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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 × ~~1~~2, 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°H × ~~1~~0.90°W (8.00 in. × ~~1~~0.50 in.) of visual angle and the 3 × ~~3~~ matrix subtended 5.44°H × ~~7~~.07°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°H × ~~0~~.57°W (0.63 in. × ~~0~~.50 in.) in both displays.

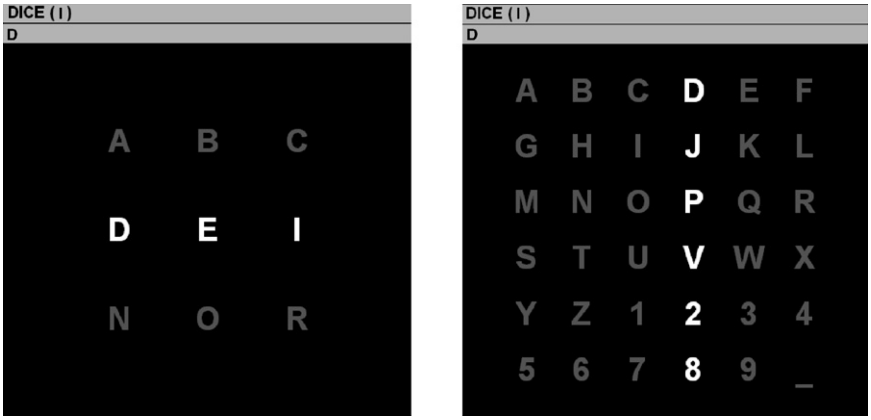
The user's task was to focus attention to one letter of the matrix and note the number of times the target character intensified. The first of the five sessions served as a training session to gather data used to derive classification coefficients for the subsequent experimental sessions. Thus, online 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



DICE (I)
D

A B C
D E I
N O R

DICE (I)
D

A B C D E F
G H I J K L
M N O P Q R
S T U V W X
Y Z 1 2 3 4
5 6 7 8 9 _

Fig. 1. The 3 × ~~3~~ and 6 × ~~6~~ matrices used in this study. The rows and columns intensify for 100 ms every 175 or 350 ms. The word at the top is the word to be copy-spelled. The letter in parentheses is the current target letter (i.e., "I"). For the 3 × ~~3~~ matrix, a P300 should be elicited when the third column or second row intensifies; similarly, for the 6 × ~~6~~ matrix, a P300 should be elicited when the third column or second row intensifies. Online feedback is provided directly below the word being copied.

been previously shown to classify responses effectively and it compared well with other methods (Donchin et al., 2000; Farwell and Donchin, 1988). It provides a spatiotemporal vector of coefficients (channel by sample) that can be easily implemented online, and it is well established as a successful classification technique (Donchin, 1969; Donchin et al., 2000; Farwell and Donchin, 1988; Krusienski et al., 2005; Sellers and Donchin, 2006).

SWDA seeks the optimal discriminant function by adding features (in this case, channels × ~~time~~ elements) to a linear equation in a stepwise fashion based on which feature explains the largest amount of unique variance. SWDA operates by performing a series of forward and backward regression procedures, in discrete steps. Starting with no initial model terms, the single feature accounting for the most variance is added to the model. For any feature to be entered into the model, it was required to account for a significant amount of variance at the level of $P < 0.10$. In other words, for a feature to be added to the model, the model must improve by a $P$-value of 0.10, as compared to the model without the feature being included. In each step the model evaluates every feature to determine the single feature that produces the highest $P$-value and this feature is then selected for inclusion.

After each entry, a backward stepwise regression is performed to remove any features that no longer meet the predetermined criterion to remain in the model, in this case a $P$-value of $>0.15$ was used. This procedure is conducted because it is possible that a feature will no longer account for a significant amount of unique variance after additional features have entered the model. The forward and backward regression process is repeated until the model includes a predetermined number of features (10 in the present study) or until no additional features satisfy the entry/removal criteria. Pilot studies showed that the $P$ to enter ($<0.10$) and $P$ to remove ($>0.15$) values were reasonable values to use for entering and removing features. The SWDA analysis was implemented in Matlab 7.0 using the Statistics Toolbox STEPWISEFIT function.

