

Portable Brain Computer Interface (BCI) in the Intensive Care Unit (ICU)

by

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Table of Contents

| | |
|---|-----|
| List of Tables | iii |
| List of Figures | iv |
| List of Abbreviations | v |
| Abstract | vi |
| Chapter 1: Introduction | 1 |
| 1.1 BCI for Intensive Care Unit (ICU) Patients | 3 |
| 1.2 BCI Technical Challenges | 5 |
| Chapter 2: Literature Survey and Conventional Solutions | 7 |
| 2.1 Canonical Correlation Analysis (CCA): | 9 |
| 2.2 Power Spectral Density Analysis (PSDA): | 10 |
| Chapter 3: Partition-Based Feature Extraction and Score Space Fusion | 12 |
| 3.1 Data acquisition and experimental setup: | 12 |
| 3.2 Task and the SSVEP paradigm: | 13 |
| 3.3 CCA and PSDA score space partitioning: | 14 |
| 3.4 Feature extraction and score space fusion: | 18 |
| 3.5 SSVEP identification performance utilizing the fusion spaces: | 19 |
| Chapter 4: Discriminative Transformation of the Fusion Space | 22 |
| 4.1 Principal Component Analysis (PCA): | 22 |
| 4.2 Linear Discriminant Analysis (LDA): | 25 |
| 4.3 Comparison to Benchmark Systems Utilizing the Discriminative Feature Extraction via Multivariate Linear Regression (MLR) Method: | 28 |
| Chapter 5: Conclusion | 31 |
| References | 32 |
| Related Publications | 38 |

List of Tables

| | |
|---|----|
| Table 1. Actual frequency conversion values from Hertz to Milliseconds vs. our system's performance over 4 epochs | 15 |
| Table 2. SSVEP identification accuracies of CCA, PSDA, and the fusion score spaces | 20 |
| Table 3. SSVEP identification performance utilizing PCA..... | 24 |
| Table 4. SSVEP identification performance utilizing LDA | 26 |
| Table 5. Comparison of the SSVEP identification performance amongst CCA, LDA, and MLR..... | 29 |
| Table 6. Information transfer rates (ITRs) of CCA, LDA, and MLR in bits/min | 30 |

List of Figures

| | |
|---|----|
| Figure 1. CCA-based target frequency identification | 10 |
| Figure 2. Experimental setup and electrodes location | 13 |
| Figure 3. The training session's experimental paradigm..... | 14 |
| Figure 4. Impact of the insufficient screen refresh rate on the SSVEP identification performance | 16 |
| Figure 5. Subjective responses demonstrated in the CCA plot of 2 different subjects..... | 17 |
| Figure 6. Partitioning CCA and PSDA's score spaces..... | 17 |
| Figure 7. Block diagram of the proposed method..... | 22 |
| Figure 8. SSVEP identification performance before and after applying PCA on the fusion spaces from the 1 st and 3 rd partitioning cases | 24 |
| Figure 9. LDA's performance before and after the log transformation..... | 27 |

List of Abbreviations

- SSVEP: Steady-State Visual Evoked Potential
- BCI: Brain-Computer Interface
- CCA: Canonical Correlation Analysis
- ICU: Intensive Care Unit
- PSDA: Power Spectral Density Analysis
- PCA: Principal Component Analysis
- LDA: Linear Discriminant Analysis
- EEG: Electroencephalogram
- ITR: Information Transfer Rate
- SNR: Signal-to-Noise Ratio

Abstract

Steady State Visual Evoked Potentials (SSVEPs) have been the most commonly utilized Brain Computer Interface (BCI) modality due to their relatively high signal-to-noise ratio, high information transfer rates, and minimum training prerequisites. Up to date Canonical Correlation Analysis (CCA) and its extensions have been widely utilized for SSVEP target frequency identification. However, reliable and robust SSVEP identification performance is still a challenge, particularly for portable BCI systems operating in an Intensive Care Unit (ICU) department filled with various source of noise. As such, I propose an innovative partition-based feature extraction method that entails partitioning the score spaces of CCA and Power Spectral Density Analysis (PSDA) in three cases, extract efficient descriptors from each partition, then concatenate the extracted measures to generate more discriminative fusion spaces. Moreover, I investigate transforming the fusion spaces to lower dimensions utilizing Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Finally, to validate the proposed method, I compare the performance of the partition-based feature extraction and score space fusion method to a well-established SSVEP identification method based on Multivariate Linear Regression (MLR). The experimental results of this investigation report that the proposed method enhances the identification performance of the CCA-based BCI system from 63% to 78%. The identification performance is further improved to 98% after the discriminative transformation with LDA outperforming MLR, which achieved an average overall 86% identification accuracy. As such, the proposed method is a promising approach to implement and operate BCI systems in the ICU.

Chapter 1: Introduction

Brain Computer Interfaces (BCI) are systems that provide direct communication pathways and/or control channels between the user's brain and external devices (Sagahon-Azua et al. 2017). The BCI technology is based on measuring the brain's neural activity invasively or noninvasively utilizing various modalities, such as ElectroEncephaloGraphy (EEG), Magnetoencephalography (MEG), near-infrared spectroscopy (NIRS), functional magnetic resonance imaging (fMRI), ElectroCorticography (ECoG), and intracortical electrode recordings (Bashashati et al. 2007; Coyle et al. 2004; Gilja et al. 2011; Hwang et al. 2013; Leuthardt et al. 2004; Mellinger et al. 2007; Sitaram et al. 2007; Sitaram, Caria, and Birbaumer 2009). However, EEG-based BCIs have been the most commonly utilized systems due to their advantages, such as high temporal resolution, portability, noninvasiveness, and low cost (Bashashati et al. 2007; Hwang et al. 2013). EEG is essentially a BCI modality that allows recording the electrical potential, which is generated as a results of the firing of neurons inside the brain, from the scalp of the head (Niedermeyer, E., & da Silva 2005).

Generally, BCI systems operate by detecting unique brain activity patterns (i.e. neural responses), triggered consciously or unconsciously via an external stimuli (Bashashati et al. 2007). As such, to recognize those neural responses, BCI systems leverage brain activity patterns, such as selective sensation (SS) (Yao et al. 2013), steady state somatosensory evoked potentials (SSSEPs) (Müller-Putz et al. 2006), P300 evoked potentials (Donchin, Spencer, and Wijesinghe 2000), sensory motor rhythm (Wolpaw and McFarland 2004), and steady-state visual evoked potentials (SSVEP) (Cheng et al. 2002). The selection of the appropriate brain activity pattern is determined by the purpose of the application, the impact of the input features on the information transfer rate (ITR) of the system, and finally the required training period. Despite the diversity of brain activity patterns, SSVEP has attracted the attention of the BCI research community due to the advantages it provides, such as high signal-to-noise

ratio (SNR), relatively high ITR, minimum training prerequisites, and the ability to provide a reliable communication paradigm to implement noninvasive BCI systems (Chen et al. 2015). SSVEP is a recurrent response triggered in the brain, particularly in the occipital and parietal regions, when a user focuses their attention on a visual stimulus that flickers with a specific target frequency, and is sustained throughout the whole fixation period (Cheng et al. 2002). The SSVEP response consists of the actual target frequency in addition to its harmonic frequencies. Thus, SSVEP target frequency identification algorithms recognize the frequency components that correspond to the visual stimuli allowing SSVEP-based BCI systems to communicate the intended commands. In SSVEP-based BCI paradigms, users are exposed to visual stimuli (Citi et al. 2008). Each stimuli indicates a corresponding action, such as prosthesis movement, icons and/or alphabet letters selection. Typically, users fixate their gaze and focus their attention on a particular stimuli while disregarding the others, thus, the brain pattern corresponding to the frequency components of the visual stimuli is generated in the user's brain and is translated as the user's will to execute the desired command (Wolpaw and Wolpaw 2012).

The architecture of a BCI systems is typically comprised of a number of various modules that construct a closed and complete loop between the system's user and the device they seek to control (Müller-Putz 2011; Müller-Putz et al. 2013; Nicolas-Alonso and Gomez-Gil 2012). In the case of EEG-based BCI systems, EEG is used to record the neural responses using multiple electrodes that are positioned at the scalp of the head. Those electrodes serve to measure and, in turn, record the electrical potentials elicited in the user's brain by the external stimuli. Then, the recorded signal is filtered to disregard the irrelevant frequency range, and remove artifacts generated as a result of other physiological factors, such as eye blinking, pulse, and blood circulation (Fatourechhi et al. 2007). Following the signal filtering phase, operating a BCI system successfully necessitates a feature extraction phase. As such, effective descriptors are extracted from the filtered signal to prove or disprove the existence of a phenomenon in the brain's neural responses. This is achieved by interpreting feature spaces of the extracted measures utilizing classifiers and/or a set of predetermined rules (Lotte et al. 2007). Thus, once the system determines the user's mental state and makes a decision regarding their brain activity at the time, the output is passed to control devices, for instance, a visual display or a prosthesis.

