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A P300 event-related potential brain–computer interface (BCI): The effects of matrix size and inter stimulus interval on performance

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Abstract

We describe a study designed to assess properties of a P300 brain–computer interface (BCI). The BCI presents the user with a matrix containing letters and numbers. The user attends to a character to be communicated and the rows and columns of the matrix briefly intensify. Each time the attended character is intensified it serves as a rare event in an oddball sequence and it elicits a P300 response. The BCI works by detecting which character elicited a P300 response. We manipulated the size of the character matrix (either 3×3 or 6×6) and the duration of the inter stimulus interval (ISI) between intensifications (either 175 or 350 ms). Online accuracy was highest for the 3×3 matrix 175-ms ISI condition, while bit rate was highest for the 6×6 matrix 175-ms ISI condition. Average accuracy in the best condition for each subject was 88%. P300 amplitude was significantly greater for the attended stimulus and for the 6×6 matrix. This work demonstrates that matrix size and ISI are important variables to consider when optimizing a BCI system for individual users and that a P300-BCI can be used for effective communication.

Keywords: Amyotrophic lateral sclerosis; Electroencephalogram; Brain–computer interface; P300; Event-related potentials; Rehabilitation

1. Introduction

Several different features of scalp recorded EEG signals are being used as control signals for brain–computer interface (BCI) applications; most notably, event-related potentials (Donchin et al., 2000; Farwell and Donchin, 1988; Serby et al., 2005), spontaneous sensory motor rhythms (Wolpaw and McFarland, 2004; Pfurtscheller et al., 1996), and slow cortical potentials (Birbaumer et al., 1999). A comprehensive review is provided by Wolpaw et al. (2002). Many researchers have demonstrated BCI accuracy high enough for online communication (Farwell and Donchin, 1988; Kübler et al., 2005; Serby et al., 2005; Wolpaw and McFarland, 2004). In addition, researchers have also reported that patients with amyotrophic lateral sclerosis (ALS) can use BCI systems with accuracy levels acceptable for communication using slow cortical potentials, mu rhythms, or P300 event-related potentials (Birbaumer et al., 1999, 2000; Kübler et al., 2005; Sellers and Donchin, 2006). These findings from ALS patients are important because people who suffer from ALS and other severe motor disabilities are the most likely candidates for long-term use of BCI systems.

The current study focuses on a P300-BCI. The P300 Speller described by Farwell and Donchin (1988) presents a 6×6 matrix of characters to a user. The user's task is to communicate a specific character by attending to the cell of the matrix that contains the desired character, and counting the number of times it is intensified (or flashed). Each row and each column are intensified and the intensifications are presented in a random sequence. The sequence of 12 intensifications, each of the 6 rows and 6 columns, constitutes an oddball paradigm (Fabiani et al., 1987). The row and the column containing the character to be communicated (the target) form the rare set, and the other 10 intensifications form the frequent set (the non-targets). The target items (i.e., the target row and column) should elicit a P300 response if the observer is attending to the stimulus series, because each target stimulus intensification constitutes a rare event in the context of all other intensifications.

Classification rates using a 6×6 matrix of alphanumeric characters have been improved beyond those reported by Farwell and Donchin (1988) in online demonstrations using stepwise discriminant analysis (SWDA; Donchin et al., 2000)

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and independent components analysis (Serby et al., 2005), and in offline analyses using support vector machines (Kaper et al., 2004; Meinicke et al., 2002). While the practical value of these methods remains unclear, the initial results are impressive and have provided the impetus to continue developing P300-BCI systems that can perform faster and with higher classification accuracy. The path to improved performance has focused almost exclusively on improved signal processing techniques that maximize the signal-to-noise ratio. The purpose of the current study is to examine the impact of stimulus properties and stimulus presentation rates on performance.

1.1. The current study

This study expands upon previous research by comparing target selection rates using a 3×3 version and a 6×6 version of the matrix speller. Allison and Pineda (2003) examined matrix size manipulations and found that increasing the dimensions (i.e., the numbers of rows and columns) of the matrix, while holding the size of the matrix elements constant, resulted in larger P300 amplitudes for the attended matrix element. They tested 3 matrix sizes, 4×4, 8×8, and 12×12, and found that P300 amplitude increased as the size of the matrix increased. This result is expected since it has been shown that P300 amplitude increases with smaller probability of the occurrence of a target item (e.g., Duncan-Johnson and Donchin, 1977). However, since the Allison and Pineda (2003) study did not examine classification rates, it is unclear how their results are related to target selection. Only two studies have previously examined the effect of varying the inter-stimulus interval (ISI) between matrix intensifications; their results conflict. Farwell and Donchin (1988) reported higher classification rates with a longer ISI, whereas Meinicke et al. (2002) reported higher classification accuracy with a shorter ISI.

