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P300-based Brain-Computer Interface Paradigm Design

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1. Introduction

In this chapter, we will explore the P300 wave of visual evoked potentials (VEP), which has become the most popular form of event-related potentials (ERP) in past few decades, its applications and future advancements in the field of P300-based brain computer interface (BCI). The focus of the chapter will be on different design issues considered so far and important challenges to be considered for designing a new P300-based BCI paradigm. In addition, different applications of P300-based BCI systems will be discussed briefly.

Applications of electroencephalography (EEG) or the 'brain signals' are emerging rapidly and new ways have been innovated for communication and fast transfer of data between the brain and these applications. Over the last two decades, BCI has made significant progress and substantial research is going on to communicate with the human brain (Wolpaw et al., 2002). One of the few breakthroughs of BCI is a P300-based BCI speller (Farwell & Donchin, 1988). There have been many research studies based on the original design introduced by Farwell and Donchin (Donchin et al., 2000; Serby et al., 2005; Sellers et al., 2006; Fazel-Rezai, 2007; Ramanna & Fazel-Rezai, 2007) with the significant improvement in the accuracy and speed. The Farwell-Donchin paradigm (Farwell & Donchin, 1988) is a well known and most widely used paradigm for the visually evoked potential based BCI speller, in which, characters and numbers are represented in a grid of six-by-six matrix.

Although different variations in the visual paradigm have been analyzed (Salvaris & Sepulveda, 2009), they are mostly based on the matrix representation of characters. The P300-based speller is especially useful for people with amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis and other diseases which impair them to communicate in a normal way.

Several shortcomings of existing P300-based BCIs have been identified (Fazel-Rezai, 2007 & Fazel-Rezai & Abhari, 2009), and many research groups have tried to overcome those shortcomings. However, more progress should be made in resolving many of the challenges issues to move BCI into the realm of practicality and to take it outside research laboratories into practical applications.

The chapter will be organized as follows. In the first few sections, we will introduce the basics on the VEP and P300. In the subsequent sections, more detailed applications of BCI speller program involving the design and development issues affecting the accuracy and speed along with classic Farwell-Donchin paradigm will be discussed. Furthermore, we will share our experience of implementing innovative ideas on changing the Farwell-Donchin paradigm, leading to a new direction in terms of BCI speller paradigm. The chapter concludes with future trends in this area.

2. Event-Related Potentials (ERPs)

ERPs are electrocortical potentials generated in the brain during the presentation of stimulus. The stimulus could be generated by a sensor or a psychological event. It generates a time delay wave in EEG that can be detected by after processing EEG signals. These methods can be a simple averaging technique, in which, EEGs are averaged over total time (time from presenting the stimulus to time when EEG settles down) or advanced approaches such as linear discriminant analysis or support vector machine algorithms. There are different types of ERPs based on the source of stimulus presentation such as visual, auditory and tactile. This chapter discusses the P300 which is a form of visually evoked potential (VEP) and focuses on the P300 wave in ERP.

2.1 P300 wave

The P300 wave also known as P3 is the most important and studied component of ERPs, which can be recorded/measured after the stimulus presentation in an EEG. The P300 is observed in an EEG as a significant positive peak 300 ms to 500 ms after an infrequent stimulus is presented to a subject. The actual origin of the P300 is still unclear. It is suggested to be related to the end of the cognitive processing, to memory updating after information evaluation or to information transfer to consciousness (Bernat et al., 2001; Gonsalvez & Polich, 2002). Typical peak latency of this positive wave occurs around 300 ms for most users; therefore, it is called as P300 wave. In the typical P300-based experiments three different types of paradigms are being used; 1) single-stimulus, 2) oddball, and 3) three-stimulus paradigm.