1.1 BCI for Intensive Care Unit (ICU) Patients:

The paucity of effective and consistent communication means in hospitals can cause distress for doctors and patients, especially for patients in the Intensive Care Unit (ICU). ICU patients are voiceless and incapable of communicating their physical and emotional needs verbally (Happ 2000). 40% of communication efforts were categorized as cumbersome by patients, while more than 33% of communication sessions pertaining to expressing pain and/or discomfort were rated as futile (Happ et al. 2011). Moreover, 86% of all communication efforts is instigated by the ICU medical staff. Thus, patients can therefore experience fear, anxiety, unrecognized pain, and discomfort (Carroll 2004; Happ et al. 2011). Additionally, family members and caretakers of ICU patients expressed anxiety and distress as well due to their inability to meet the needs of their critically ill (Baker and Melby 1996). As such, this can force the hands of the medical staff to resort to unnecessary sedative medications, and it might also lead to extended length of stay in the ICU department and increased treatment costs (Carroll 2004). Furthermore, the lack of effective communication renders the critically-ill patients incapable of being active participants in their treatment.

Typically, communication with critically-ill patients in the ICU is carried out utilizing non-vocal means, mainly gestures and lip reading (Leathart 1994; Menzel 1998), both of which are ineffective communication approaches (Cronin and Carrizosa 1984; Jablonski 1994; Wagner et al. 1998). Meanwhile, the utilization of picture boards, where each picture represents a common patient need and/or complaint, demonstrated a relative communication improvement amongst the medical staff and postoperative mechanically-ventilated patients (Stovsky, Rudy, and Dragonette 1988). This approach is the closest technique to setting communication standards for voiceless and mechanically ventilated patients in the ICU.

Numerous pilot studies suggested the utilization of computer-based communication that uses gaze trackers, blinking detection and finally touch screens to facilitate communication in the ICU (Maringelli et al. 2013; Miglietta, Bochicchio, and Scalea 2004). Most of the medical staff, who were surveyed in both studies, reported improvements in their ability to address and meet the patients' needs. However, the usage of touch screens in this context might not be efficient for all patients, particularly for patients with severe motor disabilities. Moreover, 25% of patients in the

ICU are mechanically ventilated and most likely suffer from exhaustion, Neuropathy, and Myopathy. This causes a tremendous restriction on their ability to use their hands to utilize touch screens for communication purposes (De Jonghe et al. 2002). Additionally, some of these patients are awake and fully alert, however, they are locked-in and possess no control on their bodily functions, such as critically-ill patients who suffer from severe spinal cord injuries, advanced Amyotrophic Lateral Sclerosis (ALS), and strokes (Smith and Delargy 2005). As a result, using touch screens for the aforementioned population of patients is futile. Therefore, the utilization of BCI systems in the ICU, which are usually used for patient monitoring (Chang and Tsuchida 2014; Halford et al. 2015; Park et al. 2016), can facilitate effective and consistent communication between patients and their medical staff. This is due to the fact that BCI systems inherently interpret the electrical potentials of the brain into computer commands, bypassing the peripheral nerves and muscles.

Numerous efforts investigated employing BCI systems for communication in the ICU for critically-ill patients suffering from ALS, severe spinal cord injuries, and stroke (Chaudhary, Birbaumer, and Curado 2015; Daly and Huggins 2015; Marchetti and Priftis 2015; Nijboer et al. 2008; Sellers, Ryan, and Hauser 2014). The utilization of BCI systems in these efforts has been investigated during the rehabilitation period following a critical illness or when patients are discharged from hospitals and are recovering at home. The BCI systems that were used provided text-based communication tools, such as BCI spellers (Tang et al. 2017), outside the ICU department. Despite the paramount importance and the intrinsic value of the aforementioned rehabilitation-driven communication systems, they are typically slow and relatively cumbersome to learn. Moreover, they require extended periods of time to fully master. Nevertheless, the needs of patients in the ICU should be communicated and addressed rapidly and reliably, rather than through spelling of individual letters to formulate words and sentences. As such, I propose a portable BCI system based on visual attention (i.e. SSVEP) to expressive icons rendered on an Android tablet screen. Each icon depicts a symbol that illustrates a particular need of an ICU patient, such as “I feel pain”, and flickers with a specific target frequency. As such, the BCI system can recognize which icon the patient is focusing on based on the target frequency of that particular icon (Farooq and Dehzangi 2017; Herrmann 2001). Thus, patients can communicate the desired message simply by looking at the icon that illustrates their need and/or complaint. The proposed

BCI system is completely noninvasive and poses no risks to patients' health nor treatment progress. Moreover, the EEG recording device connects wirelessly with the Android tablet.

1.2 BCI Technical Challenges:

I. Calibration:

Subject-specific information is intrinsic to a high and reliable SSVEP identification performance. Therefore, to incorporate them into the decision making process, BCI systems usually require calibration at the beginning of each recording session. This requirement is not only time consuming but is also inconvenient for patients in the ICU. As such, the proposed BCI system acquires the subject-specific information throughout the feature extraction and predictive model training phases.

II. Precision of the SSVEP paradigm generation:

SSVEP is essentially a visual attention approach, where patients focus on a specific target object amongst multiple target objects, and each object flickers with a specific and fixed target frequency. The accuracy of the SSVEP paradigm generation is dictated and largely influenced by the hardware specifications of the device on which the SSVEP paradigm is generated. The proposed BCI system in this thesis utilizes an Android tablet as a visual stimuli so as to accommodate portability. However, the screen refresh rate of the Android tablet-based visual stimuli is insufficient. Moreover, the recurrent interruptions of the Android operating system also exacerbate the precision of the SSVEP paradigm generation. As such, the proposed BCI system utilizes a partition-based feature extraction method that alleviates the impact of the imprecise SSVEP paradigm generation on the identification performance.

III. Number of target objects:

Determining the appropriate number of target objects to be rendered on the visual stimuli, without overwhelming the screen's real-estate nor causing interference with the patients' visual perception, is another challenge for SSVEP-based BCI systems in general. As such,

the proposed BCI system undertakes a 2-phase divide-and-conquer approach. Initially, the system recognizes the patients' intent to initiate communication. Then, utilizing an optimized stimuli flow, the system enables patients to select their need and/or complaint effectively.

IV. The non-stationary nature of the EEG signal:

EEG signals are inherently non-stationary. They typically demonstrate session-to-session and subject-to-subject variation due to the inconsistencies of the electrodes-scalp locations and the signal quality between 2 different sessions. Additionally, the physiological and emotional state of patients are also contributing factors. As such, the proposed BCI system exploits the discriminative and complementary information of 2 widely used method for SSVEP target frequency identification, Canonical Correlation Analysis (CCA) and Power Spectral Density Analysis (PSDA), to capture a higher resolution of the subject-specific information embedded within the SSVEP responses to improve the identification performance.

Chapter 2: Literature Survey and Conventional Solutions

Despite the wide utilization of SSVEP-based BCI systems, and the advantages they offer compared to other BCI systems types, reliable SSVEP target frequency identification is still the subject of interest for a plethora of scientific investigations.

(Bin et al. 2009; Hakvoort, Reuderink, and Obbink 2011; Lin et al. 2007; Wang et al. 2006) asserted that Canonical Correlation Analysis (CCA), and Power Spectral Density Analysis (PSDA) are the most commonly employed target frequency identification methods in SSVEP-based BCI systems. While, CCA-based target frequency identification focuses solely on the correlation between 2 data sets, PSDA examines the power spectral density of the raw EEG signal. Hence, the frequency with the maximum PSD value is identified as the intended target frequency. However, PSDA has been overshadowed by CCA for a number of compelling reasons, such as, PSDA's high susceptibility to noise, particularly when utilizing a single channel for data acquisition, and the relatively long time windows for sufficient frequency resolution estimation of the spectrum, both of which exacerbate the information transfer rates and impair the real-time performance of BCI systems (Friman et al. 2007; Lin et al. 2007).

Wei and colleagues reported that CCA's performance is more robust than PSDA (Wei, Xiao, and Lu 2011), while Wei *et al.* asserted that CCA is considered state-of-the-art SSVEP target frequency identification method (Wei et al. 2013). Nevertheless, despite the promising improvements CCA offers, such as the ability to utilize harmonic frequencies, minimal subject variation, and better signal-to-noise ratio (SNR) (Bin et al. 2009; Cheng et al. 2002; Gerven et al. 2009; Lin et al. 2007), current SSVEP-based BCI technology is still not suitable for real world scenarios, particularly in an ICU environment filled with various sources of noise, electrical devices, and distractions, not to mention the impact of the technical challenges discussed in Chapter 1 Section 1.2 on the SSVEP target frequency identification performance.