Table 1
Time (Sec) and stimulus sequences per character selection (Num) for each of the matrix size × ~~ISI~~ conditions in the online experiment and in the offline simulation

| | 3 × ~~3~~ Matrix | | 6 × ~~6~~ Matrix | |
|---|---|---|---|---|
| | Sec | Num | Sec | Num |
| Online | | | | |
| 175 | 42.0 | 40 | 42.0 | 20 |
| 350 | 42.0 | 20 | 42.0 | 10 |
| Offline | | | | |
| 175 | 10.5 | 10 | 21.0 | 10 |
| 350 | 21.0 | 10 | 42.0 | 10 |

### 2.4.1. Optimizing SWDA coefficients

Offline, SWDA coefficients were derived for each of the 4 conditions (i.e., 6 × ~~6~~ matrix 175-ms ISI, 6 × ~~6~~ matrix 350-ms ISI, 3 × ~~3~~ matrix 175-ms ISI, and 3 × ~~3~~ matrix 350-ms ISI). Factors known to affect classification accuracy were varied to determine the optimal set of coefficients (Krusienski et al., 2005). These factors include moving average window (MA), decimation factor (DF), reference method (REF), and number/location of channels (ChSet). The moving average window length was either 4 or 16 samples. Similarly, the decimation factor was either 4 or 16 samples (i.e., we downsampled the data by a factor of either 4 or 16). The MA window was first applied to the data, and then the DF was applied. For example, in the MA/DF 4 condition, the data were collected at a sample rate of 240 Hz (240 samples/s), a MA window of 4 samples was applied to the data, then it was decimated by a factor of 4; thus, the input to the SWDA analysis includes every fourth sample (or every 16th sample in the MA/DF 16 condition). The data was referred to the monopolar ear reference (MR) used during data collection or re-referenced offline with a common average reference (CAR). Additionally, two different channel sets

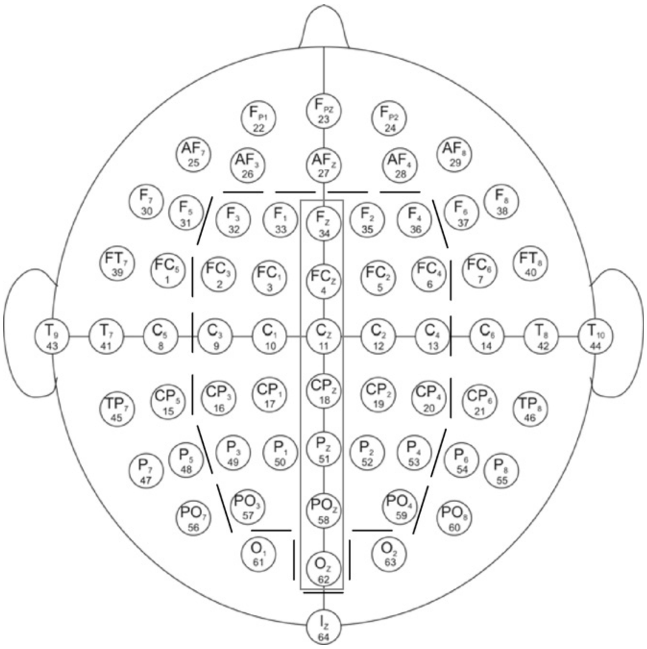


Fig. 2. The electrode montage. As noted in the text, SWDA coefficients were derived from the 7 electrodes of Set 1 (within the solid line) or from the 29 electrodes of Set 2 (within the dashed line).

Table 2
Parameter combinations for each of the eight sets of coefficients

| Set | MA/DF | REF | ChSet |
|---|---|---|---|
| 1 | 4 | MR | 1 |
| 2 | 4 | MR | 2 |
| 3 | 4 | CAR | 1 |
| 4 | 4 | CAR | 2 |
| 5 | 16 | MR | 1 |
| 6 | 16 | MR | 2 |
| 7 | 16 | CAR | 1 |
| 8 | 16 | CAR | 2 |

Coefficients were created by crossing the variables of moving average/decimation (MA/DF), reference site (REF) (i.e., monopolar to right earlobe (MR) or common average reference (CAR)), and the Channel set (Ch Set) (i.e., Fig. 2).

were used to derive classification coefficients. Channel Set 1 consisted of seven midline electrodes (beginning at Fz and moving posterior through Oz). Channel Set 2 consisted of the 29 most centrally located electrodes. See Fig. 2 for an example of the electrode montage and the two electrode sets. Crossing the variables of MA/DF, reference, and channel set results in eight unique parameter sets used to derive coefficients. The eight combinations are shown in Table 2.

