Chapter 2

Application of P300 Event-Related Potential in Brain-Computer Interface

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Additional information is available at the end of the chapter

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Abstract

The primary purpose of this chapter is to demonstrate one of the applications of P300 event-related potential (ERP), i.e., brain-computer interface (BCI). Researchers and students will find the chapter appealing with a preliminary description of P300 ERP. This chapter also appreciates the importance and advantages of noninvasive ERP technique. In noninvasive BCI, the P300 ERPs are extracted from brain electrical activities [electroencephalogram (EEG)] as a signature of the underlying electrophysiological mechanism of brain responses to the external or internal changes and events. As the chapter proceeds, topics are covered on more relevant scholarly works about challenges and new directions in P300 BCI. Along with these, articles with the references on the advancement of this technique will be presented to ensure that the scholarly reviews are accessible to people who are new to this field. To enhance fundamental understanding, stimulation as well as signal processing methods will be discussed from some novel works with a comparison of the associated results. This chapter will meet the need for a concise and practical description of basic, as well as advanced P300 ERP techniques, which is suitable for a broad range of researchers extending from today's novice to an experienced cognitive researcher.

Keywords: brain-computer interface, P300, electroencephalogram, event-related potential, paradigm and human factors

1. Introduction

Human brain is the most complex organ of the body and it is at the center of the driving block of human nervous system. In fact, more than 100 billion nerve cells are interconnected to build the functionality of human brain. Such a complicated architecture allows the brain to control the body as well as carry out the executive functions, such as making reasons, processing thoughts, and planning for next tasks. Interestingly, electrophysiology and hemodynamic response are the two techniques that have been used to study this complex organ to understand the mechanism the brain applies to finish works. Typically, electrophysiological measurements are performed by placing electrodes or sensors on the biological tissue [1, 2]. In neuroscience and neuro-engineering, the electrophysiological techniques are used for studying electrical properties by measuring the electrical activities of neurons in the form of electroencephalogram (EEG). EEG may be measured by two different approaches: invasive and noninvasive. Invasive procedures need a surgery to place the EEG sensor deep under the scalp. In comparison, noninvasive procedure places the electrodes on the scalp. One of the ways to study the brain is to stimulate it by presenting a paradigm.

The event-related potential (ERP) was first reported by Sutton [3]. An ERP is an electrophysiological response or electrocortical potentials triggered by a stimulation and firing of neurons. A specific psychological event or a sensor can be employed to generate the stimulation. In general, visual, auditory, and tactile are three major sources of ERP stimulation. For instance, ERP can be elicited by a surprise appearance of a character on a visual screen, or a "novel" tone presented over earphones, or by sudden pressing of a button by the subject, including myriad of other events. Presented stimulus generates a detectable but time-delayed electrical wave in EEG. EEG is recorded starting from the time of presenting the stimulus to the time when EEG settles down. Depending on the necessity, simple detection method such as ensemble averaging or advanced processes such as linear discriminant analysis or support vector machine algorithms are applied on EEG to measure the ERP. This chapter discusses the application of ERP in brain-computer interface (BCI) where P300 wave is of particular interest. ERP is time-locked to an event and appears as a series of positive and negative voltage fluctuation in the EEG that is referred to as P300 components.

2. P300 waveform

P300 is a form of visually evoked potential (VEP) and P300 ERP is embedded within the EEG signal recordable from the scalp of human brain. Depending on the components appearance following the eliciting event, the P300 can be divided into exogenous and endogenous. Early (exogenous) components are distributed over first 150 ms, whereas longer latency (endogenous) components elicit after 150 ms. Although the P300 positive deflection occurs in the EEG about 300 ms after an eliciting stimulus is delivered (which is the major reason it is termed as P300), latency can be within the range from 250 to 750 ms.

Although the actual origin of the P300 is still unclear, it is suggested that P300 is elicited by the decision making or learning that a rare event has occurred, and some things appear to be learned if and only if they are surprising [4]. The variable latency is associated with the difficulty of the decision making. In addition, the largest P300 responses are obtained over parietal zone of human head while it is attenuated with the electrodes that are gradually placed farther from this area.