Numerous scientific efforts investigated different EEG pattern recognition methods (CONG et al. 2013; Krusienski et al. 2011; Park et al. 2013; Spüler et al. 2014; Wu et al. 2015; Zhang, Zhou, Zhao, et al. 2013). Friman and colleagues proposed a Minimum Energy Combination (MEC) method, which is similar to Lin's CCA-based method (Lin et al. 2007), in that, they both utilize sine-cosine frequency profile reference templates. As such, this approach ensures multi-channel optimization employing spatial filters, and also increases the signal-to-noise ratio. Nevertheless, sine-cosine frequency profile reference templates cannot efficiently characterize the discriminative information embedded within the SSVEP responses, which leads to lower SSVEP identification accuracies (Zhang, Zhou, Jin, et al. 2013). Pan and colleagues introduced a phase-constrained CCA approach. In their investigation, they include the phase information, which are obtained from the training data, into the reference signals to mitigate the drawback of the sine-cosine reference templates (Pan et al. 2011). Zhou *et al* proposed a Common and Individual Feature Analysis (CIFA) method to extract and learn the SSVEP features (Zhou et al. 2016). Their proposed method has been demonstrated to outperform CCA. Zhang and colleagues argued that maximizing the correlation between the multi-dimensional EEG signal and the sine-cosine reference signals could lead to improved SSVEP identification performance. As such, they proposed a Multiway extension of CCA (MCCA) (Zhang et al. 2011). Furthermore, Zhang *et al* proposed the L1-regularized method, which is an extension of the MCCA method (L1MCCA) (Zhang, Zhou, Jin, et al. 2013). Both MCCA and L1MCCA have been demonstrated to outperform CCA's SSVEP identification performance. Vu and colleagues investigated maximizing the correlation between the collected EEG signals and the frequency profile reference templates (Vu, Koo, and Choi 2017), thus, they proposed a deep CCA (DCCA) method that entails utilizing deep neural networks to learn the nonlinear transformations of 2 datasets into a space where they are highly correlated. In their investigation they concluded that DCCA enhances the signal-to-noise ratio and achieves a more robust SSVEP identification performance than CCA. However, they observed that these empirical results are largely dependent on the experimental conditions and individual subjects.

2.1 Canonical Correlation Analysis (CCA):

CCA is a multivariate statistical technique utilized to find pairs of linear combinations (i.e. canonical variables) for 2 sets of variables in a way that maximizes the correlation between the canonical variables (Lin et al. 2007). After finding the 1st pair of linear combinations, CCA also finds the 2nd pair, which has the 2nd highest correlation and is uncorrelated with the 1st pair. The process of obtaining the linear combinations persists until the number of the linear combinations pairs equals the number of variables in the smaller set. CCA's coefficients serve to characterize the correlation between the 2 sets of variables.

Conventional correlation methods examine the correlation between 2 variables, whereas CCA extends ordinary correlation and investigates the correlation between 2 sets of variables, which is more suitable for real-world problems (Harmony et al. 1990; Storch and Zwiers 1999) and it's therefore commonly utilized in statistical and information mining (Friman et al. 2001; Storch and Zwiers 1999).

Assume the multidimensional variables X, Y have linear combinations $x = X^T W_x$ and $y = Y^T W_y$. As such, CCA obtains the weight vectors, W_x and W_y , to maximize the correlation between X , and Y as follows:

$$\max_{W_x W_y} \rho(X, Y) = \frac{E[x^T y]}{\sqrt{E[x^T x]E[y^T y]}} \quad (1)$$

$$= \frac{E[W_x^T X Y^T W_y]}{\sqrt{E[W_x^T X X^T W_x]E[W_y^T Y Y^T W_y]}} \quad (2)$$

Where the highest canonical correlation is denoted by the maximum value of ρ taking into account W_x and W_y , while projections onto W_x and W_y (i.e. x and y) denote the canonical variants.

Figure 1 demonstrates the utilization of CCA for target frequency identification, where f_1, f_2, \dots, f_m denote the number of target frequencies, X indicates the raw EEG signal, Y represents the frequency profile reference signal comprised of the fundamental target frequency, and its

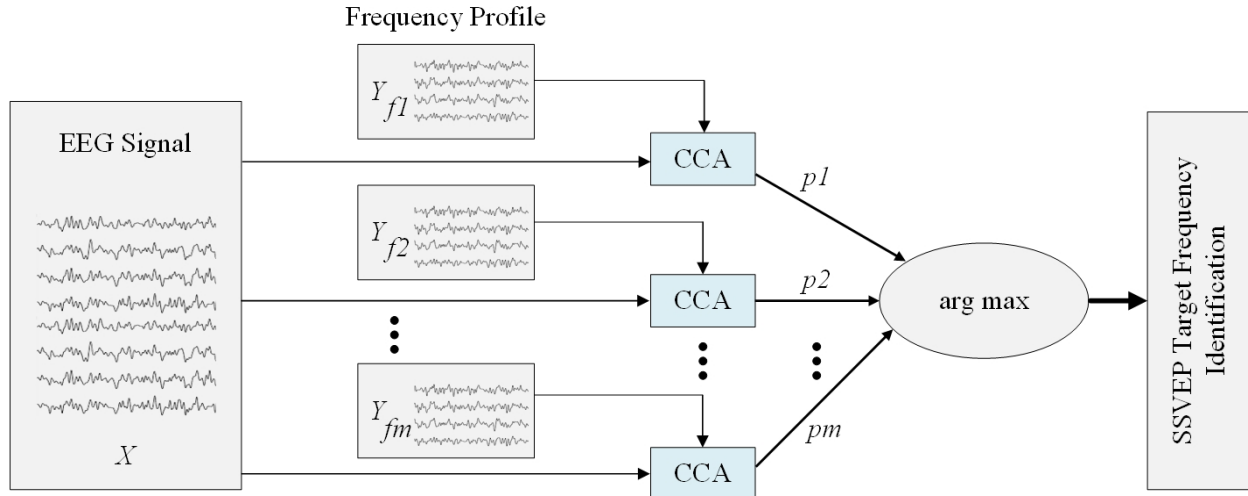


Figure 1. CCA-based target frequency identification

harmonics. The frequency profile reference signal is a pure sinusoidal signal at the intended target frequency. As such, for each target frequency the correlation between the EEG signal and the frequency profile reference signal is calculated. Subsequently, the frequency from the reference signal with the maximum correlation with the EEG signal is identified as the intended target frequency the user is focusing on (Lin et al. 2007).

Both the raw EEG signal and the frequency profile reference signal are utilized as the inputs to CCA. Subsequently, the output ρ is the canonical correlation employed for frequency identification as follows:

$$f = \max_i \rho_i \quad i = 1, 2, \dots, m \quad (3)$$

Where ρ_i represent the CCA coefficients.

2.2 Power Spectral Density Analysis (PSDA):

PSDA is one of the most commonly used methods for SSVEP target frequency identification (Cheng et al. 2002). The method utilizes a Fast Fourier Transform (FFT) to examine the frequency spectrum. As such, the frequency with the highest PSD value is recognized as the target frequency.

However, this requires the selection of the optimal bipolar lead with high signal-to-noise ratio. In other words, the channel with the most significant SSVEP amplitude is selected (Wang et al. 2005).

The signal-to-noise (SNR) ratio is:

$$SNR = 10 \log_{10} \left(\frac{n P(f_m)}{\sum_{k=1}^{n/2} P(f_m + k f_{res}) + P(f_m - k f_{res})} \right) \quad (4)$$

As such, SNR is obtained by the ratio of power $P(f_m)$ to the mean value of the power in n adjacent points, while f_m ($m = 1, 2, \dots, M$) denotes the target frequencies and M indicates the number of target frequencies. Finally, f_{res} represents the power spectral density's frequency resolution.

The spectrum's amplitude $P(f_m)$ is computed by:

$$P(f_m) = |FFT(x)| \quad (5)$$

Where x denotes the EEG signals, and $FFT(x)$ represents the 250-point of Fast Fourier Transform (FFT). Thus, since the sampling rate with which the EEG data was collected is 250 Hz, the frequency resolution f_{res} is $\frac{250}{250} = 1$ Hz.

Hence, SNR can be employed to identify the intended SSVEP target frequency as follows:

$$f = \max_m SNR \quad m = 1, 2, \dots, M \quad (6)$$

Chapter 3: Partition-Based Feature Extraction and Score Space Fusion

In this chapter, the data acquisition, the experimental setup, and the novel signal processing solution are discussed. First the EEG signal is recorded and filtered to remove noise, contaminant factors, and irrelevant frequency ranges. Following the calculation of the Canonical Correlation Analysis (CCA) coefficients and the Power Spectral Density Analysis (PSDA) power scores, the score spaces of both CCA and PSDA are partitioned into 3 different cases. Subsequently, 4 features are extracted from CCA's score space, and 2 features are extracted from PSDA's score space. Both feature spaces are then concatenated to generate more discriminative fusion spaces.