The single-stimulus paradigm includes one type of stimuli called target. In a typical oddball paradigm, the subject is normally presented with target and standard (or irrelevant) stimuli. The three-stimulus paradigm consists of target, standard and distractor. Distractors are also referred as probes or novels. Novel stimuli in a three-stimulus paradigm are presented infrequently and produce a P300 component that is large over the frontal/central area and is different from the typical parietal maximum P300 discrimination (Comerchero & Polich, 1999). This 'novelty' P300 is called the P3a which is totally different from the P300 in response to the target stimulus (P3b). Furthermore, P3a's peak is bifurcated with shorter latency compare to P3b. It also habituates relatively faster discrimination (Comerchero & Polich, 1999). The P3a is a subcomponent of P300, which is significant in EEG produced in the frontal/central part of the scalp (Courchesne et al., 1984; Knight, 1984; Yamaguchi & Knight, 1991) also sometimes referred as novelty P300. Its generation does not depend on stimulus novelty but is solely based on the target discrimination (Comerchero & Polich, 1999) and habituation (Soltana, M., & Knight, R, 2000). The P3b is referred to as the maximum potential P300 from the target stimulus (Courchesne et al., 1975; Squires et al., 1975). It has been used for cognitive purposes in the field of psychology. The P3b has been successfully applied for task experiments related activities are as a measurement of workload.

3. P300 detection

P300 detection is usually done by averaging method, in which several trials are averaged (Farwell & Donchin, 1988) due to the fact that brain signal is a combination various brain activities and artifacts such as noise is also accumulated during the recording process. During averaging, the P300 is extracted based on attended stimulus. Different approaches have been used for the feature extraction and classification of P300 based systems. In this section, we will briefly describe the necessary steps for P300 detection.

3.1 Preprocessing

Prepocessing of EEG signals is an important step before extracting any feature. It is done after data acquisition. Preprocessing usually enhances the signal and improve signal to noise ratio (SNR). A typical step in preprocessing is bandpass filtering. Bandpass filters are designed to remove DC bias and high frequency noises. In preprocessing, channel selection with respect to data decimation is determined in a way to enhance the classification performance. Segments of data are collected and moving average filter is applied for best performance (Krusienski et al., 2006).

3.2 Classification

Different classification methods have been used in P300 based BCI systems. Some of them includes linear discriminant analysis (LDA), support vector machines (SVM), stepwise linear discriminant analysis (SWLDA), Fisher's linear discriminant (FLD), Baysian linear discriminant analysis (BLDA), Pearson's correlation method, linear support vector machine (LSVM) and Gausian support vector machine (GSVM). A brief description for each of these methods is given in the following sections.

a. *Linear Discriminant Analysis (LDA)*

Linear discriminant analysis (LDA) is very popular pattern classification technique and out performs SVM classifiers for the P300 detection (Mirghasemi et al., 2006). Two modified versions of LDA are used for P300 classification: Fisher linear discriminant analysis (FLDA) and stepwise linear discriminant analysis (SWLDA).

b. *Fisher linear Discriminant Analysis (FLDA)*

Fisher discriminant analysis is a robust and easy to calculate method for determining the maximum distance between two classes. In the case of binary decision making process, both the FLDA and least-square regression are equivalent. The FLDA is more favorable classification technique against noise as compare to SVM (Blankertz et.al., 2002; Krusienski, 2006).

c. *Stepwise Linear Discriminant Analysis (SWLDA)*

Stepwise linear discriminant analysis is an extension of FLDA, in which only those features are selected for the discrimination analysis which are suitable for classification purposes, thus reduces the number of features required for classification. Farwell and Donchin used stepwise linear discrimination analysis for 6 X 6 row/column paradigm (Farwell & Donchin, 1988), which later used to assess the speed of P300-based BCI by Donchin (Donchin, Spencer & Wijesinghe, 2000) with the help of discrete wavelet transform (DWT). The data used for classification in the ERP is the combined averages for rows and columns instead of individual averages for rows and columns (Donchin et. al., 2000). This may have resulted an improvement in the accuracy and the communication rate for the BCI system.

d. *Baysian Linear Discriminant Analysis (BLDA)*

Baysian linear discriminant analysis (BLDA) is an extension of FLDA. Unlike FLDA, Baysain analysis performs estimation techniques to compute the discriminant vector for classification purposes (Huang & Zhou, 2008). Target values are set through regression analysis in a Baysian frame work and training can be performed in a more quick way as compare to that of FLDA.