To generate the P300 ERP, three different types of paradigms are being used: (1) single-stimulus, (2) oddball, and (3) three-stimulus paradigm. In each case, the subject is instructed to follow the occurrence of the target by pressing a button or mentally counting [5]. **Figure 1** presents these paradigms [5, 6]. The single-stimulus paradigm irregularly presents just one type of stimuli or target with zero occurrence of any other type of target. A typical oddball paradigm can be presented to the subject with a computer screen, a group of light-emitting diodes (LEDs), or other medium to generate a sequence of events that can be categorized into two classes: frequently presented standard (nontarget or irrelevant) and rarely presented target stimuli [7]. In an oddball paradigm, two events are presented with different probabilities in a random order, but only the irregular and rare event (the oddball event) embosses the P300 peak into the EEG about 300 ms after the stimulus onset. The three-stimulus paradigm is a modified oddball task which includes nontarget distractor (infrequent nontarget) stimuli in addition to target and standard stimuli. The distractor elicits P3a which is large over the frontal/central area [8]. In contrast, target elicits a P3b (P300), which is maximum over the parietal electrode sites. Though P3a and P3b are subcomponents of P300, P3a is dominant in the frontal/central lobe with a shorter latency and habituates faster [9].

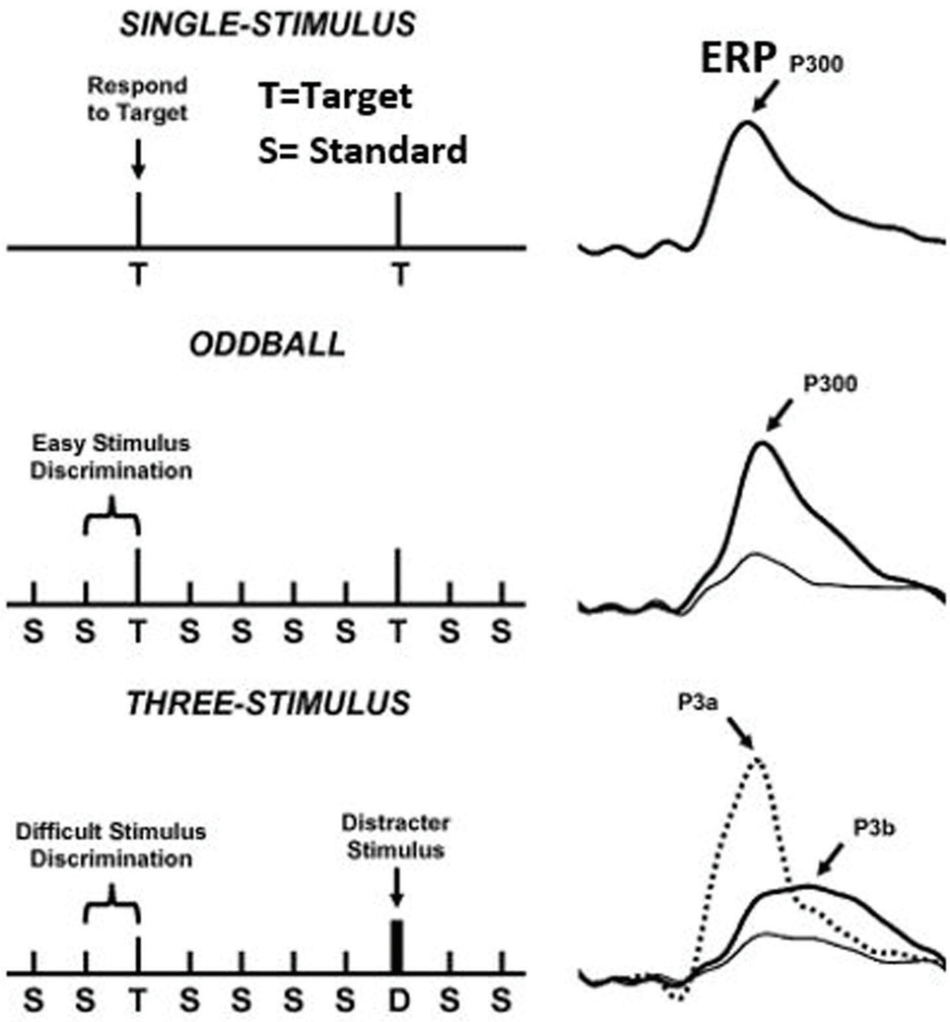

Figure 1. Schematic account of three paradigms: single-stimulus (top), oddball (middle), and three-stimulus (bottom). Elicited ERP is presented at right (adapted from Ref. [5]).