For online classification of Session 2 only Channel set 1 data from the first session (i.e., the training session) were used to derive the classification coefficients. We adopted this conservative practice for data from the initial session because classification coefficients derived from non-traditional P300 electrode locations have, in some cases, failed to generalize as well as midline electrodes. After Session 2, the eight sets of coefficients from Session 1 and eight sets of coefficients from Session 2 were cross validated, i.e., Session 1 applied to Session 2 and Session 2 applied to Session 1. The set of coefficients that classified most accurately was then used online for Session 3. After each subsequent session, the data were aggregated and this process was repeated to determine the optimal set of parameters for the upcoming session.

## 3. Results

The above mentioned confounds between matrix size and ISI necessitate several comparisons of classification accuracy. The first analysis examines the online results holding the amount of time allotted to each character constant. A subsequent analysis holds time constant (as in the online analysis), but examines classification accuracy based on classification coefficients derived from equally sized sets of training data. Recall that each condition has a different number of stimulus sequences because of the matrix size and ISI manipulations (see Table 1). This analysis examines whether or not unequal training set sizes affect the efficacy of the classification coefficients.

In the next analysis, the number of stimulus sequences is held constant at 10, the lowest number of online sequences used in the study (i.e., the number used in the 6 × 6 matrix 350-ms ISI condition). This analysis controls for the possibility that classification accuracy is higher in conditions that have more stimulus presentations. We also conducted an analysis that examines classification accuracy based on classification coefficients derived from equally sized sets of training data, while holding number of sequences constant. (This analysis used the same classification coefficients as the previous analysis that controlled for training set size.)

The final classification accuracy analysis compares generalized and user specific classification coefficients. In this analysis, we compared the user specific coefficients (used for online classification) with coefficients derived from equally sized random samples of data aggregated across users. This analysis examines the extent to which classification coefficients will generalize across users, or whether it is necessary to have user specific coefficients.

Following the classification analyses, bit rate and accuracy are compared. These results are followed by examples of classification coefficients and the waveform analysis.

### 3.1. Online classification

Three factors were included in the analysis of the online classification data, matrix size (3 × 3 and 6 × 6), ISI (175 and 350-ms), and session (2–5). Session yielded no significant effects; therefore, data were collapsed across all sessions. Accuracy in the 3 × 3 matrix condition was significantly higher than accuracy in the 6 × 6 condition ($F(1,4) = 35.51$, $P = 0.004$). Accuracy in the 175-ms ISI condition was significantly higher than accuracy in the 350-ms ISI condition ($F(1,4) = 8.12$, $P = 0.047$). The matrix size × ISI interaction was also significant ($F(1,4) = 34.66$, $P = 0.004$). As Fig. 3A shows, matrix size has little effect on accuracy when the ISI is 175 ms. However, matrix size has a large effect when the ISI is 350 ms; accuracy is more than 30% higher in the 3 × 3 condition than in the 6 × 6 condition.

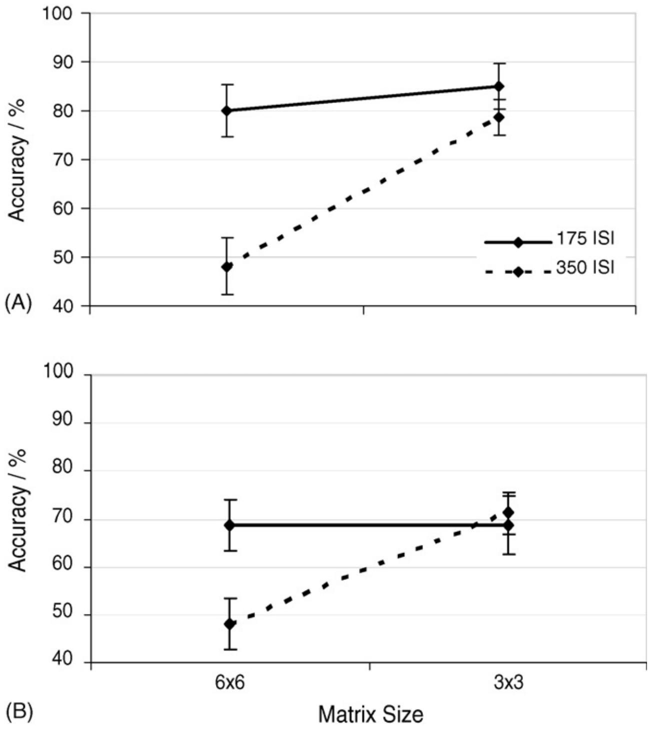


Fig. 3. Average (±S.E.) classification accuracies for all users for the four experimental conditions. The solid and dotted lines indicate the data for the 175 and 350-ms ISI conditions, respectively. (A) Actual online performance. (B) Offline performance using training sets of equal size to derive the classification coefficients.