e. *Support Vector Machine (SVM)*

Support vector machines (SVM) is a machine learning technique which is very useful for the binary classification purpose. SVMs are used with Kernal functions which define transformation function. (Müller et al., 2001; Krusienski et al., 2006; Vapnik, 1995; Blankertz et.al., 2002). The SVM are suitable for practical purposes, where high transfer rates are required along with least amount of data. (Kaper et al., 2004; Thulasidas et.al., 2006)

f. *Gaussian Support Vector Machine (GSVM)*

Gaussian support vector machines (GSVM) is a nonlinear method used for classification of the EEG data for BCI speller program (Krusienski, 2006). The GSVM are used with Kernal functions which define nonlinear transformation and may cause difficulty for computations of data for large support vectors. (Krusienski, 2006; Vapnik, 1995; Müller et.al., 2001; Blankertz et.al., 2002).

g. *Maximum Likelihood (ML)*

ML classifiers are used for feature detection using a priori knowledge (Haykin, 1983; Serby et al., 2005). They provide a wide range of decision classes with the use of threshold values set for these classes. Serby used ML method for comparison with other techniques for BCI speller programs (Serby et al., 2005).

h. *Independent Component Analysis (ICA)*

Independent component analysis is a blind source separation technique used for recovering source signals from background noise or mixture of other signals using reconstruction. Different filtering techniques are used for preprocessing the source signal before being sent to ICA. Similar to ML, in ICA threshold value calculations are based on features in the source signals. Threshold values depend on number of trials and decision making is very fast as compared to the other methods (Serby et al., 2005). ICA's can be very effective as both temporal and spatial information is provided as the a priori knowledge (Xu et al., 2004).

4. Applications of P300

P300 has several of applications developed over the past few decades. Extensive progress in the research in this field result numerous applications from P300-based speller (virtual keyboard) to smart home applications and from lie detector to sending emails over the internet browsers. We will describe these applications in detail in the following sections.

4.1 Lie detectors

Information processing in the human brain generates an activity in the brain signal and can be recorded in the form of EEG. These EEGs can further be processed to find the deceptions. Farwell and Donchin investigated that activity through experiment and find out the different brain wave activities for two groups of subjects (Farwell & Donchin, 1991). The brain activity for the subjects who committed mock crime was different than that of those who did not take part in mock crime (Farwell & Donchin, 1991). Cacioppo devised a method for the lie detection using EEG assuming that the brain would process the stimuli differently if the brain wave association for two stimuli is different (Cacioppo et al., 1994). In 1993, Farwell introduced a technique based on brain electrical activities to spot a liar (Farwell 1995). His invention was based on the fact that P300 is elicited when the subject is confronted with particular stimulus that he/she has prior knowledge of. Certain stimuli, such as a crime scene or specific gun's picture, produce P300 if they look familiar to the subject (Farwell & Smith, 2001). This stimulus could be a word, phrase, or picture (Farwell & Smith, 2001). He defined three different types of stimuli in his method: Irrelevant, Target and Probe. The subject is given a list of specific stimuli called 'Target' and instructed to perform a task which is pressing a particular button in response. 'Irrelevant' stimuli are not relevant while 'Probes' are related to the situation under investigation. Probes elicit P300 if the subject is knowledgeable. On the other hand, they have the same effect as the irrelevant for a subject who is not knowledgeable about the situation (Farwell, 1995). Even though Farwell has claimed his technique is 100% accurate (Farwell & Smith, 2001) it has never been subject to independent review.

4.2 Smart homes

Smart homes are P300 based BCI systems that can be used for controlling the various applications in a home. Guger used a P300 based BCI system for smart home with high accuracy and reliability (Guger et al., 2009). They tested the system on a virtual reality based smart home. The results showed that different trivial control commands like switching TV channels, opening and closing doors and windows, turning light on and off, using phone, play music, operate a camera, walk around the house or move to a specific location in a smart home were performed successfully (Guger et al., 2009).

4.3 P300-based internet browsing

Like many other applications of P300, internet browsing through P300 potentials is a practical approach to provide more degree of freedom to the ALS patients. The user selection of various internet links and suffering through pages was performed (Muglerab et al., 2008) which later even extended to the use of virtual keyboard and mouse (Sirvent et al., 2010) for the P300 based internet browsing.