3. P300 BCI

Humans' ability to communicate to each other plays a critical role in building relationship with society and others. With the advent of modern logistics and necessities, communication between people has become richer and more complex than any other time of human history. Furthermore, as brain science and computer technologies mature, it is critical to have an ultimate interaction interface that will develop a direct communication between the user's brain and a computer; in other words, a BCI system which facilitates to build a real-time communication between a user and a computer system. The core purpose of a BCI is to detect brain activity in EEG and communicate that activity to a computer or electronic device. BCI allows a user to voluntarily send messages or control commands bypassing the brain's natural output pathways. There have been different approaches for BCI. P300 BCI is a safe and noninvasive system, which requires the user to wear a small head cap carrying a set of electrical probes to detect brain P300 ERP. The P300 BCI has many potential advantages over many other input modes [10].

4. P300 detection

Detection of P300 requires the subject to properly recognize the stimulus event to generate a strong and perceivable P300 ERP. Noticeable P300 amplitude is also critical for information transfer, which might not be possible if the stimulation is presented too fast or the targets appear too frequently [6]. It is important to design a BCI paradigm with easily discriminable stimuli. BCI should be adjustable to the users' adaptability of signal detection by controlling the stimulus presentation at a slower rate, brighter intensity, or with otherwise increasing perceptibility. Studies also show that target-to-target interval (TTI) plays an important role in evoking larger P300 ERP [11, 12]. If the overall BCI paradigm presents the stimulation at a constant rate, targets with low probability results in longer TTL, which is also a useful means to obtain perceivable P300 amplitude [13]. In sum, for stronger P300 ERP, the BCI system should maintain a minimum probability or maximum TTI. Unfortunately, such an action reduces the frequency of the target stimulation and, thereby, reduces the overall system speed. This tradeoff has been explored in several early BCI studies [14]. It is evident that due to the nature of P300 ERP generation, P300 amplitude can be increased by incorporating high temporal uncertainty. In this case, subjects are completely unaware of the exact time when the stimulation occurs. Few articles reported that P300 amplitude becomes larger for familiar or learned items [15–17]. For example, if a list of characters is presented to a subject repeatedly, P300 amplitudes for repeated characters (which are recalled by the subject) are higher than the characters that are forgotten by the user.

In addition, there are several other factors which should be considered for P300 detection. Among these are attentional blink, which occurs in case the intervals between two different targets become less than 500 ms [18]; repetition blindness, which leaves the second target unnoticed if two identical targets flash at intervals between 100 and 500 ms [19]; and habituation, which makes fainted P300 amplitude due to the repeated presentation of the same stimulus [20]. Apart from this, human factors such as motivation, fatigue, and user comfortability affect the performance and accuracy of the P300 BCI [21–23], which should be considered in the design of paradigms.

5. Signal processing methods

A P300-based BCI measures EEG signals from the human scalp and processes them in real time to detect P300 ERP that reflect the subject's intent. As noted earlier, P300-evoked potential is elicited as positive EEG peaks in reaction to infrequent or irregular appearance of stimuli. As the EEG signals are typically on the order of 100 microvolts, appropriate signal processing strategy is critical in revealing the electrical information and relevant complex issues in relation to the distinctive cognitive functions. Moreover, optimization of accuracy in P300 detection and enhancement of the system speed heavily depends on a suitable signal processing scheme.

EEG-based BCI system can have three stages to process signals: preprocessing, feature extraction, and detection and classification of P300. Preprocessing is accomplished after data acquisition but before extracting any feature. Preprocessing is an important step which leaves the significant information intact while amplifying EEG signals and simplifying subsequent processing operations. It is also important to note that the classifier performance depends greatly on an efficient data preprocessing stage [24]. Signal strengthening ensures signal quality by improving the so-called signal-to-noise ratio (SNR). Presence of background noise may bury the interesting brain patterns into the rest of signal making it difficult to detect P300 response resulting in a bad or small SNR. On the other hand, P300 detection and classification becomes easier when the input EEG signal has high SNR. After acquiring the EEG signal from microelectrodes or macroelectrodes, the electrical information is amplified by a factor of as high as 5000–10,000 and converted from an analog to a digital signal. Though analog to digital A/D conversion can be done at a rate of few GHz, human brain does not operate that fast to justify such a high sampling frequency. EEG data is typically sampled at 256 Hz which satisfies the Nyquist sampling theorem as this rate is larger than two times the maximum frequency generated by cognitive actions, yet low enough to avoid irrelevant data [25]. To realize the high SNR, bandpass filtering is utilized to remove the DC bias and high frequency noise. Sometime, researchers also combine transformation and filtering techniques and apply to remove or abate signal components that are not of interest for the application [26, 27]. As AC current is usually of 50–60 Hz, depending on the particular living zone of the globe, a notch filter at either 50–60 Hz is used to remove power line effect on EEG. During filter set up, it should be kept in mind that certain types of artifact occur at known frequencies and cognitive activity usually limits itself in the 3–40 Hz range.

