mercimek, Prof Riccardo Poli, Dr Caterina Cinel

Please initial box

1. I confirm that I have read and understand the Information Sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these questions answered satisfactorily. ☐

2. I understand that my participation is voluntary and that I am free to withdraw from the project at any time without giving any reason and without penalty. ☐

3. I understand that, due to the nature of the stimulation used, the experiment may not be suitable to individuals who suffer, or have suffered, from epileptic seizures or have a family history of seizures, that I am aware of the potential risks associated with that, and I confirm that, to the best of my knowledge, nobody in my family (including myself) have never had epileptic seizures. ☐

4. I understand that, due to the nature of the stimulation used, the experiment is not suitable for individuals with colour-vision deficiencies, and I confirm that, to the best of my knowledge, my colour vision is normal. ☐

5. I understand that the identifiable data provided will be securely stored and accessible only to the members of the research team directly involved in the project, and that confidentiality will be maintained. ☐

6. I understand that data collected in this project might be shared as appropriate and for publication of findings, in which case data will remain completely anonymous. ☐

7. I agree to take part in the above study. ☐

Participant Name	Date	Participant Signature
____________________	______________	___________________________
Researcher Name	Date	Researcher Signature
____________________	______________	___________________________

2. Sequential Speller Ethical Approval Form (First Page)

University of Essex

Application for Ethical Approval of Research Involving Human Participants

This application form must be completed for any research involving human participants conducted in or by the University. 'Human participants' are defined as including living human beings, human beings who have recently died (cadavers, human remains and body parts), embryos and foetuses, human tissue and bodily fluids, and human data and records (such as, but not restricted to medical, genetic, financial, personnel, criminal or administrative records and test results including scholastic achievements). Research must not commence until written approval has been received (from Departmental Research Director/Ethics Officer, Faculty Ethics Sub-Committee (ESC) or the University's Ethics Committee). This should be borne in mind when setting a start date for the project. Ethical approval cannot be granted retrospectively and failure to obtain ethical approval prior to data collection will mean that these data cannot be used.

Applications must be made on this form, and submitted electronically, to your Departmental Research Director/Ethics Officer. A signed copy of the form should also be submitted. Applications will be assessed by the Research Director/Ethics Officer in the first instance, and may then passed to the ESC, and then to the University's Ethics Committee. A copy of your research proposal and any necessary supporting documentation (e.g. consent form, recruiting materials, etc) should also be attached to this form.

A full copy of the signed application will be retained by the department/school for 6 years following completion of the project. The signed application form cover sheet (two pages) will be sent to the Research Governance and Planning Manager in the REO as Secretary of the University's Ethics Committee.

1. Title of project: **Brain Computer Interface P300-based Speller with Sequential Stimulation**

2. The title of your project will be published in the minutes of the University Ethics Committee. If you object, then a reference number will be used in place of the title.
Do you object to the title of your project being published? **No**

3. This Project is: **PhD Research Project**

4. Principal Investigator(s) (students should also include the name of their supervisor):

Name:	Department:
Ahmet Can Mercimek	**CSEE**
Prof Riccardo Poli	**CSEE**
Dr Caterina Cinel	**CSEE**

5. **Proposed start date**: **January 2019**

6. **Probable duration**: **36 months**

7. Will this project be externally funded? **Yes**

8. What is the source of the funding?
Turkish Embassy

Research and Enterprise Office (smp) December 2014 Page: 1 of 6

3. Information sheet given to the participants explaining the experimental details

University of Essex

Brain Computer Interface P300-based Speller with Sequential Stimulation
14th January 2019

Invitation to our study

We would like to invite you to participate in our research project. You should only participate if you want to; choosing not to take part will not disadvantage you in any way. Also, you can take part in the study only if you do not have an own or family history of epileptic seizures and have normal colour vision. Before you decide whether you want to take part, it is important for you to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or you would like more information (see contact details below).

Background on the project

This research is in the field of Brain-Computer Interfaces (BCIs). BCIs aim at directly interpreting the intentions of computer users with regard to commands they wish to give the computer thereby freeing them from the need of using transducers of musculoskeletal movement such as the keyboard and mouse.