4.4 BCI spellers

BCI spellers can be used as a communication tool by people with neuromuscular disorders (Wolpaw et al., 1991). It is especially useful for people with amyotrophic lateral sclerosis (ALS), brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis and other diseases which impair patients to communicate in a normal way. Recently, there has been progress in improving P300 speller accuracy and speed. Various P300 stimuli presentation paradigms have been proposed. They are described in more details in the following sections.

5. P300 speller paradigms

A typical P300 speller consists of data collection, signal processing and classification (Wolpaw et al., 2000). In the data collection, a paradigm should be presented to subject to evoke the P300. P300-based BCI speller proved to be very useful in detecting the characters and symbols with high accuracy. However, there is a trade-off between increasing the communication rate and lowering the errors. Despite all the research progress made in the field of P300-based BCI speller program, there are several challenging issues that should be addressed to move the P300 BCI into practical applications. In this section, we discuss those problems and challenging issues in more detail.

a. *Crowding Effect*

Crowding effect occurs when target object is surrounded by the similar objects. It makes it difficult for the user to identify the target (Bouma 1970; Feng et al., 2007; Toet & Levi 1992; Van den Berg et al., 2007). Crowding effect may be caused by the inaccurate spatial distribution of the characters around the visual periphery of the spelling paradigm and leads to the error during spelling process (Strasburger, 2005). The matrix based design of RC paradigms is prone to this effect and it is hard to pay attention to many characters in the visual periphery. Increasing the size of characters in the visual paradigm would cause the cramming of the characters further leading to increase the crowding effect. One way to decrease the crowding effect is to scale up the size of the character while reducing the number of characters in the matrix paradigm which would provide less degree of freedom to the user due to decrease vocabulary size (Treder & Blankertz, 2010). The crowding effect can be observed in both row/column and checkerboard paradigms to be explained later.

b. *Adjacency Problem*

Adjacency errors occur most frequently in locations which are closer to the target items (Fazel-Rezai, 2007). These errors occur as the non-target items near to target flashes and attract user attention producing P300 which is averaged out with the target items. Adjacency problems can either be reduced by making sure the there is no flash in the non target items adjacent to item or by increasing the gap between the matrix elements as well as reducing the number of character/regions being intensified.

c. *Repetition Blindness*

Repetition blindness is a phenomenon which occurs due to the repetition of the two target items with non target items, causing errors during the detection process (Kanwisher, 1987). Repetition blindness may be due to lack of visual cues in the visual presentation of the paradigms. Visual paradigms with crowding effect may cause errors due to repetition blindness; however repetition blindness is less evident in recent paradigms due to their better visual presentation of stimulus (Townsend et al., 2010).

d. *Fatigue*

Fatigue is one of the causes for error in the BCI-speller programs. After several trials the subjects feels it difficult to keep concentrating due to tiredness. Fatigue can be reduced by innovation in the design of visual paradigms and make it easy for the users. Another way of avoiding fatigue could be reducing the spelling time i.e., by increasing the communication rate for typing.

e. *User Acceptability*

User acceptability is one of the important considerations for a speller program. Different speller paradigms have been proposed to provide more degree of freedom to user during spelling process. Factors such as crowding effect, adjacency problems and repetition blindness are related to the user acceptability.

In the following sections, several paradigms for the P300 generation are discussed.

5.1 Row / Column (RC) paradigm

Farwell and Donchin proposed the first BCI row-column speller in which a user is presented a with six-by-six matrix of alphanumeric characters (Farwell and Donchin, 1988) as shown in Figure 1. These characters are intensified in rows and columns in a random order. The intersection of the target row and column creates the P300 in EEG signals and, therefore, detection of the target character. Due to very low amplitude of the P300 in EEG, the classification of the P300 requires numbers of flashes to achieve high accuracy. It is the most widely discussed and used for P300 BCI. The probability of target being flashed is 0.17 (1/6), which is capable of producing robust a P300 (Polich, 1986; Polich, 1987; Duncan-Johnson & Donchin, 1982).