Once the EEG is preprocessed, variety of approaches can be applied to extract the features and classify the P300 ERP. A calibration session is exploited to develop these feature vectors. Before classification test and actual use of the P300 BCI, the classifier is trained and supervised using a classification algorithm and the feature vectors labeled as "target" and "nontarget" [27]. On the other hand, during the classification task the feature vectors corresponding to known stimuli are submitted to a trained classifier. The trained classifier discriminates the brain response best resembling to a target stimulus from nontarget stimulus. In case of a P300 Speller, the classifier detects the letter with a maximum probability [10, 28–30].

Different methods have been employed for feature extraction such as discrete wavelet transform [31], independent component analysis [32, 33], and principal component analysis [34]. As stated earlier, extracted features are given as input to the EEG classifiers for P300 ERP identification and classification applying different classification methods. Linear discriminant analysis (LDA) is a popular pattern classification technique used by Guger et al. [35]. Stepwise linear discriminant analysis (SWDA) has evolved from LDA classification method which uses only selective features. Farwell and Donchin used SWDA to classify the ERP using individual averages for rows and columns of a 6 × 6 row/column paradigm [25]. Some classification methods apply machine learning technique for the P300 detection such as support vector machine (SVM) [36]. SVM takes advantage of small data size to give high throughput at high transfer rate. However, LDA outperforms SVM classifiers for the P300 detection if the input data is comparatively larger in size [37]. Moreover, many BCI groups have exercised their study with other classifiers such as Bayesian linear discriminant analysis (BLDA), Pearson's correlation method (PCM), linear support vector machine (LSVM), and Gaussian support vector machine (GSVM) [24, 38, 39]. Although different features and classifiers have been compared, there has not been a comprehensive comparison of all different features extraction

Methods	System performance
Discrete wavelet transform (DWT); 6 × 6 targets on the menu; 36 feature vectors; feature vectors were continually ranked and either a correlation/threshold was used to select a cell	7.8 characters/min and 80% accuracy; Accuracy >90% for 5 subjects [31]. 2.3 characters/min [25]
Genetic algorithm (GA); high resource consumption; possible premature convergence	Variable accuracy, 34~90% [40]
Bayesian analysis, Bayesian linear discriminant analysis (BLDA); feature vector is labeled to the class to which it has the highest probability	Transfer rate of 7 commands/min with 95% false positive classification accuracy [41]
Linear discriminant analysis (LDA); simple, low computation	Accuracy for the able-bodied subjects was on average close to 100% and the best classification accuracy for disabled subjects was on average 100%. 15.9 bits/min for the disabled subjects and 29.3 bits/min for the able-bodied subjects. Accuracy varies with electrodes 4–32 [42]
Support vector machine (SVM); linear and nonlinear (Gaussian) modalities, faster processing	96.5% accuracy [43]. Accuracies are 66, 69, and 72% for LDA, neural networks, and SVM, respectively [44] Accuracy 84.5% and information transfer rate of up to 84.7 bits/min [45]
Maximum likelihood (ML); feature detection using a priori knowledge, uses thresholds for a set of classes	Accuracy 90% with a communication rate of 4.19 symbols/min [33]

Table 1. Summary of the signal processing methods.

and classification methods applied to the same data set. However, a research group in Ref. [24] examined multiple feature extraction and classification methods applying to the same data set. This study found that SWDA and Fisher's linear discriminant (FLD) yield the best overall classification performance in comparison to any other classifier. Most frequently used signal processing methods have been described in **Table 1** with reference to the relevant study.

6. Advantages of P300 BCI

There are properties of P300 BCI that make it attractive in many applications including daily life usages [35]: (1) the typical P300 BCI can be controlled with high accuracy; (2) the P300 BCI classifier offers fast response; (3) it may be used in gaming applications where an even shorter calibration can be used if classifier accuracy is not critical; (4) almost all healthy people and many severely paralyzed patients are able to use the P300 BCI [20, 46, 47]; (5) unlike other BCI (e.g., the motor imagery-based BCI), no special training is needed to operate this BCI; and (6) P300 BCI is noninvasive, calibration time is limited to few minutes, and it is effective for most users and more than 90% users feel comfortable with this system.