In previous research, we developed a BCI mouse capable of full 2-D motion control. Starting from our successful BCI mouse, in this project we aim at developing a correspondingly successful BCI speller, that is a virtual keyboard requiring no manual input.

The system we are developing works by presenting multiple, rapidly changing, coloured visual stimuli (shapes and letters) to the user and registering the modifications they cause in the user's brain activity recorded via electroencephalography (EEG, more on this below).

Experiment

After an initial phase of preparation (which includes setting up the EEG equipment and an possibly eye-tracker, see below) and familiarisation, requiring approximately 30-40 minutes, the experiment involves multiple sessions, each lasting only a few minutes, in which participants look at a computer screen while comfortably seated. Participants will be given the opportunity to rest in between sessions.

In each session participants will be presented with a display containing the characters of the alphabet, numbers and possibly other symbols and shapes organised in some regular configuration (e.g., a grid or a circle). The elements in the display will be briefly highlighted using different colours then rapidly returning to their original state. The order and nature of the highlighting will vary in different sessions of the experiment.

During the sessions, participants will be asked to focus on one particular character and to perform a simple mental task every time that character is highlighted. The task will depend on the particular stimulation modality adopted in the session, but it will be extremely simple, such as mentally counting the number of highlights of the target character or mentally naming its colour.

Electroencephalography (EEG)

EEG is used to measure brain activity. The EEG we use is the same type routinely used in the medical practice, and is entirely non-invasive and safe. The use of the EEG equipment requires wearing an electrode cap. A small amount of gel needs to be applied to each electrode to obtain cleaner signals from the brain. The gel is transparent, non-greasy, skin-friendly and can be easily removed.

Are there any risks associated with EEG?

EEG is a very safe procedure that is used widely and is not known to have any harmful side effects. There is no risk of electrical shock from the electrodes because the system is powered only by a battery.

Eye Tracking

If applicable to your particular experiment, eye tracking will be performed with a small and light device that is worn like a pair of glasses. The device uses invisible infrared light to monitor eye movements.

Are there any risks associated with eye tracking?

No. The infrared light emitted by the device is completely harmless. Also, there is no risk of electrical shock from the device because it is powered only by a battery.

Other potential risks and exclusions

Due to the nature of the stimuli used, our interventions may not be suitable to individuals who suffer, or have suffered, from epileptic seizures or have a family history of seizures. These, therefore, cannot take part in the study. Also, only individuals with normal colour vision can participate in the experiment due to our system relying on coloured stimuli.

Informed consent

Should you agree to take part in this experiment, you will be asked to sign a consent form before the experiment commences.

Withdrawal

Your participation is voluntary and you will be free to withdraw from the project at any time without giving any reason and without penalty. If you wish to withdraw, you simply need to notify the principal investigator (see contact details below). If any data have already been collected, upon withdrawal, your data will be destroyed, unless you inform the principal investigator that you are happy for us to use such data for the scientific purposes of the project.

Data gathered

We will collect the following data for each participant: age, gender, handedness, whether they have normal vision or corrected to normal, electrical brain activity data, and possibly eye-tracking signals.

This information is essential to compute the standard statistics on participants required for the purpose of publishing the results of our studies. The data will be stored in electronic files only accessible to project researchers.

Signed consent forms will be kept separately from individual experimental data and locked in a drawer until the end of the project.

Findings

After the end of the project, we will publish the findings of our experiments (all data published will be anonymised). We will be happy to provide you with a lay summary of the main findings and with copies of the articles published if you express an interest.

Concerns and complaints

If you have any concerns about any aspect of the study or you have a complaint, in the first instance please contact the principal investigator of the project (see contact details below). If are still concerned or you think your complaint has not been addressed to your satisfaction, please contact the Director of Research in the principal investigator's department (see below). If you are still not satisfied, please contact the University's Research Governance and Planning Manager (Sarah Manning-Press).

Funding

The research is internally funded by the University of Essex.

Ethical approval

This project has been reviewed on behalf of the University of Essex Ethics Committee and had been given approval.

Contact details

B. Subjects PCA component Variances – 3 second experiment