P300 Based Brain Computer Interfaces: A Progress Report

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Abstract. Brain-Computer Interfaces (BCI) are the only means of communication available to patients who are locked-in, that is for patients who are completely paralyzed yet are fully conscious. We focus on the status of the P300-BCI first described by Farwell and Donchin (1988). This system has now been tested with several dozen ALS patients and some have been using this approach for communication at a very extensive level. More recently, we have adapted this BCI (in collaboration with the laboratory of Dr. Rajiv Dubey) to the control of a robotic arm. In this presentation we will discuss the special problems of human computer interaction that occur within the context of such a BCI. The special needs of the users forced the development of variants of this system, each with advantages and disadvantages. The general principles that can be derived from the experience we have had with this BCI will be reviewed.

Keywords: Brain Computer Interface (BCI), P300, wheelchair-mounted robotic arm (WMRA).

1 Introduction

A Brain Computer Interface (BCI) is a device that allows users to communicate with the world without utilizing voluntary muscle activity (i.e., using only the electrical activity of the brain). Several BCI programs were established with a focus on developing new augmentative communication and control technology for those with severe neuromuscular disorders. BCI systems utilize what is known about electrical brain activity to detect the message that a user has chosen to communicate. These systems rely on the finding that the brain reacts differently to different stimuli, based on the level of attention given to the stimulus and the specific processing triggered by the stimulus. Described by Farewell and Donchin in 1988 [1], the P300 based Speller is one such BCI system that relies on a brain response known as the P300, whose attributes have been studied for over four decades.

1.1 What Is a P300?

The P300, first described by Sutton, Braren, Zubin, & John (1965) [2], is one of the components of the brain's response to specific events that can be recorded from the scalp. These "event related potentials (ERPs) are manifestations of brain activities invoked in the course of information processing. The P300 reaches its maximal

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amplitude at least 300 ms following rare task-relevant stimuli. It is the largest at the parietal electrodes, somewhat smaller at the central electrodes and minimal at the frontal electrodes.

The P300 is elicited by rare task-relevant events and if often recorded in what has come to be called the “oddball” paradigm [3]. The “oddball” paradigm requires the participant to apply a classification rule to each of the events in a random sequence of events so that each event is classified into one of two categories, one of which is presented infrequently. The participant is required to perform a task that cannot be accomplished without the categorization of the events. As the P300 is elicited by events belonging to the rare category, its latency varies with the time required for categorizing the events. The amplitude of the P300 varies with the subjective probability and the task relevance of the eliciting events. Thus, the rarer the event, the larger the P300 it elicits.

1.2 P300 Based BCI

Two decades ago, Farwell and Donchin [1] developed a P300 based BCI that enables individuals to communicate with their environment without using any neuromuscular function. This P300 BCI speller uses an Oddball paradigm to elicit a P300 to a character that the user is choosing to communicate. The user is presented with a visual matrix of characters. The rows and columns of this matrix are flashed in a random sequence. The user focuses attention on one character to be communicated. Flashes of the row and column of the attended character are the rare events in this “oddball paradigm”, Flashes of the other rows and columns compose the frequent events. Thus, the flashes of rows and columns containing the attended character elicit a P300, while rows and columns not containing this letter do not elicit a P300. Therefore, by computing the ERPs associated with flashes of every row and column in the matrix, and detecting which row and column elicited a P300 response, the BCI system can identify in real time the character the user chose to communicate.

The size of the matrix can be varied according to individual preferences and ability. The matrix’ cells may contain letters, numbers, words, sentences, pictures and/or symbols. Depending on the user’s needs and preferences, the matrix can be as small as a 2x2 with 4 stimuli (for example, “yes”, “no”, “stop”, “more”), or as large as a 9x8 to emulate a computer keyboard. The successful use of the system does not require any training of the user. However, for optimal use, the algorithm detecting the P300 needs to be “calibrated” based on the pattern of electrical brain activity of a specific user.

1.3 Speed-Accuracy Tradeoffs

As the detection of P300 requires signal averaging, a number of trials are required by the system to correctly determine the user’s selection. The speed of the system thus depends on the number of sequences of flashes required to achieve a given level of accuracy. Traditionally, speed-accuracy tradeoff is estimated by analyzing a dataset offline to evaluate the number of events the system needed to average to achieve the desired accuracy level. However, the offline analysis does not take into account factors that are related to the user of the system (e.g., ability to sustain attention during longer trials).