7. Advancement of P300 BCI

In 1988, Farwell and Donchin furnished a seminal study to demonstrate the potential of P300-based communication with a P300 ERP-based speller [25]. Since then, many P300-based BCI systems have followed this as a benchmark for P300 ERP application. However, until the year 2000, it drew very little attention from research community and no P300 BCI peer-reviewed papers were available before this time [31]. Later on, some researchers have explored the offline analysis of previously collected BCI data resulting in a moderate increase in P300 BCI articles [32, 48]. However, in the last decade, extensive studies and interests have been observed with a particular focus on the importance of P300-based BCIs. In addition to improving information transfer rate, current P300-based BCI mainly explores new electrode montage, paradigms, and applications to increase the performance of the BCI systems which can also assist disabled users in home settings [10, 28, 47]. For example, effect of contrast and color, modified stimulus presentation, enhanced users' attention, and new paradigms [49, 50] for eliciting the P300 have been introduced as new ways to improve ERPs and its classification [51, 52]. As a result of strong interest in P300 BCI, BCI community has experienced a high volume of research works involving P300 ERP in past 6 years. **Figure 2** portrays the number of peer-reviewed journal publications that were accounted by PubMed and Scopus search engines from 2000 to 2016 with the phrase "[(BCI OR Brain Computer Interface) AND (P300 OR P3)]." Even though conference proceedings were not included in the result, novel studies were reflected by the large number of articles. Although, in particular, BCIs are still slower than normal electronic input devices, such as the mouse or game controllers, endless exploration of new options with considerable success promises a P300 BCI system with substantial increase in BCI speed and accuracy and, thereby, extending P300 BCIs to new applications.

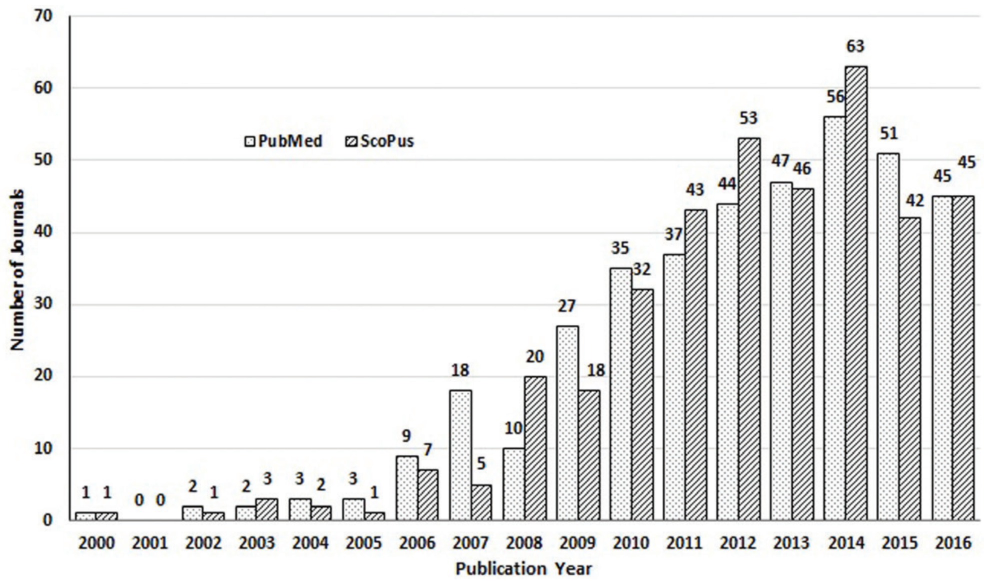

Figure 2. Number of published journal papers in PubMed and Scopus from 2000 to 2016 when the searching keyword "[(BCI OR Brain Computer Interface) AND (P300 OR P3)]" was used.

8. Applications of P300 systems

A P300 BCI is particularly suitable for selection applications [53]. For instance, the most typical application of P300 BCI is P300 speller. In such an arrangement, the visual paradigm is made up of a matrix consisting of letters of the alphabet. Depending on the requirement, a speller can be optimized for quick selection or accuracy of the spelled letters. Similarly, other P300 BCI investigations have made extensive progress to develop other attractive applications such as painting artwork, controlling smart home, designing games, stroke rehabilitation, lie detection, and furnishing Internet tasks [54]. However, recognizing the importance of P300 speller, a detail description of P300 speller is presented in the following sections.