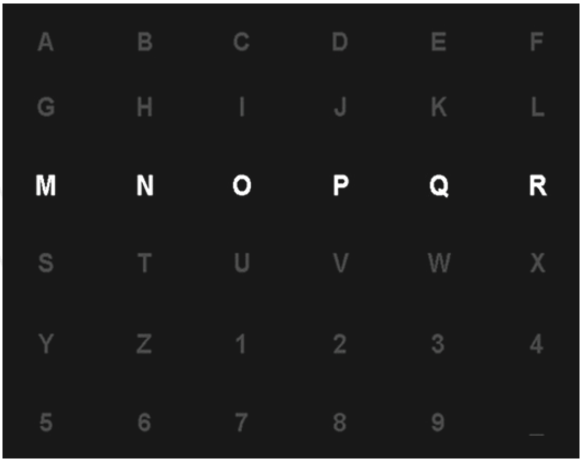

Fig. 1. Row/column paradigm (Farwell and Donchin, 1988)

The drawback with such system was that the more time required isolating the targets as more flashes are required. However fewer character set would eliminate this problem but limits the vocabulary size. Guger studied the RC paradigm for both P300 and motor imagery-based BCI system and discovered that only 89% of 81 RC subjects spell with accuracy 80-100%, while using motor imagery with 99 subjects, only 19% of subjects were able to achieve 80-100% accuracy (Guger et al., 2009).

5.2 Variations of Row / Column (RC) paradigms

The Farwell and Donchin paradigm has been quite popular among the research groups and have been tested with various configurations. Salvaris investigated modifications in the background color, font size, font style and increasing or decreasing the display area to analyze the classification difference between simple modifications to the visual protocol for the speller (Salvaris & Sepulveda, 2009). They found that although no visual protocol was the best for all subjects, the best performances were obtained with the white background visual protocol and the worst performance was obtained with the small symbol size protocol. Allison further investigated the relationship between the matrix size and EEG measures, detection accuracy and user preferences (Allison & Pineda, 2003). Their results indicated that the larger matrices evoked larger P300 amplitude and the matrix size did not significantly affect the performance or preferences. To further explore that relationship, Sellers manipulated the size of the character matrix and the duration of inter stimulus interval (ISI) between intensifications and concluded that the online accuracy was highest for the 3x3 matrix with 175-ms ISI condition, while the bit rate was highest for the 6x6 matrix 175-ms with ISI condition (Sellers et al., 2006). Guger studied the use of a row-column along with a single character paradigm of the BCI speller over the normal subjects to see the subsequent improvement in the overall accuracy of the system (Guger et al., 2009). Although the row-column paradigm provides more accuracy and bit rate as compared to the single character, Allison and Pineda suggested the multiple flash approaches may be more efficient and faster basis for a P300 BCI system (Allison & Pineda, 2003). Fazel-Rezai investigated adjacency problem in the matrix based P300- speller and suggested redesigning the matrix-based paradigm to remove the human error (Fazel-Rezai, 2007). Townsend et al. presented a checkerboard paradigm which is superior to the row-column paradigm in performance and user acceptability (Townsend et al., 2010). Checkerboard paradigm also eliminated the double flash problem as wells as adjacency problems. However, due to its visual design and increase in the matrix size to 8x9, the row column paradigm is hampered by the crowding effect (Treder & Blankertz, 2010) as the matrix may contains symbols which are hard to pay attention. Hence, it leads to less degree of freedom for the user. Other studies including tactile P300 BCI (Brouwer & Van Erp, 2010), and auditory P300 BCI (Nijboer et al., 2008) stimuli presentation approaches have also been used as an alternative to the present visual approaches.

5.3 Single Character (SC) paradigm

In a single character (SC) paradigm, a character flashes in a random order individually. Guger compared both SC and RC paradigm (Guger et al., 2009) and results suggests that only 55.3% (N=38) were able to spell with 100% accuracy in SC paradigm as compared to the 72.3% (N=81) of the subjects were able to spell with 100% accuracy in the RC paradigm.

Fig. 2. Single character paradigm (Guger et.al., 2009)

5.4 Checkerboard (CRB) Paradigm

The checkerboard paradigm (CBP) is originally based on the idea of using RCP in a checkerboard style. This eliminates the errors like adjacency problems and double flash. However it could be prone to the crowding effect as that of found in single character (SC) (Townsend et al., 2010).