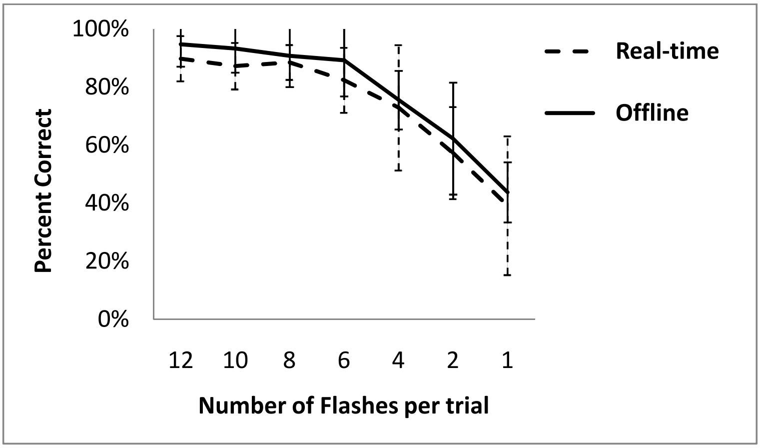

Fig. 1. Accuracy as a function of number of flashes per trial in real time and as estimated by offline analysis

We have recently examined the speed-accuracy tradeoffs of the P300 BCI speller measured in real time while participants selected characters from a 6 by 6 matrix with letters and numbers. Six young adults from the University of South Florida attended five 2-hour sessions to evaluate accuracy of spelling while manipulating the number of events (flash sequences). Accuracy was evaluated while participants spelled 50 characters under each of seven conditions: when each of the 12 rows and columns flashed twelve, ten, eight, six, four times, twice, and once. These speed accuracy data are reported in comparison to the data obtained from the offline analysis. Our results (Fig. 1) validate the effectiveness of the offline speed-accuracy estimation, although greater variability in accuracy was found in real time, particularly when a single sequence of flashes was used per character.

1.4 Adapting the BCI System for the Use of ALS Patients

As of today, most of the users of the BCI system are patients with Amyotrophic lateral sclerosis (ALS). Approximately 5,600 people in the U.S. are diagnosed with ALS each year. ALS, also called Lou Gehrig's disease, is a progressing, neurological disease that attacks the neurons responsible for controlling voluntary muscles. For the vast majority of people with ALS, their minds and thoughts are unaffected, remaining mentally sharp despite the progressive degeneration of their bodies.

With modern technology and advanced healthcare services, patients with ALS live longer. About twenty percent of people with ALS live five years or more and up to ten percent will survive more than ten years and five percent will live 20 years. As the progression of the disease is commonly rapid, and as the loss of the ability to function independently is relatively early, it is extremely important to provide these patients with a mean of performing everyday tasks even in the “locked-in” stage of the disease in which they can stay for years.

Extensive studies with ALS patients have demonstrated that the P300 BCI system can allow communication at the rate of 8 characters per minute. Since 2002, Sellers and Donchin [4] have tested the system with some 25 ALS patients at different stages of the disease in the Cognitive Psychophysiological Laboratory at the University of South Florida. A study by Sellers and Donchin [4] indicates that a P300-based BCI system can be successfully operated by patients suffering from ALS. In this study, a simplified version of the P300-speller was used. The reason for this simplification was that it was difficult for some patients to use the 6 by 6 letter matrix to spell out words. Therefore, the user focused attention to one of just four response options: "yes", "no", "pass" and "end", which were displayed and randomly flashed on a computer screen. Users were asked to either focus attention on one item, or to select the correct answer to a question asked by the experimenter. The results showed that ALS patients are able to reliably use a P300-based BCI.

Nijboer et al. (2008) [5] evaluated the efficacy of a P300 BCI speller for individuals with advanced ALS. In Phase I, six participants used a 6 x 6 matrix on 12 separate days with a mean rate of 1.2 selections/min and mean online and offline accuracies of 62% and 82%, respectively. In Phase II, four participants used either a 6x6 or a 7x7 matrix to produce novel and spontaneous statements with a mean online rate of 2.1 selections/min and online accuracy of 79%. The amplitude and latency of the P300 remained stable over 40 weeks. The results demonstrated that people who are severely disabled by ALS could communicate with the P300-based BCI and performance was stable over many months.