8.1. Smart home

A smart home populates different electronic devices which can be controlled using a P300 BCI. A virtual reality-based smart home was the test-bed of such BCI application [35]. This BCI system allowed to execute a group of modest controlling commands such as moving the cart or wheelchair, receiving or making phone calls, operating television, switching the light on and off, playing song in multimedia player, or controlling the doors and windows [35].

8.2. Internet use

P300 BCI can be used to select the Internet keys to provide assistance to amyotrophic lateral sclerosis (ALS) patients browsing the websites. Subjects can surf through Internet pages and select the desired links to browse the Internet or read the news [55].

8.3. Painting task

It was observed by the researchers that performing natural tasks bring better quality to life in ALS patients. A P300 BCI application known as "Brain Painting" (BP) offers a medium of entertainment for the patients by improving their playful mood [56].

8.4. BCI gaming

P300 BCI has been used to design paradigm to control simple games that do not require strong time constraints such as to play chess [57]. Other popular games are MindGame [58], Bacteria Hunt [59], Brain Invaders [60], etc. In MindGame, the users move depends on the brain response; if P300 ERP is stronger, the game character can move larger distance. In Bacteria Hunt, users can change the color of the image, or enlarge, or rotate it. Similarly, in Brain Invaders, the user needs to select appropriate target arms to destroy the aliens, which make the game interesting to the video gamers. As no training is required to start playing simple P300 BCI games as mentioned here, it can be useful to familiarize individuals to the BCI tools. In fact, proper design to utilize the P300 wave's strong dependence on attention would allow the scientists to study attention training and effects of engaging in a particular task.

8.5. Stroke rehabilitation

One of the sufferings of poststroke patients is that they would like to say what they want but trouble of cortical circuits will not allow them to express it through natural motor pathways. P300 BCI paradigm was used to provide a communication channel to the participants diagnosed with poststroke aphasia. P300 BCI not only allowed to activate their language circuits, but also made their poststroke recovery faster [23].

8.6. Lie detection

Different brain regions work together and generate activities to process deceptive information which elicits P300 ERP in the brain signal. The concealed information can be identified through the concealed information test (CIT) [61]. Most of the earlier experiments with lie detectors used just a few channels limiting the number of EEG features to classify these two types of information [61–64]. These studies mostly used an oddball paradigm using three different types of stimuli: target, probe, and irrelevant. Like a typical P300-based system, the targets are presented rarely though they are usually made of irrelevant items which are presented in the paradigm to ensure participants' cooperation in discriminating the target items from others. On the contrary, the irrelevant items are presented frequently, but they are neither related to the criminal act nor related to the experimental task. The underlying principle of the item is that subjects will have different responses to stimuli according to their crime-relevant status. The probes are the critical detail stimuli under investigation which appear infrequently. Probes elicit P300 only for subjects who are knowledgeable or deceiving the information. Otherwise they act similarly as irrelevant for the subject. However, to ensure reliable differences between liars and truth-tellers it is important to engage multiple channels resulting in ERP features from different brain areas. One study investigated the functional connectivity of the brain network under deception condition [65]. They found the correlation between different EEG signals from multiple channels to understand the interactions between the brain regions and functional connectivity. Their results suggest that incorporation of additional features helps separating innocent group from the liars with about 90% accuracy.

8.7. P300 speller

Perhaps most important and popular use of P300 BCI is P300 speller. BCI speller has been utilized as a communication tool for the last two decades by people suffering from various neuromuscular disorders such as ALS, brainstem stroke, brain or spinal cord injury, cerebral palsy, muscular dystrophies, multiple sclerosis, and other impaired patients who are unable to use the normal neuronal pathway [66]. Persistent research in BCI to improve the accuracy and speed of P300 speller has resulted in numerous P300 stimuli presentation paradigms. They are discussed in details in the following sections.

8.8. Row/column (RC) paradigm

The Farwell and Donchin matrix speller paradigm was the first BCI row-column speller (**Figure 3**). They used an alphabetical square matrix interface to produce P300 in EEG [25]. Rows and columns of this 6 × 6 matrix were constructed with alphanumeric characters. These characters are flashed randomly following either a row or a column and the subject is asked to mentally count the number of times that the attended character is flashed. During the brain signal measurement in the parietal area, the P300 ERP appears in EEG as evoked response. However, the nonflashing rows and columns do not generate P300. Due to the nature of the stimulation mechanism and to increase the accuracy of detection, the P300 system requires multiple trials to reach an acceptable accuracy. In practice, the nontarget rows also generate P300 for a very short amount of time but the amplitude is too faint to detect. The computational device can determine the target row and column after averaging several P300 ERP responses. Due to the averaging task, it may take a longer time to detect a character.