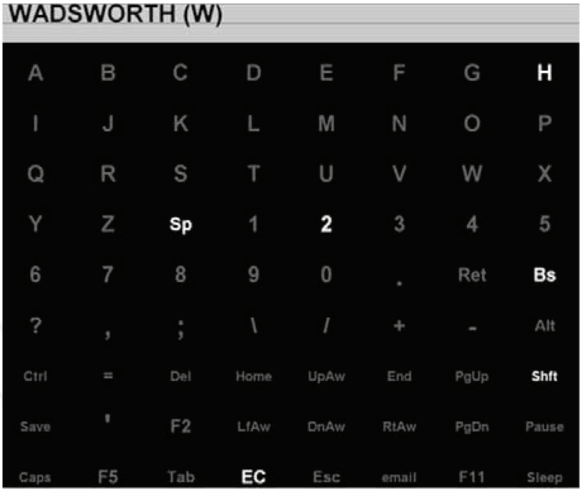

Fig. 3. Checkerboard paradigm of 8 x 9 matrix (Townsend et.al., 2010)

5.5 Region-based paradigm

In the region based (RB) paradigm (Fazel-Rezai & Abhari, 2009), seven sets of characters arranged into seven different regions in level 1 as shown in Figure 4. These regions are intensified to the user in random order. After successful selection of a region, characters in the selected region are again subdivided into seven regions consisting of single characters in level 2. The single characters are again intensified in a random order to find the particular character. The 7-region paradigm not only provides more input character set, but also reduces the crowding effect and adjacency problem. In this section, we discuss two

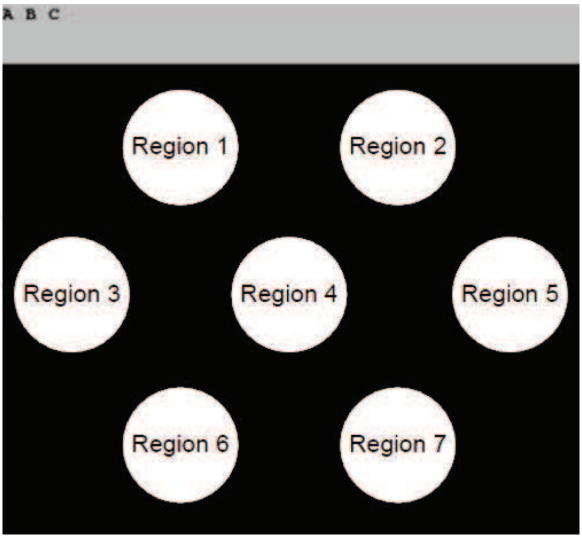

Fig. 4. Location of seven regions in the RB paradigm

variations of RB paradigm (RB1 and RB2). In RB1 paradigm, characters are placed in seven regions in alphabetical orders. However, in RB2, the frequency of characters usage (Zim, 1948; Lewand, 2000) was considered in distributing them into regions. Characters with close probability of usage were placed in one region. The list of characters used in seven regions in RB1 and RB2 paradigms in level 1 is shown in Table 1. In level 2, each region consists of only one character from the selected region in level 1.

	RB1 Paradigm	*RB2 Paradigm*
Region 1	A B C D E F G	E T A O N R I
Region 2	H I J K L M N	S H D L F C M
Region 3	O P Q R S T U	U GY P W B V
Region 4	V W X Y Z 1 2	K X J Q Z 1 2
Region 5	3 4 5 6 7 8 9	3 4 5 6 7 8 9
Region 6	0 / * - + . ?	0 / * - + . ?
Region 7	" ! @ # $ % &	" ! @ # $ % &

Table 1. List of characters in each region in level 1 of RB1 and RB2 paradigms.

6. A Comparison among SC, RC and RB Paradigms

In this section, we present results obtained by the BRAIN (Biomedical research And INnovation) team in the Biomedical Signal Processing Laboratory, the University of North Dakota.