3.1 Data Acquisition and Experimental Setup:

The EEG signals were recorded from 10 healthy subjects, aged between 20-30 years of age. The experiment took place in a lab environment and subjects were seated on comfortable chairs approximately 20 inches away from a 10.2-inch Liquid Crystal Display (LCD) Android tablet screen with a 2560 x 1800 screen resolution (See Figure 2). The Cognionics EEG device was utilized to record the EEG signals wirelessly using 8 channels with 250 Hz sampling rate. The channels were primarily located on the occipital and parietal areas of the brain as it has been established that these areas of the brain contribute significantly to the SSVEP identification performance (Lin et al. 2007). After the completion of the data collection process, the EEG signals are filtered utilizing a 5th order Butterworth bandpass filter and a 60 Hz notch filter to remove noise, contaminant factors, and irrelevant frequency ranges. Subsequently the CCA coefficients and the PSDA power scores are calculated.

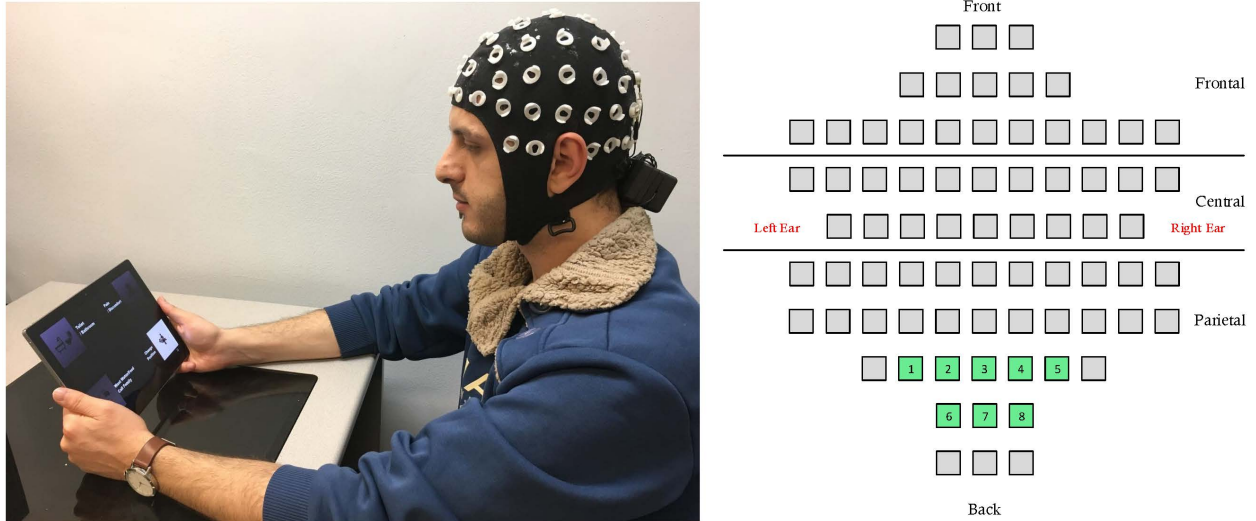


Figure 2. Experimental setup and electrodes location

However, unlike CCA, which generated a 1-dimensional feature space, PSDA generates a feature space whose dimensionality equals the number of channels utilized to record the EEG signals, in our case PSDA generated an 8-dimensional feature space. Therefore, a channel selection approach was implemented to select the channel with the best SSVEP responses for the partitioning process as discussed in Chapter 2 Section 2.2.

3.2 Task and The SSVEP Paradigm:

For this investigation, 4 target frequencies, represented by 4 different 600-pixel icons rendered on each corner of the tablet's screen, were utilized. The target frequencies employed in this experiment were 10 Hz, 12 Hz, 15 Hz, and 8.5 Hz (See Figure 3). Figure 3 illustrates the experimental paradigm utilized during the data collection process. Initially, the system recognizes that the subject is focusing on the Call Nurse icon and transitions to the main menu screen. On The main menu screen, the 4 target frequencies are represented by 4 different icons rendered on each corner of the screen in an effort to minimize any interference with the subjects' visual perception.

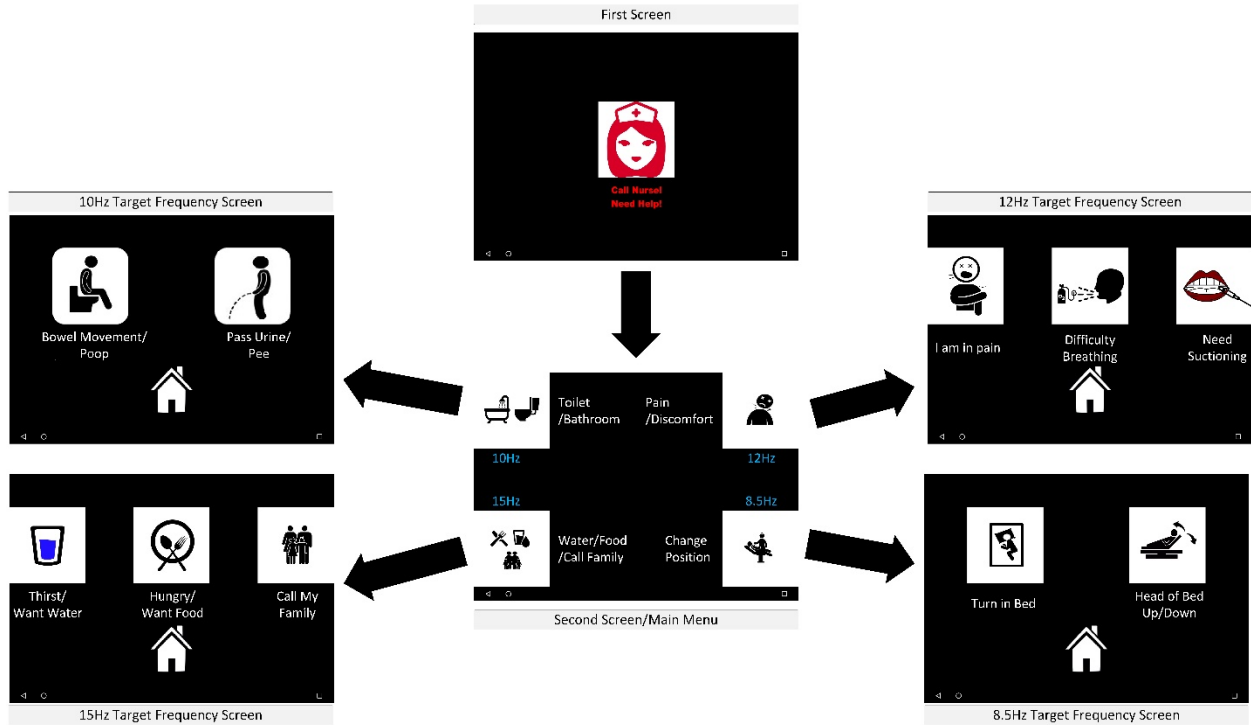


Figure 3. The training session's experimental paradigm

The task involved subjects focusing on 1 target frequency at a time, such as 12 Hz which is represented by the Pain/Discomfort icon on the top right corner of the screen. If the subject transitions to the correct corresponding 12 Hz target frequency screen, the attempt is considered a successful call and is labeled (1), otherwise it is considered unsuccessful with a label of (0). Hence, subjects are instructed to record 10 successful calls per each target frequency. However, all subjects needed more than 10 attempts to record the 10 successful calls (approximately 75 calls per subject), generating a dataset size sufficient enough to validate the proposed method and evaluate the generalization capabilities of the predictive models.

3.3 CCA and PSDA Score Space Partitioning:

To accommodate portability, the proposed system in this thesis utilizes an Android tablet as visual stimuli. However, the SSVEP paradigm generation on the tablet is inaccurate, which in turn exacerbates the SSVEP identification performance (See Table 1 and Figure 4). This is mainly

attributed to the hardware limitations of the visual stimuli, particularly the insufficient screen refresh rate, and the intermittent Android operating system interruptions. s

Table 1. Actual frequency conversion values from Hertz to Milliseconds vs. our system's performance over 4 epochs

| Target Frequencies | Hz to ms | 1st Epoch | 2nd Epoch | 3rd Epoch | 4th Epoch | Average |
|---------------------------|-----------------|------------------|------------------|------------------|------------------|----------------|
| 8.5Hz | 117.647 | 115.7391 | 116.913 | 116.6957 | 113.2083 | 115.639 |
| 10Hz | 100 | 98.92308 | 100.1923 | 100.1154 | 100.1538 | 99.84615 |
| 12Hz | 83.3333 | 82.125 | 83.5 | 83.40625 | 83.40625 | 83.109375 |
| 15Hz | 66.6666 | 65.71795 | 66.79487 | 66.69230769 | 65.95 | 66.28878 |

Table 1 reports the actual time required to render the target objects on the screen throughout 4 consecutive epochs of a 10-second SSVEP segment. The actual frequency conversion values are demonstrated in the 2nd column (i.e. Hz to ms). As such, we observe a discernable divergence as the conversion values during various epochs deviate from the desired conversion timing. Moreover, Figure 4 illustrates how peaks are not occurring precisely on the intended target frequency due to the fact that in different fractions of a second, the rate of the flickering stimuli deviates from its original and desired values reported in the 2nd column of Table 1. Therefore, the SSVEP identification performance is impaired.