Figure 3. The row-column (RC) paradigm. One row (MNOPQR) is flashing.

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In general, reducing the number of characters would eliminate the longer detection time but not without a loss in spelling characters option. So far, this is the mostly used and discussed P300 speller in BCI community.

8.9. Single character (SC) paradigm

This is possibly one of the simplest spellers designed so far. It randomly flashes one character at a time with very short interflash interval (**Figure 4**). This paradigm also uses a 6 × 6 alpha-numeric matrix like the RC paradigm. It was reported that the RC paradigm takes less time than the SC paradigm to flash all the characters at least once. Nevertheless, in Ref. [35] it was noticed that if the number of flashes is constant, the SC speller produces stronger P300 ERP than the RC speller.

8.10. Region-based (RB) paradigm

The major idea behind the region-based (RB) paradigm is to distribute the characters in larger area than the RC paradigm. Here, choice of an object is split in dual selection levels which decreased the near-target effect and human error and adjacency problem significantly [49, 67]. In this paradigm, space of the visual paradigm is divided into seven different regions (**Figure 5**). The desired characters are split into seven groups and each group is placed into a single region as shown in **Figure 5**. For any given spelling task, user has few seconds to focus on the characters before the action of each level. This action produces the P300 ERP for the first-level target. It is important to note that, instead of the rows and columns as in Farwell and Donchin RC paradigm, regions are flashed in a random order by repeatedly changing its color between black and white. Choice of color needs to be justified with the purpose of the application. For simple spelling task, common black-white transition usually outcomes better contrast. Combined action of these two levels is needed to detect a single character. For instance, the first level is used to select the desired region containing the character of interest while the second level is used to select the target character from the enlarged region. Expansion at the second level largely increases the intercharacter space so that each character

Figure 4. Single character (SC) paradigm: single character (M) is flashed.

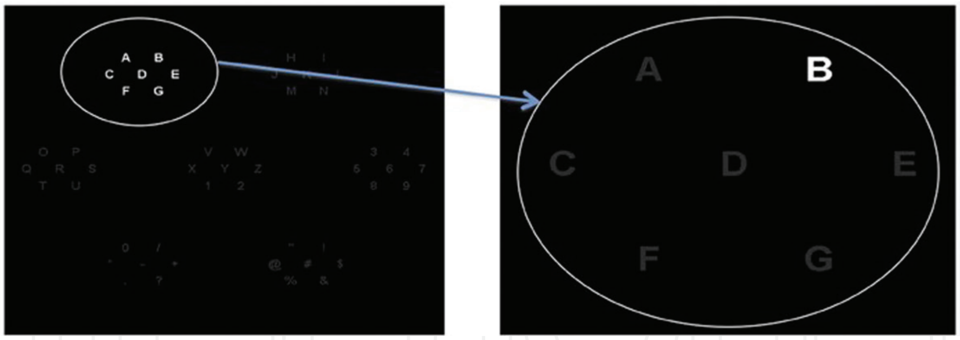

Figure 5. Region-based (RB) paradigm with the locations of seven regions, where a region of a set of seven characters “ABCDEFG” in level 1 is expanded in level 2 for spelling a single character “B”.

is highly visible to the user. Each time a target is flashed, a strong P300 ERP potential is expected in the EEG wave. Although Farwell and Donchin paradigm allows one to spell 36 characters, the use of seven-region RB paradigm allows to spell 49 characters. In addition, this arrangement allows to manipulate and distribute the characters spatially on the screen considering their probability of linguistics use in a word. As paralyzed people need to spell the desired word with a minimum movement, the arrangement of the letters can be adjusted accordingly to optimize the performance [10]. Later on, RB paradigm was modified by implementing the findings about the probability of characters’ usage [68]. In fact, it was developed considering the frequency of use of the characters. The list of characters used in seven regions in the first level of this modified edition is presented in **Table 2**. In a comparative study, it was found that the overall spelling accuracies averaged for the same set of subjects, trials, and characters for RC, SC, and two variations of RB paradigms were 85, 72.2, 86.1, and 90.6%, respectively [14, 69]. It is interesting to note that other than P300 BCI, application of RB paradigm has been extended to other BCI modalities too [54, 70–72].