6.1 Experiments

The experiments were approved by the Internal Review Board (IRB-201006-372) at University of North Dakota. Six subjects (all males, between 20 to 25 years old) participated in the experiment. Each participant completed four experimental paradigms in a random order and three trails were taken for each session. All the subjects were asked to spell two words (WATER and LUCAS). Products of g.tec (Guger Technologies, Austria) including g.GAMMAbox and g.USBamp for recording and g.BSanalysis for classification were used. Six flashes with flash time 100 ms and blank time of 60 ms were considered. EEG signals were recorded from eight channels at FZ, CZ, PZ, OZ, P3, P4, PO7, and PO8 locations. An electrode at the FPZ location was considered as a ground channel and one electrode on the right earlobe was considered as a reference channel. Data was sampled with a frequency of 256 Hz and filtered by a 0.1 Hz highpass, a 30 Hz lowpass filter. Linear discriminant analysis (LDA) was used for classification purpose.

6.2 Results

The results for two target characters 'WATER' and 'LUCAS' to find the corresponding accuracy for each phrase for six subjects. We then find the combined averaged accuracy for both phrases against each user and plotted as Fig. 4. A summary of individual accuracies can be seen in Table 2.
The graph in Figure 5 shows the combined average accuracy for the two words for each user as shown in the last row of Table 2. It can be seen from the graph that the average accuracy for RB1 and RB2 is greater than that of RC and SC.

Subjects	Paradigms							
	RC		SC		RB1		RB2	
	WATER	LUCAS	WATER	LUCAS	WATER	LUCAS	WATER	LUCAS
Subject 1	93.3	100	73.3	66.7	100	86.7	96.7	96.7
Subject 2	93.3	73.3	53.3	46.7	93.3	76.7	96.7	80
Subject 3	100	100	93.3	100	100	100	100	100
Subject 4	93.3	60	93.3	66.7	100	100	96.7	93.3
Subject 5	60	53.3	60	46.7	83.3	83.3	96.7	86.7
Subject 6	93.3	100	86.7	86.7	93.3	96.7	96.7	100
Average	88.9	81.1	76.7	68.9	95.0	90.6	97.3	92.8
	85		72.8		92.8		95.1	

Table 2. Accuracy (in percentage) of spelling two words (WATER and LUCAS) for four paradigms.

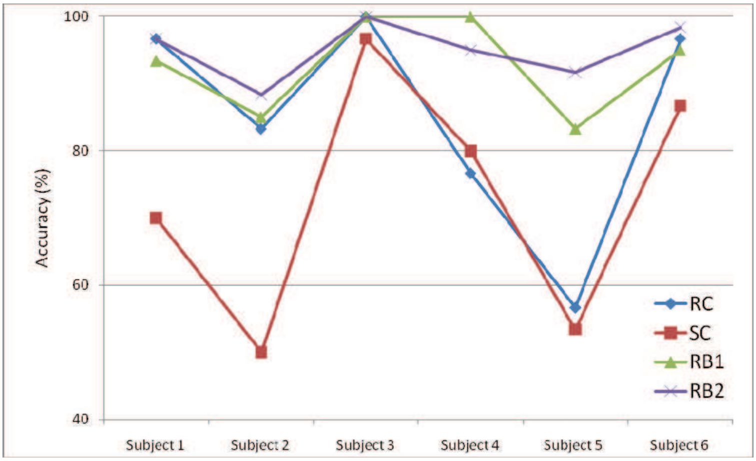

Fig. 5. Average accuracy for two phrases for six subject in four paradigms

The overall improvement in accuracy for the RB paradigms is much better for this set of subjects with minimal training and no prior experience with RB paradigm. Furthermore, fewer numbers of errors were reported as compared to RC and SC paradigms. However, RC paradigm reported less number of errors as compared to that of SC paradigm. We also determine the user acceptability for all four paradigms and a questionnaire was filled out by the subjects at the end of experiment. Users rated on a scale from 1 to 10, where 1 is lowest and 10 is highest, for parameters such as level of fatigue and difficulty to use the paradigm. The level of fatigue was highest for SC paradigm and found lowest for RB1. However, RB2 showed more fatigue among the users as compared to that of RC. One might attribute this due to most frequently use characters were placed in RB1. However, there is a substantial improvement in user acceptability in terms of difficulty to use parameter as asked in the questionnaire. Subjects found RB1 most easy to use while RB2 was rated as second highest. Both RC and RB1 have marginal difference, but SC rated as most difficult to use as shown in Fig. 6.