BCIs that use event-related responses such as the P300 may have a significant advantage over those that use spontaneous EEG signals in that they do not require lengthy training periods to achieve effective BCI use. However, it is not yet clear whether or not long-term use of a P300-BCI will attenuate the P300 signal. Several studies have examined P300 amplitude and latency across time (e.g., Cohen and Polich, 1997; Kinoshita et al., 1996; Polich, 1989; Ravden and Polich, 1998), but not in the context of use in a BCI. Sellers and Donchin (2006) evaluated the robustness of the P300 signal accuracy in patients tested over 10 experimental BCI sessions and reported minimal effects on performance.

The current study examines the effect of matrix size and ISI on classification accuracy in the selection of target items. We cross the ISI and matrix size manipulations to create four experimental conditions. We also examine the consistency of a user's performance over time.

2. Methods

2.1. Subjects

Five people (four men age 25, 49, 21, 33, and a woman age 58) participated in this study which consisted of five sessions spread out over 3 weeks. Two users had had no prior BCI experience. Three users had had previous BCI experience but no experience with the P300 Speller paradigm. One user participated in three 15-min sessions of free spelling (i.e., in which the user freely chooses the attended character) interspersed in the five sessions of the study period. The study was approved by the New York State Department of Health Institutional Review Board, and each user gave informed consent.

2.2. Data acquisition and processing

EEG was recorded using a cap (Electro-Cap International, Inc.) embedded with 64 electrodes distributed over the entire scalp (Sharbrough et al., 1991). All 64 channels were referenced to the right earlobe, and grounded to the right mastoid. The EEG was bandpass filtered 0.1–60 Hz, amplified with a SA Electronics amplifier (20,000×), digitized at a rate of 240 Hz, and stored. All aspects of data collection and experimental design were controlled by the BCI2000 system (Schalk et al., 2004).

2.3. Task, procedure, and design

The user sat 1.4 m from a video screen and viewed the matrix display. He or she was given the option to either recline or sit upright. The 6×6 matrix subtended $8.30°\text{H} \times 10.90°\text{W}$ (8.00 in. × 10.50 in.) of visual angle and the 3×3 matrix subtended $5.44°\text{H} \times 7.07°\text{W}$ (5.25 in. × 6.75 in.). The distance between each character was 1.54°H and 2.66°W (0.82 in. × 1.5 in), for the 6×6 and 3×3 matrices, respectively. The size of each character was $0.70°\text{H} \times 0.57°\text{W}$ (0.63 in. × 0.50 in.) in both displays.

The user's task was to focus attention to one letter of the matrix and note the number of times the target character intensified. The first of the five sessions served as a training session to gather data used to derive classification coefficients for the subsequent experimental sessions. Thus, online feedback of classification results was not presented to the user in the training session. Such feedback was provided in the four final sessions (see below).

Each session was composed of eight runs and each run was composed of "copy-spelling" a four-letter word. (In copy spelling, the target letter is specified so that data for offline analyses can be properly coded.) At the beginning of each run, the first letter of the word was presented in parentheses at the end of the word (see Fig. 1). The letter in parentheses was the target letter. Immediately after the prescribed number of column and row intensifications (e.g., 20 sequences of 12 flashes in the 6×6 matrix 175-ms ISI condition) the classifier would make a decision. After a 2.5 s delay, the result of the classifier would appear in the feedback line of the display window. Then, 2.5 s later, the next character of the word was presented in parentheses at the end of the word and the user switched attention to this new character. Hence, the total duration between characters was 5.0 s. This process continued until all four characters of the word had served as the target letter. All data were collected in this 'copy-speller' mode, in which the user was not given the option to correct mistakes.

We used two different matrix sizes (3×3 and 6×6) and two different ISIs (175 and 350-ms) so that there were a total of four experimental conditions. In each of the five experimental sessions, the user experienced two consecutive runs in each condition. The four conditions were presented in a counterbalanced fashion. The variables of matrix size and ISI had independent effects on the time needed to complete the presentation of a single character. Because we decided to keep the time allotted to select a character constant for all conditions, each condition contains different numbers of stimulus sequences per character. For example, a 6×6 matrix requires twice as many flashes to complete one sequence of intensifications (i.e., flashes of 6 rows and 6 columns) compared to a 3×3 matrix (flashes of 3 rows and 3 columns). To keep the time allotted for each character selection fixed, each stimulus (i.e., row or column) was presented twice as many times in the 3×3 condition as in the 6×6 condition, and twice as many times in the 175-ms ISI condition as in the 350-ms ISI condition. Table 1 presents time per character selection and number of stimulus sequences for each of the four experimental conditions.

2.4. Deriving classification coefficients using SWDA

Stepwise linear discriminant analysis (SWDA) was used to determine coefficients for online classification (Draper and Smith, 1981). SWDA has