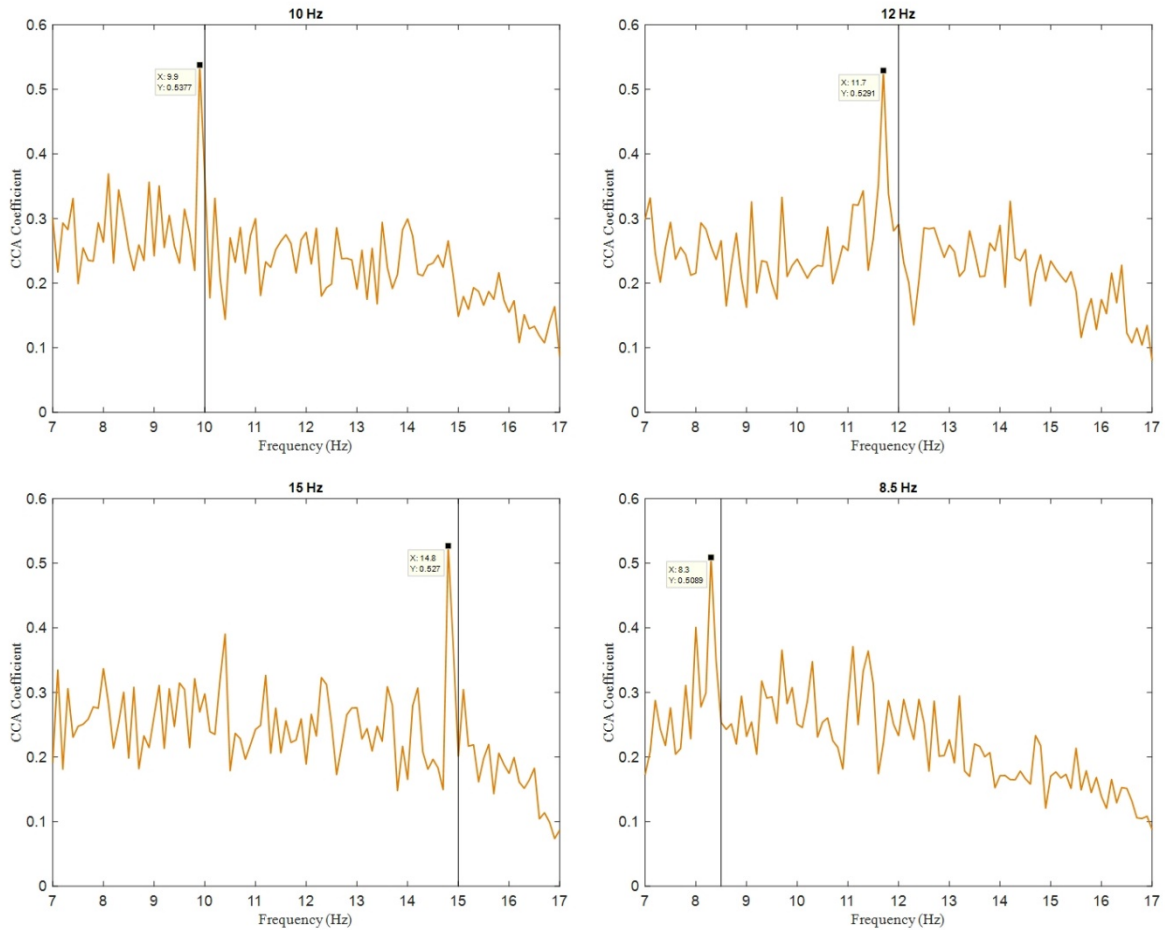


Figure 4. Impact of the insufficient screen refresh rate on the SSVEP identification performance

Additionally, I hypothesize that there are subject-specific information embedded within the SSVEP responses on the target frequencies and the non-target frequencies as well (See Figure 5). Figure 5 demonstrates the subjective responses in the CCA plot of 2 different subjects over the whole frequency range.

As such, to mitigate the impact of the insufficient screen refresh rate, and the implications of the subject variation challenge, and to incorporate the subject-specific information into the training phase of the predictive model, I propose exploiting the discriminative and complementary information of CCA and PSDA simultaneously via partitioning their score spaces in 3 different cases (Farooq and Dehzangi 2017) (See Figure 6):

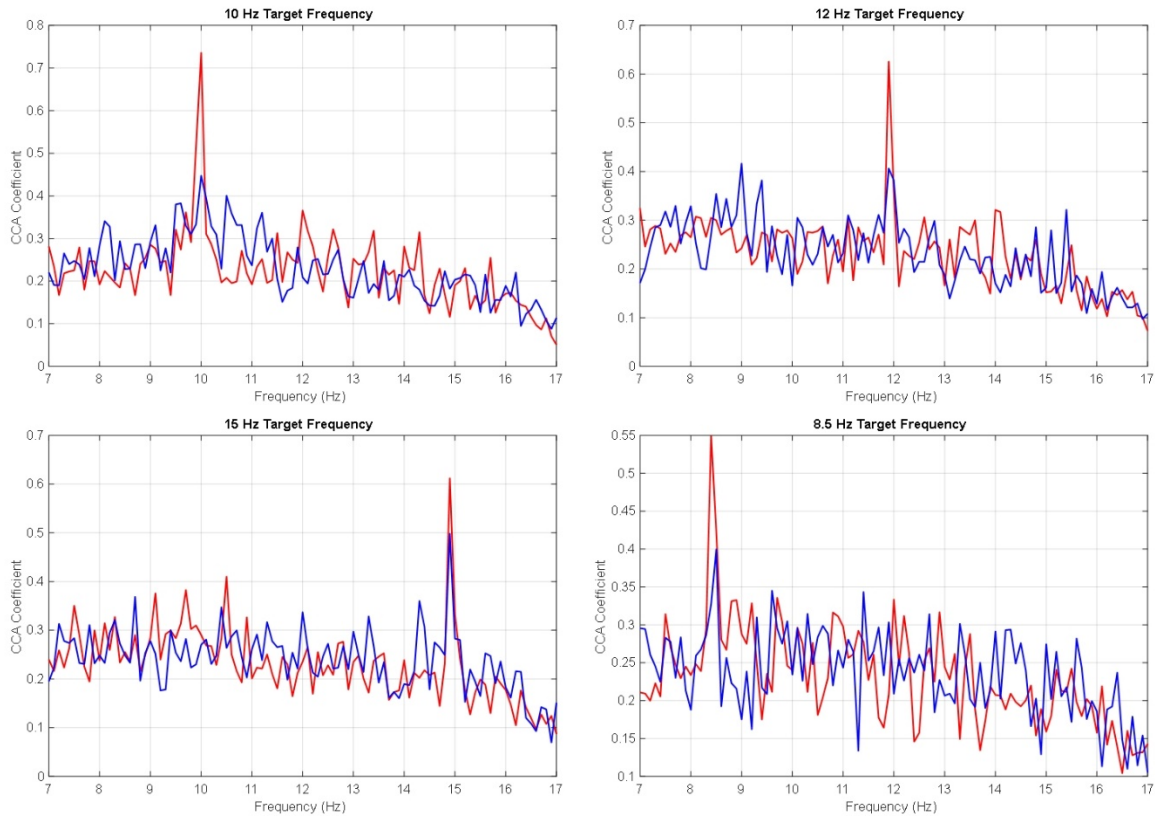


Figure 5. Subjective responses demonstrated in the CCA plot of 2 different subjects

1. Partitioning the range that covers the target frequencies into 4 non-overlapping partitions (i.e. P2, P4, P6, and P8 highlighted in green).
2. Partitioning the range that encompasses the non-target frequencies into 5 non-overlapping partitions (i.e. P1, P3, P5, P7, and P9).
3. Partitioning the range that encapsulates both the target and non-target frequencies into 9 non-overlapping partitions (i.e. P1, P2, ..., and P9).