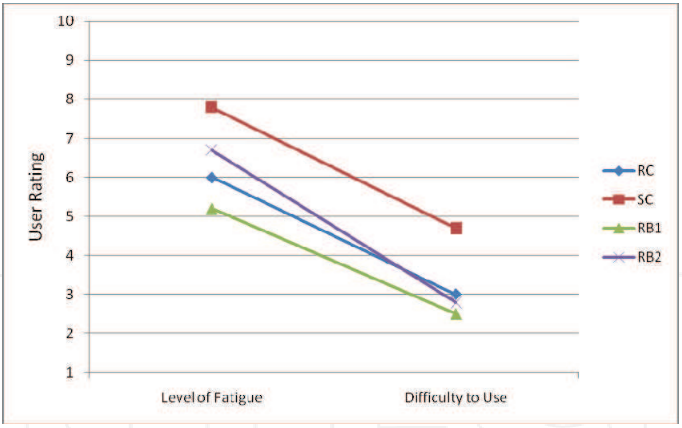

Fig. 6. Average of two parameters rated from 1-10 by six users for all four paradigms.

6.3 Region accuracy

We further extended our experiments to find out which one of regions had lesser probability of errors. This will help us to place the most frequently characters in the regions with the least probability of error. This will further reduce the probability of error as less frequently used characters can be fit into the high error region as compared to most frequently characters. For that purpose, another experiment was performed to determine and analyze the accuracy rate for each region. We have used the same experiment method and material as described in Section 6.1. A single set of seven characters i.e., ABCDEFG was considered for all the seven regions, so that each user has same set in each region. This helps us to compare the error for each region.

Twenty random trials were performed for each individual user. The results are shown in Fig. 7. It shows the total errors occurred for each individual region. It can be seen from that graph that maximum number of errors occurs for region 4 which is located in the center in RB paradigm.

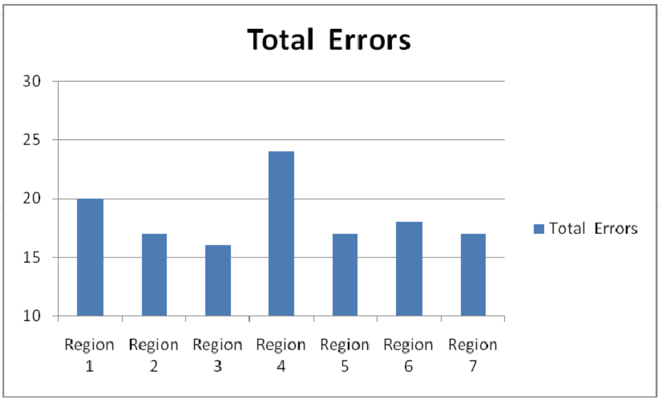

Fig. 7. Total number of errors for each region for 5 subjects

7. Future trends in research

P300-based BCI can be very helpful to the people with neuromuscular disorder. BRAIN team at the Biomedical Signal Processing Laboratory, the University of North Dakota is working further to improve the overall accuracy and user acceptability of the BCI speller program. It is planned to further improve the results by incorporating more subject data. Further research on RB paradigms is going on to make it more robust and easy to use for the subjects.

8. Acknowledgment

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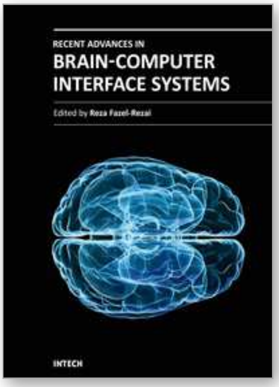

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Brain Computer Interface (BCI) technology provides a direct electronic interface and can convey messages and commands directly from the human brain to a computer. BCI technology involves monitoring conscious brain electrical activity via electroencephalogram (EEG) signals and detecting characteristics of EEG patterns via digital signal processing algorithms that the user generates to communicate. It has the potential to enable the physically disabled to perform many activities, thus improving their quality of life and productivity, allowing them more independence and reducing social costs. The challenge with BCI, however, is to extract the relevant patterns from the EEG signals produced by the brain each second. Recently, there has been a great progress in the development of novel paradigms for EEG signal recording, advanced methods for processing them, new applications for BCI systems and complete software and hardware packages used for BCI applications. In this book a few recent advances in these areas are discussed.