### 3.1.1. Presentation time and training data constant

As stated above, the number of stimulus sequences in each condition is not equal because we wanted to keep the time for each character selection uniform throughout. Thus, one possible explanation for higher accuracy in the 175-ms ISI condition is that more data are available for the SWDA analysis, and the resulting classification coefficients are less variable. To examine this possibility, the analysis was conducted using coefficients derived from equal amounts of training data (i.e., 25% of the data in the 3 × 3 matrix 175-ms ISI condition; 50% for the 3 × 3 matrix 350-ms ISI condition; 50% for the 6 × 6 matrix 175-ms ISS condition; and 100% for the 6 × 6 matrix 350-ms ISI condition). Accuracy in the 3 × 3 matrix condition was significantly higher than accuracy in the 6 × 6 matrix condition ($F(1,4) = 15.83$, $P = 0.016$). More importantly, the matrix size × ISI interaction was significant ($F(1,4) = 51.66$, $P = 0.002$). Overall accuracy was reduced, but the pattern of results remained the same (see Fig. 3B). Thus, the amount of data used for training cannot account for the low level of classification accuracy in the 6 × 6 matrix 350-ms ISI condition.

## 3.2. Number of sequences constant

The confound between time per character presentation and the number of sequences was examined in the following analysis. The 6 × 6 matrix 350-ms ISI condition used only 10 sequences, the lowest number of any of the four conditions. Therefore, the analysis on accuracy was conducted after 10 sequences of flashes, in all four conditions. (For this reason, the on- and offline values for the 6 × 6 350 ms ISI conditions are equal in Table 1.)

The factors of matrix size, ISI, and session, were entered into the ANOVA. As with the online analysis, no effects including session were significant, so we collapsed the data for all sessions for each user. Accuracy in the 3 × 3 matrix condition was higher than accuracy in the 6 × 6 matrix condition ($F(1,4) = 14.49$, $P = 0.019$). In addition, the matrix size × ISI interaction (see Fig. 4A) shows that accuracy in the 3 × 3 matrix 175-ms ISI condition, is approximately 5% higher than the 6 × 6 matrix 175-ms ISI condition. In contrast, accuracy in the 3 × 3 matrix 350-ms ISI condition is approximately 20% higher than the 6 × 6 matrix 350-ms ISI condition ($F(1,4) = 11.00$, $P = 0.030$). These results are similar to the online accuracy results in that the 175 ms ISI is less affected by the matrix size manipulation.

### 3.2.1. Number of sequences and training data constant

The following analysis held the number of sequences and the training set sizes constant. This analysis was conducted with coefficients derived from equally sized training sets, the same coefficients used in the analysis reported in Section 3.1.1. Classification accuracy was significantly higher in the 3 × 3 matrix condition than in the 6 × 6 matrix condition ($F(1,4) = 10.29$, $P = 0.033$). In this analysis, the effect of session was significant. Accuracy improves as more sessions are conducted ($F(1,4) = 5.31$, $P = 0.015$). However, the matrix size × ISI interaction was not significant. Fig. 4B shows that classification accuracy for all conditions is reduced (except of course for the 6 × 6 matrix 350-ms ISI condition, because the size of the training set does not change). This result shows that by controlling for the number of sequences presented and the size of the training set, the matrix size × ISI interaction present in the previous comparisons can no longer be detected.

