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An Overview on P300 based Brain Computer Interfaces

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Abstract

In this paper, we review the different techniques of BCI which are already using in various P300 based BCI application system and compare how the P300 is efficient than the other conventional BCIs. P300 is positive going event related potential component which evoked the process of decision making. This ERP component is used in Brain Component Interface (BCI). BCI is a straight way communication between the brain and a computer or any other external devices. BCI can translate user brain activity into corresponding commands for communication with or without using conventional communication. Here the P300 signals are elicited from the EEG and then further procedure are going to be processed. We discuss the methods of pre-processing, feature extraction and classification.

Keywords*: P300, Brain Computer Interface, Event related potential, Electroencephalography.*

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1. Introduction

Brain computer interface is the communication way between the human brain and computer or an electronic device. BCI substitutes conventional communication pathways as nerves and muscles with EEG signals and the hardware and software that translate those signals into actions. According to the type of input signals, BCI can be categorized into two approaches, one is exogenous BCI and another is endogenous BCI. Exogenous BCI uses the brain signals are P300 and SSVEP and Endogenous BCI use SCPs and Sensorimotor rhythms. The neuron activity is used by the exogenous BCI which elicited in the human brain by an external stimulus such as visual or auditory evoked potentials. Advantages of this BCI are, it does not require extensive training so that their control signals can be easily and quickly set-up.

There are various event related potential components are used in BCI which are categorized into two groups, visual and auditory ERPs, they are, C1, N1, P1, N2, P2, LPC, N400 and P300. Here P stands positive going and N stands for negative going. C1 is the first major visual event related potentials component. It is the largest at the posterior midline electrode site. It can be positive going component or small for stimuli on the horizontal midline or negative going component. The C1 wave typically onset 40-60 ms post stimulus and peaks 80-100 ms post stimulus. P1 is

the first positive going visual event related potential component. The C1 wave is followed by P1 wave, which is largest at the lateral occipital electrode sites and typically onset 60-90 ms post stimulus with a peak between 100-130 ms. N1 or N100 is the negative going, visual as well as auditory sensory responses, and event related potential component measured by electroencephalography. The P1 is followed by N1, which is the earliest component peaks 100-150 ms post stimulus at the anterior electrode sites and then there appear to be at least 2 posterior N1 components that typically peak 150-200 ms post stimulus. P2 or P200 is another positive going component which followed by N1 wave at anterior and central scalp sites. Its peak normally observed near about 200 ms which is changing between about 150 and 275 ms after the beginning of some external stimulus. The N2 or N200 is a negative going event related potential (ERP) component. It peaks observed at 200-350 ms post-stimulus over anterior scalp sites.

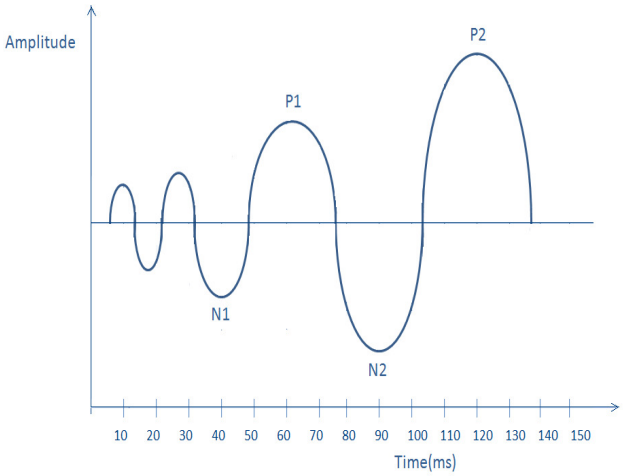

Fig.1: ERP Components P1, P2, N1, N2

N400 is the time locked EEG signals known as ERP. It is negative going deflection that peaks around 400 ms post stimulus at the beginning. It can be stretch from 250-500 ms and is representing maximal over Centro parietal electrode sites. Late positive component (LPC) is also a positive going event related potential component which is very important in explicit recognition memory studies. It is usually found to be largest over parietal scalp sites and its peak observed be around 400-500 ms after the rapidly beginning of a stimulus and then it permanent for a few hundred milliseconds. Another component of ERP is the P300 which is the largest ERP among all the ERP components. P300 is an event related potentials which evoked the process of decision making. P300-based Brain–computer interfaces (BCIs) are based on the P300 brainwave, which was first introduced by Sutton, Braren, Zubin, & John in 1965. It can be evoked by either a visual or auditory stimulus that a user has to concentrate upon while different non-target stimuli are also presented [23]. In (Picton, 1992) the characteristics of the P300 signal are described more nearly. Usually P300 is occurred when an occasional target stimulus is detected from the several non-target stimuli by the user. This is called an "oddball paradigm" [23]. Advantage of P300-based BCI (P300 BCI) system is that it does not require any time consuming or specific training.