Figure 6. Partitioning CCA and PSDA's score spaces

Figure 6 illustrates partitioning the frequency range 7 Hz to 17 Hz of both CCA and PSDA's score spaces. The intuition behind the partitioning scheme is to enclose each target frequency within a specific partition in order to capture the subject-specific information on and/or near the target frequencies. Moreover, the partitioning scheme serves to evaluate whether augmenting the extracted measures from the non-target frequency partitions on the features extracted from the target frequency partitions enhances the SSVEP identification task (Farooq and Dehzangi 2017).

3.4 Feature Extraction and Score Space Fusion:

Feature extraction is an essential process that allows effective descriptors and informative features to be obtained and employed to facilitate subsequent generalization steps. Thus, 4 measures were extracted from the CCA score space:

1. Power:

Serves to calculate the summation of the absolute squares of the signal's time-domain observations, divided by the length of that signal. Power of a signal can be computed as follows:

$$P = \frac{1}{T} \sum_{t=1}^T (P_{ij})^2 (t) \quad (7)$$

2. Mean:

Serves to obtain the mean values within each partition, and it's calculated as follows:

$$\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i \quad (8)$$

3. Standard deviation:

Serves to measure and quantify the variation of the EEG data within each partition, and it's calculated as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N - 1}} \quad (9)$$

4. Entropy:

Serves to compute the temporal distribution of the signal's energy within each partition as follows:

$$E(s) = - \sum_{i=1} s_i^2 \log(s_i^2) \quad (10)$$

And 2 features were extracted from PSDA's score space:

1. Mean
2. Standard deviation

This is because PSDA inherently generates the power scores of the signal, which eliminates the need to extract them as a feature. Moreover, due to the infinitesimal magnitudes of those power scores, extracting entropy as a viable measure was impeded, and it was therefore disregarded. As such, the extracted measures are then concatenated together to construct the fusion spaces as follows:

I. 1st partitioning case:

24-dimesnional fusion space → 4 features X 4 partitions from CCA + 2 features X 4 partitions from PSDA.

II. 2nd partitioning case:

30-dimensional fusion space → 4 features X 5 partitions from CCA + 2 features X 5 partitions from PSDA.

III. 3rd partitioning case:

54-dimensional fusion space → 4 features X 9 partitions from CCA + 2 features X 9 partitions from PSDA.

3.5 SSVEP Identification Performance Utilizing The Fusion Spaces:

To evaluate the SSVEP identification performance utilizing the fusion spaces generated from each partitioning case, 3 different classifiers were employed; Decision Tree, Linear Support Vector

Machine (SVM), and K-Nearest Neighbor (K-NN) with K=1. Furthermore, to validate the performance of the predictive models, leave-one-out Cross Validation was used. This entails utilizing all samples of the dataset except 1 for the training phase, while the remaining sample is used for the testing phase. The process is repeated iteratively until all samples are utilized for training and testing. As such, the summation of the prediction performance of each iteration is calculated and the average prediction performance is reported as the SSVEP identification accuracy.

Table 2 reports the identification performance of the proposed partition-based feature extraction and score space fusion method.

Table 2. SSVEP identification accuracies of CCA, PSDA, and the fusion score spaces

| Subject | CCA | PSDA | Target Frequency Partitions | | | Non-Target Frequency Partitions | | | Target + Non-Target | | |
|----------------|------------|------------|-----------------------------|------------|------------|---------------------------------|------------|------------|---------------------|------------|------------|
| | | | Decision Tree | SVM | KNN | Decision Tree | SVM | KNN | Decision Tree | SVM | KNN |
| 1 | 86% | 67% | 96% | 96% | 98% | 81% | 75% | 71% | 81% | 96% | 83% |
| 2 | 77% | 83% | 86% | 84% | 87% | 57% | 44% | 36% | 82% | 86% | 77% |
| 3 | 40% | 26% | 60% | 42% | 34% | 49% | 43% | 45% | 37% | 47% | 52% |
| 4 | 59% | 19% | 77% | 85% | 78% | 31% | 54% | 44% | 75% | 79% | 59% |
| 5 | 67% | 41% | 89% | 76% | 69% | 31% | 42% | 32% | 73% | 71% | 68% |
| 6 | 55% | 35% | 88% | 88% | 75% | 34% | 45% | 29% | 86% | 80% | 71% |
| 7 | 62% | 29% | 63% | 80% | 68% | 42% | 53% | 46% | 63% | 74% | 63% |
| 8 | 71% | 39% | 71% | 83% | 75% | 40% | 49% | 49% | 76% | 76% | 68% |
| 9 | 47% | 17% | 59% | 81% | 73% | 34% | 42% | 40% | 60% | 79% | 63% |
| 10 | 61% | 17% | 49% | 62% | 55% | 56% | 44% | 36% | 49% | 62% | 41% |
| Average | 63% | 37% | 74% | 78% | 71% | 46% | 49% | 43% | 68% | 75% | 65% |

From Table 2 we observe that CCA, which represents the BCI system's performance, achieved an average overall identification accuracy of 63%, while PSDA achieved an average overall accuracy of 37%. These identification accuracies were improved to 75% utilizing the fusion space constructed from the 3rd partitioning case. The performance is further improved to 78% when classifying the fusion space generated from the 1st partitioning case utilizing SVM. However, the

identification performance is undermined when classifying the fusion space generated from the non-target frequency partitions, achieving 49% utilizing SVM. As such, I conclude that while CCA and PSDA carry heterogeneous information, they tend to be complementary in nature. Moreover, from the 1st and 3rd partitioning cases, it is evident that the impact of the various challenges that have been discussed in Chapter 1 Section 1.2, has been mitigated to a certain degree, concluding the validity of the proposed method (Farooq and Dehzangi 2017). Additionally, further analysis will disregard the fusion spaces from the non-target frequency partitions (i.e. 2nd partitioning case) as their fusion space evidently degrades the SSVEP identification performance.

Chapter 4: Discriminative Transformation of the Fusion Space

To further enhance the performance of the proposed method, minimize the impact of statistical redundancies, reduce the computational complexity, and eliminate the undesired characteristics of high dimensional feature spaces, discriminative transformation utilizing Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) is investigated and discussed in this Chapter.

Figure 7 illustrates the block diagram of the proposed method. After pre-processing the data, the score spaces of CCA and PSDA are partitioned in 3 cases to generate the fusion spaces. Subsequently, the fusion spaces are transformed to lower dimensions utilizing PCA and LDA.

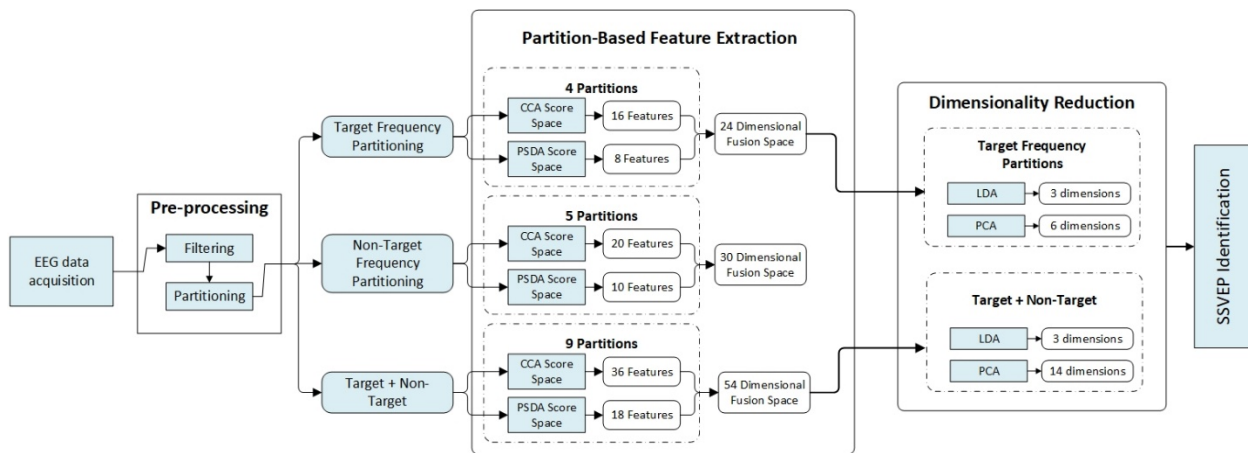


Figure 7. Block diagram of the proposed method

4.1 Principal Component Analysis (PCA):

PCA is a linear and unsupervised dimensionality reduction method that serves to reduce the dimensions of a dataset, while maintaining the essential information. The method also seeks to

find directions on which the variance of the dataset is maximized.