8.11. Checkerboard (CB) paradigm

A standard RC presentation method has couple of limitations which were addressed by the CB paradigm (**Figure 6**). First of all, in checkerboard paradigm in Ref. [50], row-column

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

Table 2. List of characters in each region in the first-level of region-based paradigm.

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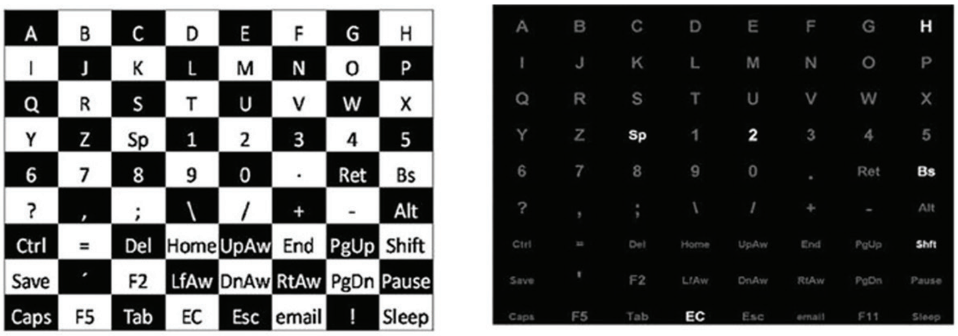

Figure 6. Standard checkerboard (CB) paradigm with a 9 × 8 matrix (adapted from Ref. [50]).

paradigm was modified to eliminate the error caused by adjacency problem as it was discussed by Fazel-Rezai [73] as human error in P300 BCI. So the error resulting from the nontarget items receiving apparent target responses is reduced to a great extent. Second, 72 characters in a standard 9 × 8 matrix are distributed in two virtual levels where each level is a virtual checkerboard, a modification to row/column (RC) paradigm implemented in a checkerboard (CB) paradigm. This eliminates the chances of the same character flashing twice in succession, thereby increasing the time between successive flashes of a target character.

9. Future use of P300 BCI

There exist many future directions to improve the information throughput in P300 BCIs, which also equally true for many other types of BCI systems. To uncover the applications of P300 ERP to other modalities, underlying physiological mechanism and brain response in each of the particular application need to be carefully investigated. For example, study to unfold more insight of the cognitive process showed that neurofeedback can be applied to augment the cognitive diagnosis [74]. In order to increase the BCI accuracy, error correction mechanisms can be incorporated into the BCI system. It will also increase the user acceptability of P300 BCI. Although improving information throughput of BCI is of paramount importance, many other aspects of BCIs also demands substantial consideration. For example, future BCIs need to be faster, inexpensive, and easy to use. Fortunately, BCI community comprises of many other disciplines, such as engineering, cognitive and neuroscience, semantics, mathematics, psychology, clinical science, and software writing. Eventually, scientists and researchers from various avenues continuously help finding a universal platform for BCI development utilizing available resources free for academic research. In particular, future expansion of BCI application depends a lot on the thorough investigation of users' comfort in using BCI. So different conditions should be well explored to find reasons behind why most users may or may not like a BCI system or paradigm. Many articles have introduced questionnaires and surveys to learn the comfort zone of the P300 BCI users [52, 56]. To promote the use of BCI to the target users with new applications, record and study of the human factors should be employed.

10. Conclusion

An ERP is a change in voltage which is time-locked to a specific sensory, motor, or cognitive event. ERP provides a distinctive pattern as an indication of how the stimulus is processed. Many BCI applications have been developed based on ERP as a response to stimulus. Among these, P300-based BCI is the most prominent ERP BCI. Over the last two decades, countless P300 BCI works have exploded beyond laboratory experiments with the help of modern high-speed computational and sensor technologies. Because of its noninvasive nature and stable performance, P300 applications range from the potential improvement of the lifestyle to the financial benefits. In fact, fundamental research on recording hardware, signal processing methods, stimulus presentation parameters, supporting interaction paradigm, and neuro-physiology will further refine the P300-based BCI design. Though a BCI design is accomplished with keeping a specific application in mind, further insightful study and research can revive opportunities toward exploring other usability areas which are still not unearthed. This chapter has covered several aspects and applications of P300 ERP in BCI research. The interfacing paradigm of a P300 BCI can be designed to capture the ERP-evoked potentials in a manner so that many human factors are properly taken care of to diminish their overall negative impact. Many new applications are also emerging with efficient design of the control interface and associated signal processing scheme.

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