Now-a-days P300 is very popular than the other BCI system and Researchers attracted towards a number of P300 BCI paradigms due to several conclusions: (1) the P300 response is easy to calculate, (2) no user training require, (3) it working with the various subjects also consider which are related to neurological disease, and (4) gives a destination oriented control signal which is specially suited for spelling and power of direction applications [25]. Various methods of using P300 interface have been proposed i.e. for moving the cursor, robot and writing text. The drawback of this interface (P300) is that they require the user to move his eyes but it is difficult or not possible for a completely paralyzed person.

2. Methodology

A. Pre-processing

Signal preprocessing is also known as signal enhancement. To extract the feature we have to first pre-process the data. It is done after data acquisition. It usually increases the signal and improve signal to noise ratio (SNR). A typical step in preprocessing is band pass filtering. Band pass filters are designed to remove high frequency noises and DC bias. In preprocessing, channel selection with respect to data decimation is determined in a way to increase the classification performance. Segments of data are collected and moving average filter is applied for the most suitable achievement [26]. Artifacts are unwanted signals present in BCI. Artifacts have various origins, which include the utility frequency like noise, body and eye movements, or blinks. We can handle artifacts by three main approaches: avoidance, rejection and removal. By artifact avoidance the user should not execute any movement which may result in EEG artifacts. This can reduce artifacts, but obviously we cannot stop eye movements and blinks, so sometimes these artifacts may occur. Because of constant restraining from blinking by user can cause fatigue.

Another approach is the rejection of all trials which are introduced by artifacts. This can be done in any way manually or automatically. By a manual artifact rejection procedure, we determine which of the trials are introduced through visual examination and in automatic artifact rejection an algorithm may be implemented which is able to determine contamination of artifacts. Artifact rejection may reduce the size of the training set; this can lead to consequences in the classification accuracy. In artifact removal, some algorithms may use in order to remove the artifact. It leaves the brain-originated signal intact which is desired. High-pass filtering of the signal is the simplest method for artifact removal. The eye artifacts generally occur in the low frequency range of 0–4 Hz, we may reduce the EOG artifacts by filtering these components out.

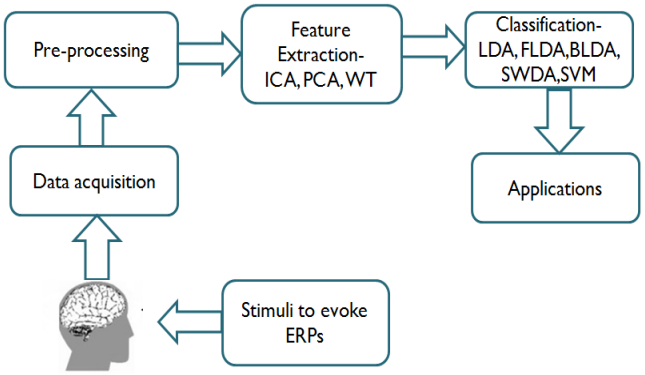

Fig.2: Steps of Brain Computer Interface

B. Feature Extraction Method

Feature extraction is one of the key issues of signal processing for P300 based brain-computer interface systems (BCI). Essential features are extracted from the brain signal after getting the noise-free signals from the signal improvement phase. There are different methods used for feature extraction from EEG signals like Adaptive Auto Regressive parameters (AAR), Fast Fourier Transformations (FFT), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Genetic Algorithms (GA), Wavelet Transformations (WT), and Wavelet Packet Decomposition (WPD). From all these methods PCA, ICA, AR, WT, WPD, FFT are usually used in Brain computer interface but from that ICA, PCA and WT are used for P300.

a) Independent Component Analysis

Independent Component Analysis (ICA) is used preprocessing as well as feature extraction method. ICA forms the components which are independent to each other. From the independent components essential features were extracted using ICA. One of the more important applications

of ICA is Blind Source Separation (BSS). This helps to selecting the independent signals separation from brain signal [3].

b) Principal Component Analysis

Principal Component Analysis (PCA) is the procedure of collecting and analyzing important numerical data (statistical procedure) which uses to convert the correlated variable into uncorrelated variable. Here, in BCI, PCA is used as a feature extraction method as well as pre-processing technique. It is one of the tool for examine and for reducing the dimension of the data without losing any information [4]. Also uses to find the clusters in data set. It reduces the dimensions of signals by removing the artifacts and by forming the principle components PCA [3].

c) Wavelet Transform

Wavelet Transformation is also used for feature extraction and was formulated by Morlet and Grossman in 1984. In various studies this method used to perform feature extraction with B-spline characters. This function permitted to act as high as well as low pass filter. Filter coefficient is getting by using multiple resolution analysis [3].

