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Toward An Adaptive P300 Based Brain Computer

Mohammed J. Alhaddad
Information Technology Department
King Abdulaziz University
Jeddah, 21589 , P O Box 80200, Saudi Arabia

Mahmoud Kamel
Information System Department
King Abdulaziz University
Jeddah, 21589 , P O Box 80200, Saudi Arabia

Noura Al-Otaibi
Computer Department
King Abdulaziz University
Jeddah, 21589 , P O Box 80200, Saudi Arabia

Abstract—BCI represents a new communication way for people who suffering from neuromuscular impairment. In other words, BCI allow them to communicate with outside an environment, control prosthetic or other external devices by using only their brain activity. BCI system based on change of brain activity such that p300 potential. In BCI based on P300, the paradigm with some possible choices – such that letters or image – are present to users. One of the major problems in P300 application is the difficult to find a P300 response from a single trial. Hence several trials are performed for each element in order to decrease the error in prediction. This led to spend long time for predicted the user intent. For this purpose, this study concerns on Bayesian method that can take adaptive decision about stopping a data acquisition modules as soon as reach to reliable decision. The main advantage of using adaptive number of trials is increased a communication speed with keeping a good classification accuracy.

Keywords- P300; BCI; Aggregation; Bayesian theory; Adaptive.

I. INTRODUCTION

Some people who suffering from neurological diseases can be highly paralyzed and enable of any motor functions but they still have some cognitive abilities. The only way to communicate with their environment is by using their brain activities. Brain-Computer interfaces (BCI) researches aim to developing systems that help those disabled people to communicate by use computers and their brain waves [1]. Researches on BCI is a fast growing field and several EEG based techniques have been proposed for realizing BCI [1]. Researchers proposed various methodologies, applications of BCI and investigated the physiological nature of the experimental paradigms. However, the main challenge in BCI is improve the usability and practicality of these systems. Thus, researchers put most of their efforts on developing new algorithms to improve the speed and accuracy of the prediction mechanisms in BCI applications [2].

There are different kinds of brain activity that can be used in BCI systems. Different internal and external events cause different patterns in the brain waves. Many of these patterns have been studied for use in a BCI context for example visual evoked potentials (VEP), slow cortical potentials (SCP), mu/ beta rhythms and P300 evoked potentials [3, 4]. The BCI framework that interests for us is based on P300 Event Related Potentials (ERP) which is natural responses of the brain to some specific external stimuli [5]. In brief, P300 is a peaking signal pattern which occurs after the presentation of a rare audio/visual event, as in Figure 1. It is observed nearly 300 ms after the stimulus onset which gives the name to the signal pattern [2]. Since the presence of P300 based on the brain response to some external event, it possible to use them in BCI systems to determine the user intentions [6].

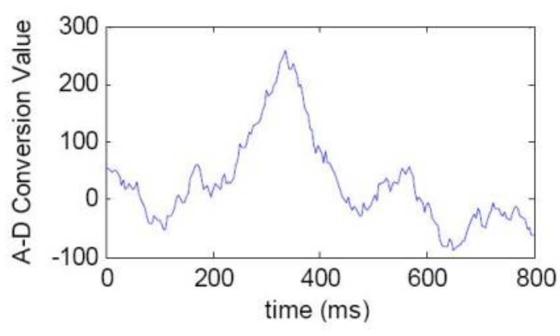

Figure 1. A typical P300 signal. A rising pattern occurs nearly 300ms after the presentation of the target stimulus.

As an example of most useful P300 applications, spelling system and smart home. These paradigms enable paralyzed people to express their thoughts and feelings by using the brain activity without need for voluntary motion and any external help. In this application the subject is focus on target elements and count a number of times that it is intensified. The p300 is elicited after intensification a target image [7]. One of the major problems in P300 application is the difficulty to find P300 response from a single trial i.e. (single intensification of each elements). The reason is that measured EEG signals are highly affected by noise. Accordingly, impossible to distinguish the target responses from the non-target one within single trial. Hence, several trials are performed for the same target element in order to decrease the error in prediction [1]. However, there is a trade-off between the time consuming for predicted a correct element and the accuracy of prediction. If a number of trials increase, the accuracy of prediction is improved. On the other hand, the repetition of trials spend a long time of prediction mechanism. In fact, the challenge in this application is how can reduce the time of prediction target element with keep a good accuracy. This study proposed a method that allow for take adaptive decision about stopping a data acquisition modules. In other words, this method allow a number of flash (stimuli) to varying from one element to next based on user performance and noise level in signal. The benefice of adaptive method is allow dynamically stopped for presented another flash of the element when system able to take reliable decision about target element. This mechanism increase the communication speed and bit rate. In contrast, a fixed method has a continues presentation of elements flash even after obtained a good accuracy. This lead to increase a time of selection the target element and reduce a bit rate.