With PCA, datasets are transformed linearly into a lower dimensional and new coordinate mapping, where principal components are uncorrelated and are, in essence, linear functions of the original observations. Furthermore, in the lower dimensional representation of the dataset, the largest variance can be found on the 1st coordinate, and the 2nd largest variance can be found on the 2nd coordinate, and so on. This ranking process entails computing the covariance matrix, and the eigenvectors and eigenvalues of the covariance matrix as follows:

$$\text{Cov}(x, y) = \frac{1}{n-1} \sum_i (x_i - \bar{x})(y_i - \bar{y}) \quad (11)$$

To simplify the visualization, the 3 axes; x, y, and z are considered. As such, the covariance matrix is:

$$= \begin{pmatrix} \text{cov}(x, x) & \text{cov}(x, y) & \text{cov}(x, z) \\ \text{cov}(y, x) & \text{cov}(y, y) & \text{cov}(y, z) \\ \text{cov}(z, x) & \text{cov}(z, y) & \text{cov}(z, z) \end{pmatrix} \quad (12)$$

Assume x_i is the eigenvector, whose eigenvalues is denoted by φ_i . Then, the eigenvectors and eigenvalues are computed as follows:

$$R x_i = \varphi_i x_i \quad (13)$$

Hence, the rank of the matrix is denoted by the number of eigenvalues of the covariance matrix.

Table 3 summarizes the SSVEP identification accuracies after applying PCA on the fusion spaces to reduce 75% of their dimensionality and maintain 25%. From Table 3 we observe that PCA has improved the identification performance from 63% to 72% when classifying the fusion space generated from the 3rd partitioning case, utilizing SVM, and further improved the performance to 78% employing the same classifier to classify the fusion space generated from the 1st partitioning case.

Table 3. SSVEP identification performance utilizing PCA

| Subject | CCA | PSDA | PCA | | | | | |
|----------------|------------|------------|-----------------------------|------------|------------|---------------------|------------|------------|
| | | | Target Frequency Partitions | | | Target + Non Target | | |
| | | | Decision Tree | SVM | KNN | Decision Tree | SVM | KNN |
| 1 | 86% | 67% | 92% | 94% | 96% | 85% | 92% | 73% |
| 2 | 77% | 83% | 76% | 89% | 74% | 68% | 76% | 63% |
| 3 | 40% | 26% | 40% | 52% | 29% | 34% | 43% | 34% |
| 4 | 59% | 19% | 69% | 86% | 78% | 57% | 85% | 71% |
| 5 | 67% | 41% | 60% | 73% | 60% | 57% | 66% | 55% |
| 6 | 55% | 35% | 83% | 88% | 70% | 78% | 84% | 65% |
| 7 | 62% | 29% | 79% | 79% | 63% | 59% | 68% | 63% |
| 8 | 71% | 39% | 75% | 80% | 78% | 78% | 79% | 66% |
| 9 | 47% | 17% | 68% | 75% | 65% | 50% | 74% | 68% |
| 10 | 61% | 17% | 59% | 62% | 50% | 51% | 56% | 47% |
| Average | 63% | 37% | 70% | 78% | 66% | 62% | 72% | 61% |

However, when comparing the SSVEP identification performance before and after applying PCA on the fusion spaces, we note that PCA did not ameliorate the identification performance (See Figure 8).

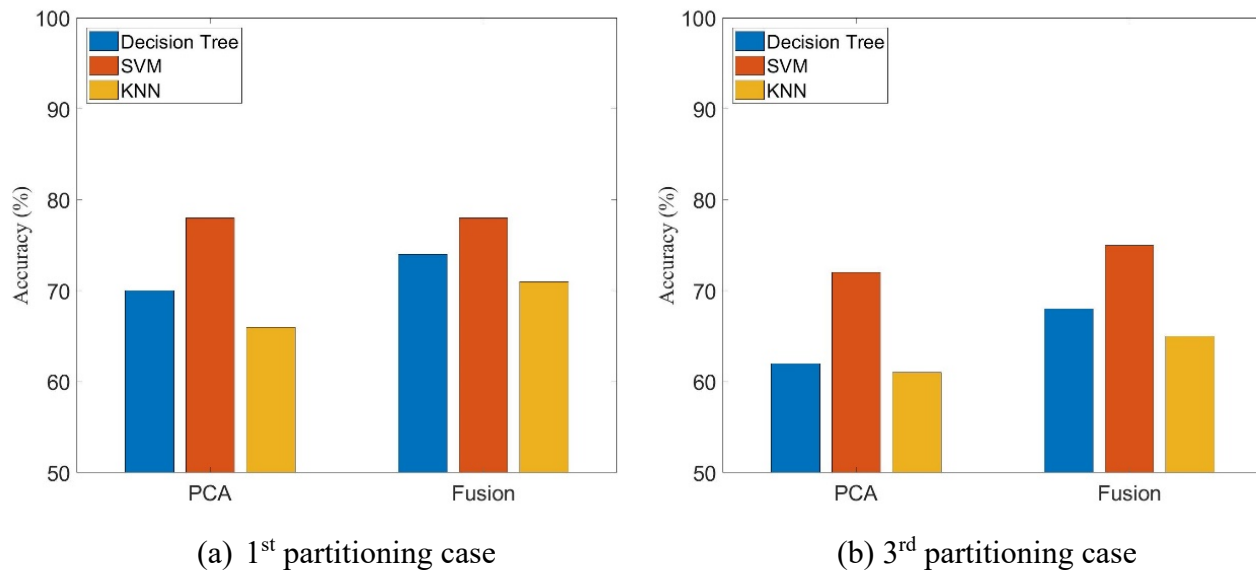


Figure 8. SSVEP identification performance before and after applying PCA on the fusion spaces from the 1st and 3rd partitioning cases

Figure 8 illustrates the identification performance before and after applying PCA. From Figure 8 we observe that the 24-dimensional fusion space constructed from the target frequency partitions (Figure 8.a) demonstrated similar SVM performance before and after PCA utilization. However, Decision Tree and KNN's performances slightly exacerbated after PCA utilization. On the other hand, the 54-dimensional fusion space demonstrated a worse identification performance across all 3 classifiers after applying PCA (Figure 8.b).

PCA's success stems from the fact that the method preserves information while transforming datasets to lower dimensions. However, the computational cost of the eigenvectors can be impractical in high dimensional spaces due to the proportional nature between the covariance matrix and dimensionality of the data samples. As such, from the experimental results we conclude that utilizing PCA is not an efficient solution to improve the identification performance.

4.2 Linear Discriminant Analysis (LDA):

LDA is a linear and supervised dimensionality reduction method that aims to transform a dataset to a lower dimensional space while maintaining class-separability information. This is achieved by finding the axes that maximize the linear class separation utilizing the within-class scatter matrix and the between-class scatter matrix, which are computed as follows:

The within-class scatter matrix:

$$S_w = \sum_{i=1}^c S_i \quad (14)$$

Where S_i indicates the scatter matrix of every class, which is computed as follows:

$$S_i = \sum_{x \in D_i} (x - m_i)(x - m_i)^T \quad (15)$$

And m_i represents the mean vector

While the between-class scatter matrix is calculated as follows:

$$S_b = \sum_{i=1}^c N_i (m_i - m)(m_i - m)^T \quad (16)$$

Where m represents the overall mean, whereas m_i and N_i indicate the sample mean and the size of class i respectively.

As such, to obtain the linear discriminants, LDA seeks to find a transformed space where the within-class matrix is minimized and the between-class matrix is maximized by solving the generalized eigenvalue problem for the matrix $S_w^{-1} S_b$ as follows:

$$S_w^{-1} S_b v = \lambda v \quad (17)$$

Where v and λ represent the eigenvector and the eigenvalue respectively.

Subsequently, the selection of the linear discriminant for the transformed subspace is achieved by sorting the eigenvectors in a decreasing eigenvalue order (i.e. rank the eigenvectors from the highest to the lowest in terms of their corresponding eigenvalue) and select the highest k eigenvectors to construct a $k \times d$ -dimensional eigenvector matrix W .

Finally, the projection matrix, where the samples are transformed onto the new subspace, is calculated as follows:

$$Y = XW \quad (18)$$

Where X is a matrix of n samples of size $n \times d$ dimensions, and Y is the projection of the $n \times k$ -dimensional samples.

Table 4 reports the SSVEP identification accuracies after transforming the fusion spaces from the 1st and 3rd partitioning cases to lower dimensions utilizing LDA.

Table 4. SSVEP identification performance utilizing LDA

| Subject | CCA | PSDA | LDA | | | | | |
|----------------|------------|------------|-----------------------------|------------|------------|---------------------|------------|------------|
| | | | Target Frequency Partitions | | | Target + Non-Target | | |
| | | | Decision Tree | SVM | KNN | Decision Tree | SVM | KNN |
| 1 | 83% | 67% | 100% | 100% | 100% | 94% | 96% | 94% |
| 2 | 77% | 83% | 94% | 97% | 97% | 97% | 100% | 100% |
| 3 | 40% | 26% | 58% | 71% | 57% | 91% | 96% | 93% |
| 4 | 59% | 19% | 92% | 94% | 88% | 99% | 97% | 99% |
| 5 | 67% | 41% | 89% | 92% | 94% | 92% | 98% | 98% |
| 6 | 55% | 35% | 94% | 92% | 96% | 96% | 100% | 100% |
| 7 | 62% | 29% | 90% | 86% | 85% | 91% | 94% | 93% |
| 8 | 71% | 39% | 93% | 90% | 93% | 100% | 100% | 100% |
| 9 | 47% | 17% | 76% | 89% | 80% | 95% | 99% | 100% |
| 10 | 61% | 17% | 89% | 87% | 73% | 100% | 99% | 100% |
| Average | 63% | 37% | 88% | 90% | 86% | 96% | 98% | 98% |

From Table 4 we observe that the identification performance significantly improved to 90% when classifying the 24-dimensional fusion space with SVM. The performance is further improved to 98% when classifying the 54-dimensional fusion space utilizing SVM and KNN.