C. Classification Methods

Classification is used to classify the P300 signals after extracting the features. There are various classification methods which are used to design a BCI system like Linear Discriminant analysis (LDA), Fisher's Linear Discriminant analysis (FLDA), Stepwise Linear Discriminant analysis (SWLDA), Bayesian Linear Discriminant analysis (BLDA), Support Vector Machine (SVM), Gaussian Support Vector Machine (Gaussian SVM), Maximum Likelihood (ML). In this we surveys about LDA, FLDA, SWDA, BLDA and linear SVM which are mostly used in P300 based BCI.

a) Linear Discriminant Analysis

Linear Discriminant analysis (LDA) is the method used in machine learning, statistic etc. are to find a linear combination of characteristic features or divide two or more classes of objects . The conclusions are shown together with used as a http://en.wikipedia.org/wiki/Linear_classifier for dimension reduction before later classification.

b) Fisher's Linear Discriminant Analysis

Fisher's Linear Discriminant analysis (FLDA) is mainly used as classifiers in P300 based BCI systems [10, 11, 12]. The main idea of FLDA is to find projection from the N-dimensional feature space onto a one-dimensional space for that the ratio of the variance between the two groups versus the variance within the classes is more.

c) Stepwise Linear Discriminant Analysis

Stepwise Linear Discriminant Analysis (SWLDA) has been used in locked-in patient studies of the P300 BCI speller [13, 14]. It is consider as an extension of the LDA with filter feature selection. SWLDA adds and removes scopes from a linear discriminant model which is based on their statistical significance in regression so that prepare model that is adjustable to the training data. It shows that SWLDA better than another classification methods in P300 BCIs [10].

d) Bayesian Linear Discriminant Analysis

Bayesian Linear Discriminant Analysis (BLDA) is an extension of the FLDA [26]. It has been also used in P300 BCI patient studies [15]. BLDA is based on a probabilistic regression network. BLDA also used to classify or recognize the P300 signals from the data set of BCI Competition [4, 18].

e) Linear Support Vector Machine

Linear support vector machine (SVM) is another classification method which is regarded as the more accurate classifiers in P300 BCI research [10, 16]. The fundamental idea of a linear SVM is to search the separating hyper plane between two classes, hence the distance between the hyperplane and the nearest points from both classes is maximum. In other way, we require to extendthe margin between the two classes [17]. It is not necessary in case that the two classes are always linearly separable. The linear SVM idea was also generalized to the case where the data points are allowed to fall within the margin by adding a regularization term.

3. Application

a) Lie Detectors

P300-based lie detection systems use the service for the P300 component to detect concealed information [22].

b) Smart homes

P300 based BCI systems smart homes are used for controlling the various applications in a home. Used a P300 based BCI system for smart home with reliability and high accuracy [20, 21, 26]. 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 [20, 21, 26].

c) P300 based Games

The P300-based BCI is currently a very popular in that system which increases the capabilities of the disable people, called as assistive technology development. There are some simple games are designed in P300 based BCI for the locked-in patients. There are various existing P300 BCI games are mind game, mind puzzle, billiard puzzle, a face card game, bacteria hunt etc [1].

d) P300 Speller

There are various types of P300 speller are introduced in BCI system like Single Character (SC), Checkerboard (CB) and Region based (RB) speller paradigm.

Farwell and Donchin were introduced the first P300 based BCI speller paradigm in 1988 which is single character paradigm. This P300 speller contains 6×6 matrix having characters and numbers sequentially. Each row and column get flashed randomly and users were detected or instructed to focus on one symbol in the matrix and count the number of times its highlighting in mind. Thus no training of the users is required. For identification of the right column and row combined with a P300 Farwell and Donchin used the model based techniques are area and peak picking to detect the P300.

Another is Checkerboard which contains 8x9 matrix (original CB) having 72 items (virtual CB). In this speller items in White and Black Square are randomly populate in 6x6 matrixes. Then

randomly populated matrix are flashed each character in sequentially i.e. first row of white matrix, second row of black matrix, third row of white matrix, fourth row of black matrix and so on. Region based paradigm contains the 7 groups of characters are located in different regions. Each and every group of characters is flashed randomly and users have to pay attention on the one of the 7 groups in specific character.

4. Conclusions

P300 BCI is very popular BCI among all the BCI system. It is the only system which is regularly used by the paralyzed patients (locked-in patients) with the help of different BCI applications. There are various new approaches to improve the P300 based BCI flexibility and accuracy are currently being suggest in the general P300 BCI research. Even in current form of P300 based BCI, not only reveals comparatively high speed and accuracy but also it able to be no user training require, after a short calibration. To increase the accuracy or improve speed of the classifier using a limited amount of data for training linear or non linear SVM, BLDA, SWDA, accuracy may be increased by adding audio or tactile modalities to the visual P300 BCI design.

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