The paper is organized as follows: in next section, review of previous studies of adaptive methods is present. In third section, the description of methods is provided. In next section, the results are discussed. In the last section, the conclusion is presented.

II. LITERATURE REVIEW

Many aspects of BCI systems are currently being investigated. Research areas include evaluation of invasive and non-invasive technologies to measure brain activity, development of new BCI applications, evaluation of control-signals (i.e. patterns of brain-activity that can be used for communication), development of algorithms for translation of brain-signals into computer commands, and the development and evaluation of BCI systems specifically for disabled subjects [7]. Because a field of BCI is fast grown and number of publication is increased in last few years, it is impossible to give exhaustive review in this field. So in this section we provide a review of some p300 based BCI that used an adaptive number of trials techniques based on user performance. In 2008 Lenhardt et al [8], the online p300 speller system with an adaptive method was presented. The main goal was increase information transfer rate and enhance classification accuracy. The adaptive approach was used based on the averaging number of stimulus over trials and then scaled the result to [0… 1]. As a result, the mean transfer rate obtained by the adaptive number of trials was 50.61 bit/min and the classification accuracy 87.5%.

In 2005 Serby et al [9], Independent Component Analysis (ICA) was used to separate P300 source from the background noise. They used a matched filter together with an averaging and a threshold techniques for detecting the existence of P300 wave. The processing method was evaluated offline on the data recorded from six healthy subjects. As a result, the method achieved a communication rate 5.45 symbols/min with an accuracy of 92.1% compared to 4.8 symbols/min with an accuracy of 90% in Donchin's work. On the other side, the online interface was tested with same six subjects. It was designed to adapt with the subject performance. Namely, if the P300 response can discriminate from ongoing signal, the decision is immediately taken. Serby used averaging result of the matched filter over several intensification until threshold was reached. The average communication rate was 4.5 symbols/min with 79.5% accuracy.

In 2007 Hoffman PHD thesis [10], described probabilistic approach for taken adaptive decision. This approach was applied for p300 paradigm that contain six different images. Each image was flashed in random order with ISI of 400 ms. After the classification of single trial, the class probability for each stimulus was computed. Then the probability of sequence stimulus was determined. In brief, the adaptive mechanism has done by compare the maximum probability sequence with a certain threshold. If the maximum is larger than the threshold, the command associated with large probability is executed. Otherwise, a second block of stimuli is presented. Then, the classifier output of the second block is combined with the first block by bays rule and compared the maximum with threshold. Here, this research used a Bayesian approach with the certain threshold for take adaptive decision. Then, compute the probability of each individual image instead of deal with the probability of sequence as in [10].

III. METHODOLOGY

This study proposed method for adaptive stopping of intensification repetitions when system reaches for effective classification result. Specifically, the Bayesian approach is used with the certain threshold for aggregated classifier results from several trials and make adaptive decision. Presently, this method applied on the smart home paradigm contains six images of some devices. On the other hand, the architecture of the system consists of six modules, as shown in Figure 2.

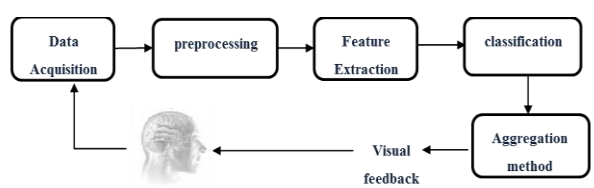

Figure 2. Functional Model of a BCI System. The signals are obtained by a signal acquisition system, processed by signal enhancement methods and classified in a specific BCI application.

a) Data Acquisition

The brain activity record by the bio signal measurement. The EEG was recorded using a cap (Electro-Cap International, Inc.) based on the International 10–20 system [11]. The adaptive method was applied on the dataset mention in [7]. The data recorded from 32 channels with the sampling rate 2048 Hz. The paradigm used for collect data consist of six image, each were flash in random sequences. Each subject's data consist of four sessions, each session consist of six runs and each runs consist of 22.5 blocks in average. Each block consists of six images intensification. Each image intensified for 100 ms and interstimuli interval was 400 ms.

b) Pre-processing

Pre-processing algorithms necessary for improving the EEG signal quality and eliminated unnecessary information from signal [2].

Pre-processing operation used in this study were similar that performed in [7]. These operations stated as follow:

Electrode selection. Eight electrodes were selected for processing. These electrodes are (Pz, CZ, Fz, Oz, P3, P4, P7, and P8).

Referencing. Average data from electrodes T7 and T8 were subtracted from other electrodes.