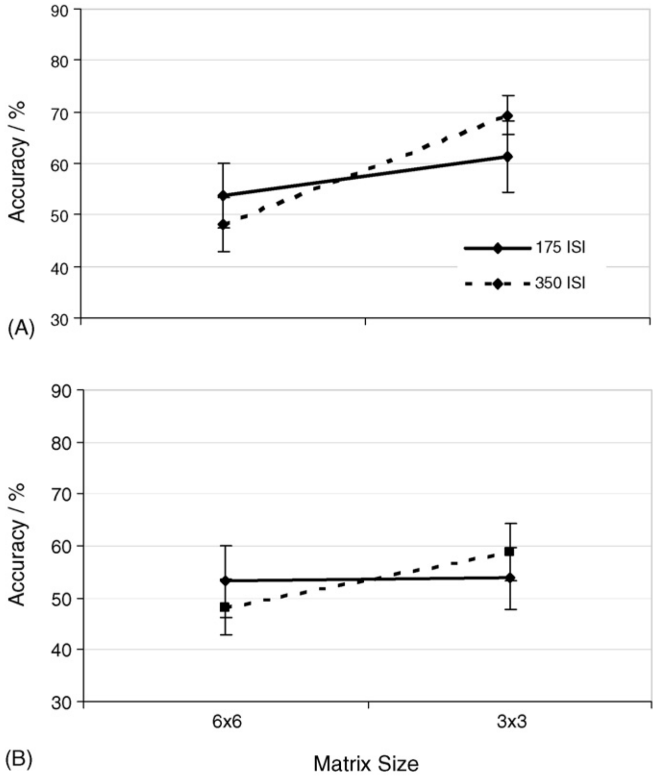


Fig. 4. Average (±S.E.) classification accuracies for all users for the four experimental conditions. The solid and dotted lines indicate the data for the 175 and 350-ms ISI conditions, respectively. (A) Offline performance after 10 sequences of intensifications. (B) Offline performance after 10 sequences of flashes, and training sets of equal size to derive the classification coefficients.

## 3.3. General versus user specific coefficients

One way to examine the extent to which the ERP response is different, or similar, across users is to examine the performance of classification coefficients derived from a composite of all user's data. The current analysis compares such 'general' coefficients to the user specific coefficients used online. To derive general coefficients, a random sample of data from all users equal to the amount of data used to derive the user-specific coefficients was aggregated, and coefficients were then created using the method described in Section 2.4.1. In this approach, if the general coefficients classify as well as the coefficients specific to a given user, the user's responses are considered to be similar to one another. On the other hand, if user specific coefficients classify more accurately, the user's ERP response is considered to be unique.

Classification results were entered into a 3-way repeated measures ANOVA including the variables of coefficients (general and user specific), matrix (3 × 3 and 6 × 6), and ISI (175 and 350-ms). Our analysis is limited to effects including coefficients because the other effects have been examined in Section 3.1. The only significant effect was the main effect of coefficients. Mean classification rates for the general and user specific coefficients were 44.84% and 72.97%, respectively ($F(1,4) = 273.42$, $P < 0.0001$). This result indicates a significant amount of user individuality in the ERP response.

### *3.4. Bit rate comparison*

Measurement of bit rate is a method commonly used to assess BCI performance (e.g. Serby et al., 2005; Wolpaw et al., 2000, 2002). Table 3 shows bits/min and associated accuracy for each subject and each experimental condition. The top half of the table shows online values and the bottom half of the table shows the values in the offline comparison that held number of stimulus presentations constant. The following formula described in Pierce (1980) was used to calculate the number of bits transmitted per trial:

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left( \frac{1 - P}{N - 1} \right) \qquad (1)$$

where $N$ is the number of possible targets, and $P$ is the probability that the target is accurately classified. Bit rate (bits/min) can then be computed by dividing $B$ by the trial duration in minutes.

An ANOVA analogous to those performed on the accuracy data was also performed on the bit rate data of the online results and on the offline results holding the number of sequences per character constant; the factors of matrix size, ISI, and session were entered into both of the analyses. In the analysis of the online data two effects reached statistical significance. Bits/min in the 175-ms ISI condition were significantly higher than the bits/min in the 350-ms ISI condition ($F(1,1) = 8.92$, $P = 0.040$). In addition, the increase in bits/min from the 3 × 3 to the 6 × 6 matrix for the 175-ms ISI condition is greater than the increase for the 350-ms ISI condition, as evidenced by the significant matrix size × ISI interaction ($F(1,4) = 18.96$, $P = 0.012$). In the offline analysis that constrained the number of sequences, only one effect reached statistical significance. Bits/min were higher for the 3 × 3 matrix than for the 6 × 6 matrix ($F(1,1) = 12.06$, $P = 0.026$).