1.5 The P300 BCI Controls and Operates a Robotic Arm Mounted to a Wheelchair

Originally, EEG-based BCI systems were adapted to control simple functions, such as choosing letters from a screen to spell out words (e.g., [1], [6], [7], [8]), or moving a cursor on a screen. More recently, attempts have been made to adapt BCIs to steer robots (e.g., [9], [10]) and wheelchairs (e.g., [11], [12], [13], [14]), as well as to control implantable neuroprostheses [15] and robot arms [16]. Research on BCIs controlling these new devices is in a very early stage. We have recently demonstrated that the P300 BCI can be used to communicate a selected character from a 5x3 matrix to the controller of a wheelchair-mounted robotic arm (WMRA) [17] (see illustration of the communication between the BCI and the Robotic arm in Fig 4) [18]. To control the WMRA via the BCI the user is presented with a visual matrix whose rows and columns intensify randomly. Each of the symbols in the matrix corresponds to a specific direction or task command (Fig. 2). The chosen character from the BCI display is sent to the WMRA control program, which translates it into a Cartesian velocity in the proper direction and executes the algorithm to move the arm.

To test the application of the P300 BCI as a controller of the WMRA, six healthy young adults from the University of South Florida were presented with a 5x3 visual matrix with letters (see Fig. 3). Every row and column intensified for 75 ms every 50 ms. Each sequence of flashes contained 8 intensifications (5 columns and 3 rows) and lasted for 1 sec. We tested the accuracy of character selection as a function of number of sequences of flashes (number of intensifications). The letters in the BCI display (Fig. 3) corresponded with the symbol matrix of the WMRA interface (Fig. 2). In other words, the user was presented with the alphabet speller matrix, which was mapped to the robot actions. For example, the letter “B” corresponds with the arrow directing the robot to move forward.

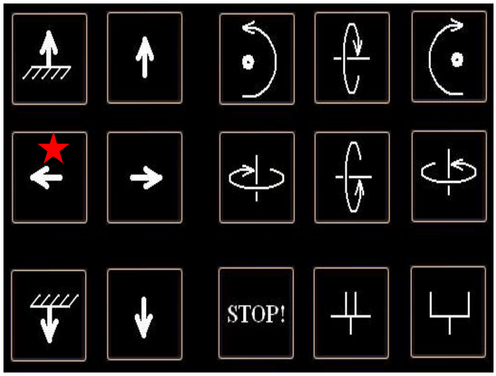

Fig. 2. Display of the Robotic arm controller

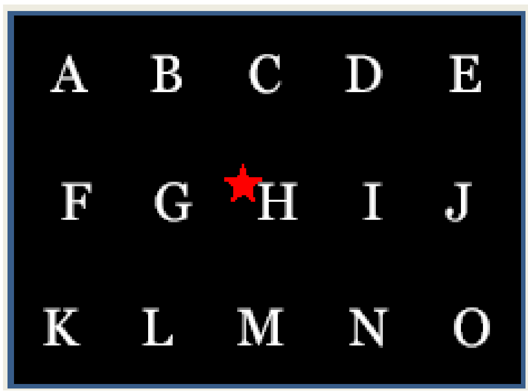

Fig. 3. A 5 X 3 display of the BCI. Each letter corresponds to a specific direction of the WMRA as seen in Fig 2.

Fig. 4 illustrates the operation of the WMRA via the BCI. In Fig. 5 is a user operating the WMRA by choosing characters from the BCI display. For safety of the user, the movement of the robotic arm was kept slow by keeping the scaling factor low.

Accuracy level was measured by comparing the character to spell with the character selected by the BCI system after it examines the recorded data in real time. Number of flash sequences may be viewed as the amount of data that were available for averaging and signal extraction. It can also be discussed in terms of speed as the more flash sequences were collected for each character, the longer the trial was before the system reached a decision. As was expected, accuracy dropped as a function of flash sequences. However, this reduction in accuracy level was minimal to moderate. When asked, participants informed the tester that they preferred the 4 and 6 sequences of flashes over the longer sequences. The common explanation was that it was easier to stay focused for shorter periods of time. Below is the accuracy data obtained when participants spelled 50 characters of each set of sequences (12, 10, 8, 6, 4, and 2). Fig. 6 shows the mean percentages correct for each sequence. Number of maximum characters per min and number of correct characters per minute are also presented.