Filtering. A six order forward-backward Butterworth band bass filter was used for filter selected data. Cutoff frequencies were set to 1 and 12 Hz.

Downsampling. A data from selected electrode were downsampled to 32 Hz.

Single trial extraction. Single trial extracted at stimuli onset and ended after one second from stimuli onset.

Windsorizing. Windsorizing was used for reduce the outliers effect in signal amplitude. The amplitudes value of sample from each selected electrodes were lying above 90th and below 10th were set to those value 90th and 10th respectively.

Normalization. Samples from each electrode were normalized to interval [-1, 1].

c) Feature Extraction

In this module, the most relevant information for classifying the EEG patterns is investigated. Mainly, goal of feature extraction is reducing the complexity of the data by optimizing the computational effort needed for the classifier [2]. In this study, features vector was constructed by concatenated the samples from selected electrodes. The dimensional of feature vectors were $N_e \times N_s$ where N_e was a number of selected electrodes and N_s was a number of sample in each trials [7].

e) Classification

The classifier algorithms are necessary to determine the stimuli that evoked the P300 responses (i.e. the target responses). In consequence, predict the element that the subject focused on it. The input of this algorithm is the feature vector that extract from previous module and output is the user intent i.e. (target response) [10].

The classifier used in this study is a BLDA (Bayesian Linear Discriminant Analysis) similar used in [7]. The classifier was trained on three sessions and tested on one left session. Each trial yields six classifier outputs and each classifier output corresponding one flash of the image. The information from several trials is aggregated by the Bayesian approach as description in the next section.

f) Aggregation Method

Aggregation method used for combine a classifier output from different trials. Because the EEG high affected with noise and system may cannot take a decision from single trial, a multiple trials were necessary applied. So, after classification single trials, the classifier result must aggregate from several trials. Often, aggregation methods in BCI context were ensemble average and summation scores. Here, the Bayesian approach is used for fused the classifier output from several trials to reduce the uncertainty. "Bayesian approach provides a consistent framework for the quantification and manipulation of uncertainty and it allows us to make optimal predictions given all the information available to us" [12]. A general form of Bayes theory is [13]:

$$P(w_i|x) = \frac{P(x|w_i)P(w_i)}{P(x)} \tag{1}$$

where x is random variable, $w_i \in \{w_1, \dots w_n\}$ is finite state of n categories, $P(x|w_i)$ is a conditional probability density function for x given class w_i, $P(w_i)$ is prior probability of class w_i, $P(w_i|x)$ is posterior probability, $P(x)$ is evidence factor (unconditional measurement probability density) that can express in terms of the conditional probability distributions as [14]:

$$P(x) = \sum_{i=1}^{n} P(x|w_i)P(w_i) \tag{2}$$

if a different measurements x used with assumption each representation is a conditional independent, we can write a joint probability distribution as follow [14]:

$$P(x_1, \dots, x_R|w_i) = \prod_{k=1}^{R} P(x_k|w_i) \tag{3}$$

where $P(x_k|w_i)$ is the measurement process model of the kth representation. The Eq. (2) can rewritten to include different measurements as:

$$P(x_1, \dots, x_R) = \sum_{i=1}^{n} P(x_1, \dots, x_R|w_i)P(w_i) \tag{4}$$

By substitute Eq. (3) and (4) into Eq. (1):

$$P(w_i|x_1, \dots, x_R) = \frac{P(w_i)\prod_{k=1}^{R} P(x_k|w_i)}{\sum_{i=1}^{n} P(w_i)\prod_{k=1}^{R} P(x_k|w_i)} \tag{5}$$

Eq. (5) is used for fusion data from multiple information sources [10]. Here, in p300 application the Bayesian combination is used for aggregate classifier output from several trials. First, a result of classifiers is converted into class probability. A class probability is computed by used a Leave-One-Out Approach as mention in [10]. After probability is computed for each classifier outputs, a composition probability is computed from currently presented blocks.

The scenario of the systems by using a Bayesian theory as follow:

- First, the subject focuses on the one of six images that flashes in random order this consider one trial contain six sub trials.

- The EEG signal corresponding each flash of image is extracted and analysis.
- The single EEG signal is classified by classifier. Then compute the probability of classifier output for each flash in trial.
- The maximum probability of each flash in trial is selected and compare to certain threshold. If the maximum probability larger than threshold the corresponding action of maximum probability is executed. If the maximum probability less than threshold a next trials is executed. The same procedure is done except combination the probability of each element on first trial with probability of each element on second trial by using Eq. (5).

The threshold was setting in the same way proposed by Hoffmann [10]. Huffman was setting threshold t to value such that 100*(1-t) % represent a percentage of accepted wrong decision. Figure 3, show the Bayesian approach for combined information from several trials.