The condition yielding the highest bits/min does not yield the highest level of accuracy, in neither the online nor the offline analysis. For example, in the online comparison, 5.25 is the highest mean bits/min, it results in 80.00% accuracy, and it is achieved in the 6 × 6 175-ms ISI condition. In contrast, a bit rate of 3.34 bits/min yields an accuracy of 85.00%, in the 3 × 3 175-ms ISI condition. However, this is not surprising: bit rate is influenced by the number of alternative choices and the 6 × 6 and 3 × 3 matrix sizes have 36 and 9 choices, respectively. The offline data in the bottom half of the table presents a different pattern. The 3 × 3 matrix 175-ms ISI condition yielded 7.70 bits/min, even though accuracy was highest in the 3 × 3 350-ms ISI condition. This too is not surprising, because the time required to make each selection influences bits/min and the selections in the 3 × 3 matrix are made in half the time. (Compared to the 6 × 6 matrix, only half as many stimuli are needed to present all of the columns and rows in the 3 × 3; therefore, for the 3 × 3 matrix, the desired number of 10 sequences is reached in half of the time.)

It is also informative to examine bits/min and accuracy for each user and compare one user to another. In the online conditions that held time per character constant at 42 s, bit rate was highest for all users in the 6 × 6 matrix 175-ms ISI condition, because of the above mentioned reasons. In contrast,

Table 3
Accuracy and bits/min for each user for each of the four conditions

| Subject | 3 × 3 | | | | 6 × 6 | | | |
|---|---|---|---|---|---|---|---|---|
| | 175 ISI | | 350 ISI | | 175 ISI | | 350 ISI | |
| | Accuracy | Bits/min | Accuracy | Bits/min | Accuracy | Bits/min | Accuracy | Bits/min |
| Online | | | | | | | | |
| 1 | 68.75 | 2.07 | **78.13** | 2.57 | 62.50 | **3.31** | 40.63 | 1.68 |
| 2 | 65.63 | 2.06 | **68.75** | 2.00 | 53.13 | **2.67** | 46.88 | 2.29 |
| 3 | 96.88 | 4.20 | 78.13 | 2.65 | **96.88** | **6.96** | 50.00 | 2.75 |
| 4 | **96.88** | 4.20 | 93.75 | 3.87 | 87.50 | **5.93** | 50.00 | 2.33 |
| 5 | 96.88 | 4.20 | 75.00 | 2.49 | **100.00** | **7.39** | 53.13 | 3.03 |
| Mean | **85.00** | 3.34 | 78.75 | 2.71 | 80.00 | **5.25** | 48.13 | 2.41 |
| Offline | | | | | | | | |
| 1 | 37.50 | **3.12** | **68.75** | 3.86 | 25.00 | 1.55 | 40.63 | 1.68 |
| 2 | 37.50 | **3.26** | **56.25** | 2.65 | 37.50 | 2.95 | 46.88 | 2.29 |
| 3 | 78.13 | **11.45** | 71.88 | 4.31 | **84.38** | 10.74 | 50.00 | 2.75 |
| 4 | 68.75 | **8.35** | **81.25** | 5.80 | 50.00 | 5.01 | 50.00 | 2.33 |
| 5 | **84.38** | **12.34** | 68.75 | 4.37 | 71.88 | 8.89 | 53.13 | 3.03 |
| Mean | 61.25 | **7.70** | **69.38** | 4.19 | 53.75 | 5.83 | 48.13 | 2.41 |

*Top*: Online data. *Bottom*: Offline simulation using only 10 stimulus sequences. The bold values are the highest accuracies and bit rates for each user and for all users together.

the condition that reached the highest level of accuracy varied from subject to subject. No subject performed best in the 6 × 6 matrix 350-ms ISI condition. In the offline analysis, which held number of stimuli constant, a different pattern emerged. Bit rate was highest for all subjects in the 3 × 3 matrix 175-ms ISI condition. The condition that resulted in highest accuracy varied from user to user, but as in the online condition, no user achieved highest accuracy in the 6 × 6 matrix 350-ms ISI condition. These results show that, while bit rate follows a similar pattern across users, accuracy shows a more idiosyncratic pattern, and although bit rate is an objective measure of information transfer it should be used with caution because accuracy below 50% is not sufficient to operate a BCI.