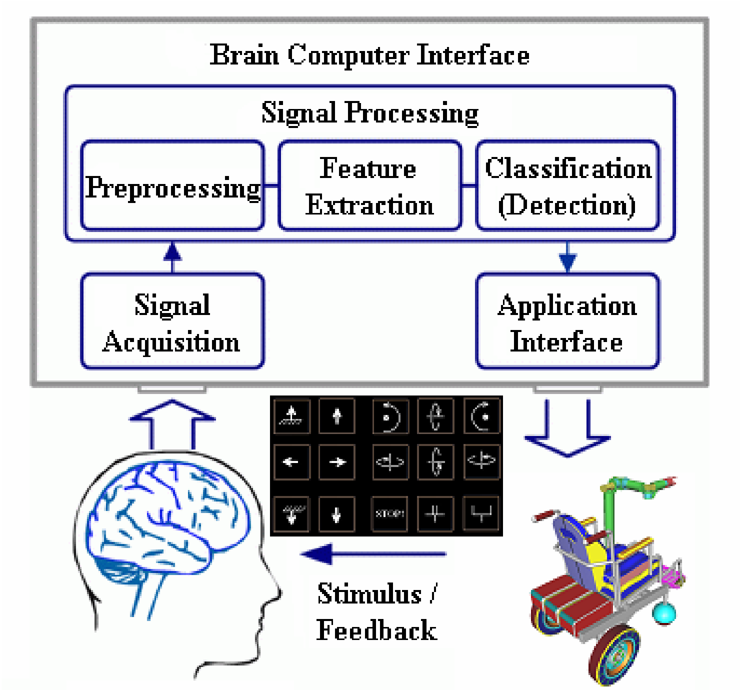

Fig. 4. An illustration of the communication between the BCI and the controller of the WMRA

Fig. 5. A user controlling the WMRA by choosing characters from the BCI display

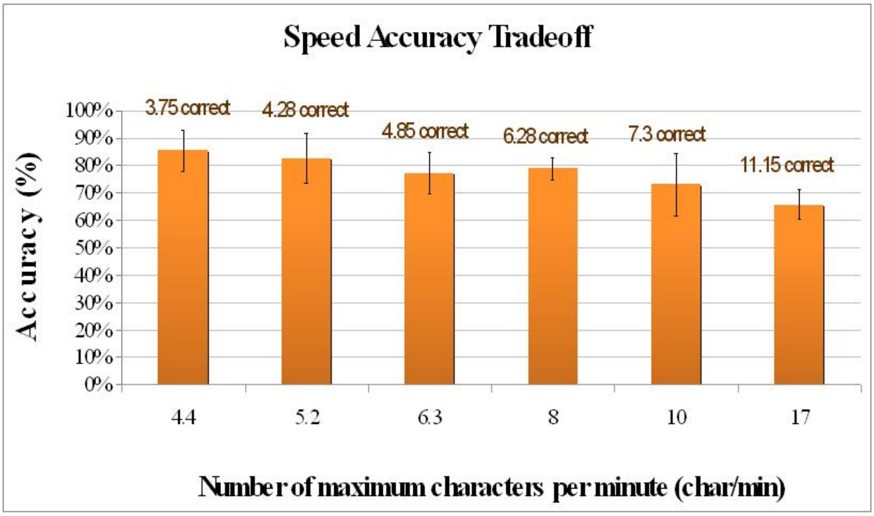

Fig. 6. Accuracy data (% correct) for each of the # of flash sequences (from left to right: 12, 10, 8, 6, 4, 2). For each bar of the # of flash sequences we provide the maximum number of characters per minute (on the bottom of each bar) and the number of correct characters per minute (on top of each bar).

There are a few potential challenges which merit consideration. The step by step manipulation of the arm is not effective in reaching our goal for a system that will be used for daily activities such as bringing a glass of water from the kitchen or opening the door. Rather than characters representing one specific movement, the display of the BCI should contain high-level commands, which can then be executed autonomously by the robot via task level planning control. The challenge is to develop a system that will be able to dynamically estimate and represent the user's intentions in relations to the changing environment, to communicate these intentions in the most efficient manner to the robotic arm which will have the intelligence to perform the task effectively and safely. More specifically, our current goals are to transform the mobile robotic arm into a task oriented system which is programmed to perform tasks in a changing environment efficiently, program the Application Module in the BCI system to represent the environment and the user's intentions effectively and in a flexible manner, and to improve the speed of task selection by evaluating alternative classification techniques with a goal of detecting the P300 using a substantially smaller number of trials than is currently required using the Stepwise Discriminant analysis in the current version of the P300 Speller.

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