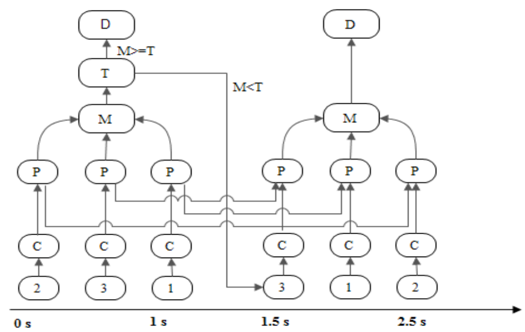

Figure 3. Bayesian theory used for aggregated data from several trials. Each trial contain 3 different stimuli with ISI 500 ms. Each stimuli classified by classifier then class probability was computed. Then, If a maximum probability stimulus exceeds a threshold, the corresponding action was executed. While if the maximum probability less than a threshold a next trial was executed and re-compute the probability of each image by combine evidence form two trials.

g) Feedback

Feedback is the element that selected by the program according to its interpretation of the subject's EEG signals. The subject will consider as a reward the correct selection of an element by the program (positive biofeedback). Otherwise, an incorrect element (negative biofeedback) will push the subject to concentrate more on the stimulus, trying to control it better [15]. In this study, the analysis –as first stage- has done offline, so feedback not important. Feedback is necessary when the experiment used on real time.

IV. RESULT AND DISCUSSION

In this section, the results of aforementioned method of adaptive technique are presented. The Bayesian approach is proposed for combine evidence from several trials. A dataset gathering from three disable subjects. Each subject data consists of four sessions. Four cross-validations are used for compute average classification accuracy. Precisely, three sessions are used to train the classifier and one left session used for testing. The average classifier accuracy for three subjects shown in Fig 4. Subject 1 reach to 100% after 10 blocks (i.e. 24 s). While system consume 48s to determine a target action on fixed approach. In other word, subject 2 reach to 100% after 11 blocks (i.e. 26.4 s). The best performance was achieved by subject 3 which it reach to 100 % after 7 s. On contrast, fixed method take 48 s to make a reliable decision. From these results, it clearly that the adaptive method seem better than fixed one for aggregate evidence from several trials. Fixed number of trial take a long time even reach to reliable decision.

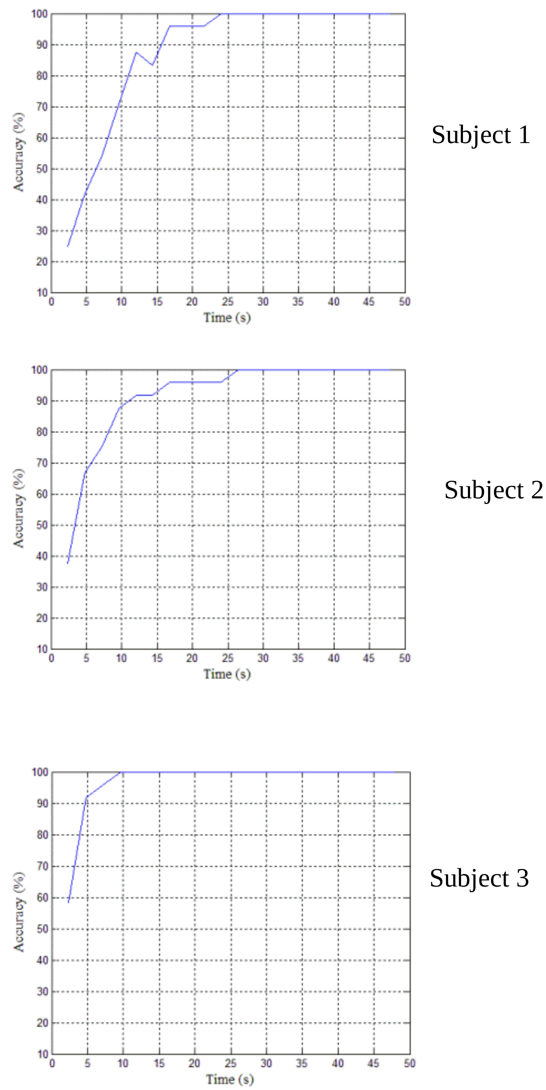

Figure 4. Average classification accuracy Vs. time obtained by BLDA for three disable subjects.

V. CONCLUSION

In this research the adaptive aggregation method that is Bayesian approach used with certain threshold for take adaptive decision about input signal. The main advantage of this approach is improved the communication speed with keep a good classification accuracy. This method achieves a high classification accuracy compared with non-adaptive method. In future work, we will apply this method for real time experiment and test the adaptive method with different paradigm such that speller system. Also, we study different aggregation methods for fused a classifier results from different trials.

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