As such, we can conclusively infer that LDA outperforms PCA significantly. This is mainly because LDA generates linear mappings that maximizes the class separation in the low dimensional representation of the data. However, LDA has the tendency to make strong assumptions about the dataset, in particular, LDA assumes that the dataset is normally distributed, which is an inaccurate assumption for most real-world problems. As such, to ensure that LDA's performance was not impacted as a result of that assumption, the power scores were normalized using the natural log transformation (Farooq and Dehzangi 2018). The fusion spaces are then transformed to lower dimensions using LDA and then passed to SVM for classification (See Figure 9).

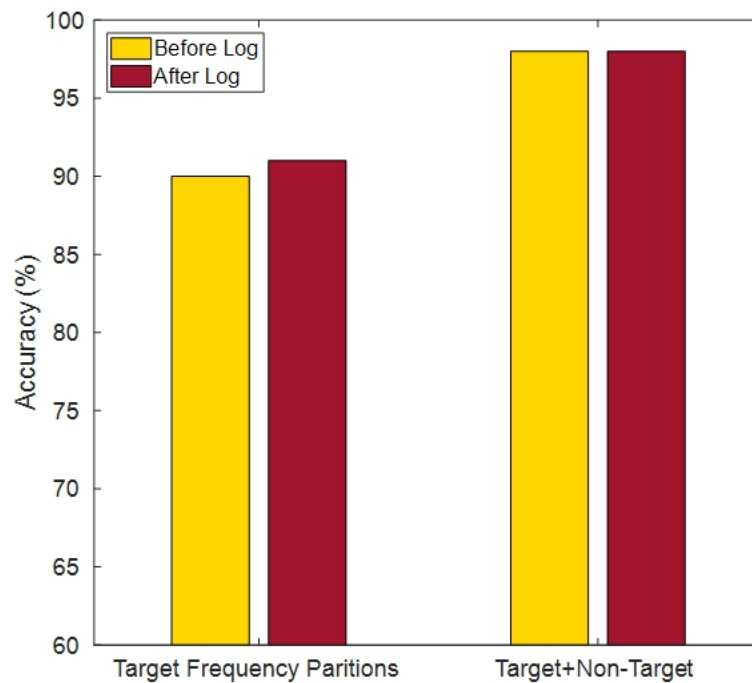


Figure 9. LDA's performance before and after the log transformation

From Figure 9 we observe that the log transformation slightly improves the 24-dimensional fusion space, however, the identification performance of the 54-dimensional fusion space remains consistent despite the log transformation of the power scores.

4.3 Comparison to Benchmark Systems Utilizing the Discriminative Feature Extraction via Multivariate Linear Regression (MLR) Method:

Wang et al suggested a Multivariate Linear Regression (MLR) approach, which was conclusively proven to be more robust than CCA (Wang et al. 2016). In their investigation, they transform the input space to lower dimensions using PCA, then utilize MLR to find optimally discriminative subspaces and extract discriminative features. Subsequently, they feed MLR's discriminative subspaces to K-Nearest Neighbor, where $k=5$, for classification utilizing the hold-one-out cross validation. Following the same aforementioned steps, I examined the performance of their proposed method on my dataset to draw a more comprehensive comparison between their method, and the method proposed in this thesis.

Table 5 demonstrates the SSVEP identification performance of CCA, LDA, and MLR. From Table 5 we conclude that while MLR evidently outperforms CCA achieving an overall average identification accuracy of 86%, the 24-dimensional fusion space, generated from the 1st partitioning case demonstrates a 4% improvement in performance, while the 54-dimensional fusion space further improves the performance by 12% achieving an average overall identification accuracy of 98% after transforming both fusion spaces utilizing LDA and passing the transformed fusion spaces to SVM for classification.

Table 5. Comparison of the SSVEP identification performance amongst CCA, LDA, and MLR

| Subjects | CCA | LDA | | MLR |
|----------------|------------|-----------------------------|---------------------|------------|
| | | Target Frequency Partitions | Target + Non-Target | |
| 1 | 83% | 100% | 96% | 67% |
| 2 | 77% | 97% | 100% | 89% |
| 3 | 40% | 71% | 96% | 87% |
| 4 | 59% | 94% | 97% | 87% |
| 5 | 67% | 92% | 98% | 94% |
| 6 | 55% | 92% | 100% | 90% |
| 7 | 62% | 86% | 94% | 85% |
| 8 | 71% | 90% | 100% | 82% |
| 9 | 47% | 89% | 99% | 94% |
| 10 | 61% | 87% | 99% | 85% |
| Average | 63% | 90% | 98% | 86% |

Furthermore, to examine another aspects of the system's performance in order to evaluate the validity of the proposed method, I investigate the information transfer rates (ITR) of CCA, LDA, and finally MLR. As such, I follow (Meinicke et al. 2003) to calculate the information transfer rates:

$$B = t/60 \left(\log_2 M + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{M - 1} \right) \quad (19)$$

Where B indicates the ITR in bits/min, t denotes the trial time, M represents the number of the target objects rendered on the visual stimuli, and P indicates the selection probability of the desired target object (i.e. accuracy).

Table 6 summarizes the ITRs of CCA, LDA, and MLR. From Table 6, we note that the average overall ITR of MLR across all 10 subjects is 24.1 bits/min. This ITR is slightly improved to 25.1 bits/min utilizing the LDA-transformed 24-dimensional fusion space, and further improved to 27.3 bits/min employing the LDA-transformed 54-dimensional fusion space. As such, we can decisively infer that the proposed partition-based feature extraction method and discriminative fusion space transformation utilizing LDA yielded higher information transfer rates than MLR.

Table 6. Information transfer rates (ITRs) of CCA, LDA, and MLR in bits/min

| Subjects | CCA | LDA | | MLR |
|----------------|-------------|-----------------------------|---------------------|-------------|
| | | Target Frequency Partitions | Target + Non-Target | |
| 1 | 23.3 | 27.8 | 26.8 | 19 |
| 2 | 21.7 | 27 | 27.8 | 25 |
| 3 | 11.8 | 20 | 26.8 | 24 |
| 4 | 16.9 | 26.2 | 27 | 24 |
| 5 | 19.0 | 25.7 | 27.3 | 26 |
| 6 | 15.8 | 25.7 | 27.8 | 25 |
| 7 | 17.7 | 24.1 | 26.2 | 24 |
| 8 | 20.1 | 25.2 | 27.8 | 23 |
| 9 | 13.7 | 24.9 | 27.6 | 26 |
| 10 | 17.4 | 24.4 | 27.6 | 24 |
| Average | 17.7 | 25.1 | 27.3 | 24.1 |

Chapter 5: Conclusion

In this thesis, I addressed and discussed the technical challenges BCI systems face today, particularly when operating them in an ICU environment. Moreover, to accommodate portability, the BCI system proposed in this thesis utilizes an Android tablet for visual stimulation. However, due to the insufficient screen refresh rate and the recurrent Android operating system interruptions, the SSVEP identification performance is impaired. As such, to mitigate the impact of the aforementioned challenges I proposed a partition-based feature extraction method, which entailed partitioning the score spaces of CCA and PSDA, extracting their discriminative and complementary information from each partition, and concatenating the extracted measures to generate discriminative fusion spaces. The fusion spaces are then transformed to lower dimensions utilizing PCA and LDA. Finally, to validate my findings, I drew a comprehensive comparison between the proposed method and multivariate linear regression method, which is a well-known and established SSVEP identification method. The experimental results demonstrated that the proposed method improved the identification performance from CCA's 63% to 78%. The performance is further improved to 98% utilizing LDA, which outperformed MLR's 86% identification accuracy. As such, the proposed partition-based feature extraction and score space fusion is a very promising approach to operate BCI systems in the ICU.

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Related Publications

- Farooq, M. and Dehzangi, O., 2017, May. High accuracy wearable SSVEP detection using feature profiling and dimensionality reduction. In *Wearable and Implantable Body Sensor Networks (BSN), 2017 IEEE 14th International Conference on (pp. 161-164)*. IEEE.
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