### 3.5. Waveforms and classification coefficients

To illustrate the variability within subjects and across conditions, Figs. 5 and 6 show waveforms and classification coefficients for each of the four conditions for each of two users. Figs. 5 and 6 show waveforms and classification coefficients for the users with the ERP responses that varied most and least, respectively, across conditions. Note that, in Fig. 5A, the largest positive deflection occurs at a different time in each of the four conditions. In contrast, in Fig. 6A, the largest positive deflection occurs at nearly the same time in each condition. Figs. 5 and 6 also demonstrate the complex relationship between the EEG response to the stimuli and the classification coefficients produced by the SWDA algorithm. While the waveform for only 1 channel (Pz) is presented, the topography (column B in Figs. 5 and 6) shows that the classification coefficients are distributed amongst many channels. Red coefficient values indicate positive values and blue indicate negative values; the actual coefficient values are arbitrary because the coefficients are scaled to be within the range of 10 to −10.

An ANOVA was performed on the waveform amplitude data to ascertain whether any statistical differences exist between amplitude values for the different experimental conditions at discrete time points in the ERP. This particular waveform analysis was adopted because it allows the data to be in a similar format to when it was used to derive the SWDA coefficients, albeit with only one channel. For each condition and target type

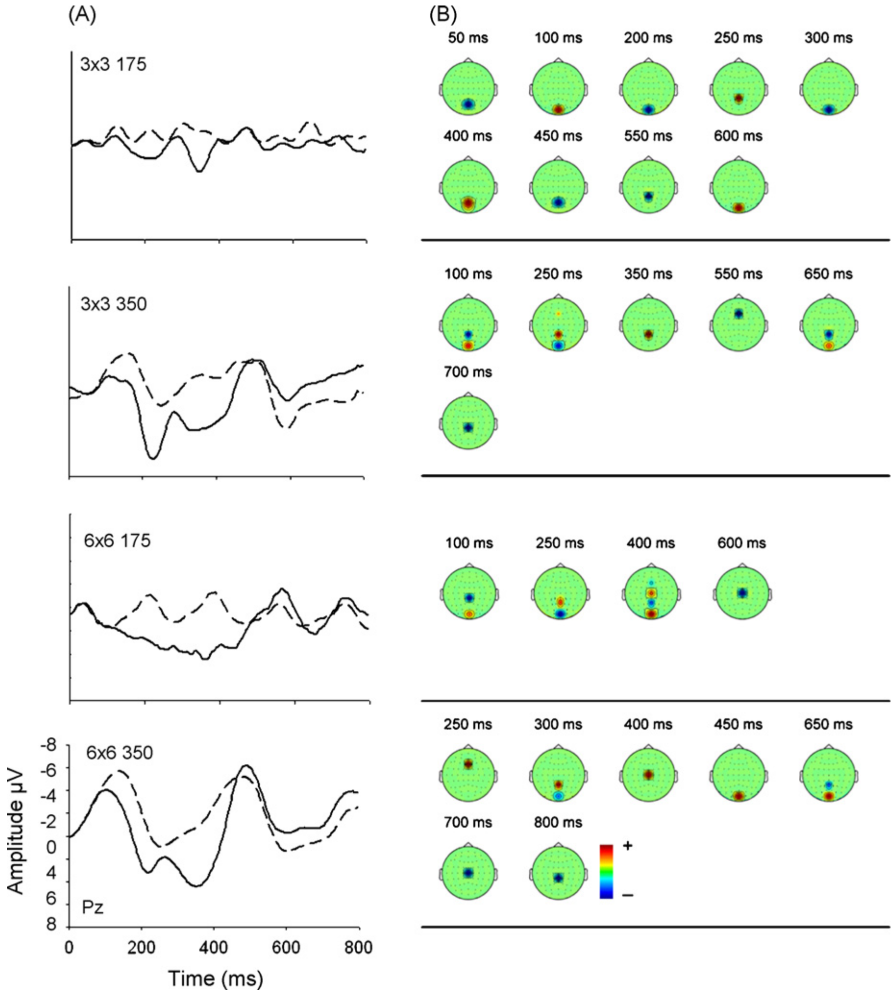


Fig. 5. (A) User 4's average waveforms for target (solid lines) and non-target responses (dashed lines) for each of the four conditions from electrode Pz. (B) Classification coefficients corresponding to each of the four experimental conditions. Positive values are shown in red and negative values are shown in blue. The time at which the coefficients are applied is noted above each topography, and the electrode location is noted in each topography.

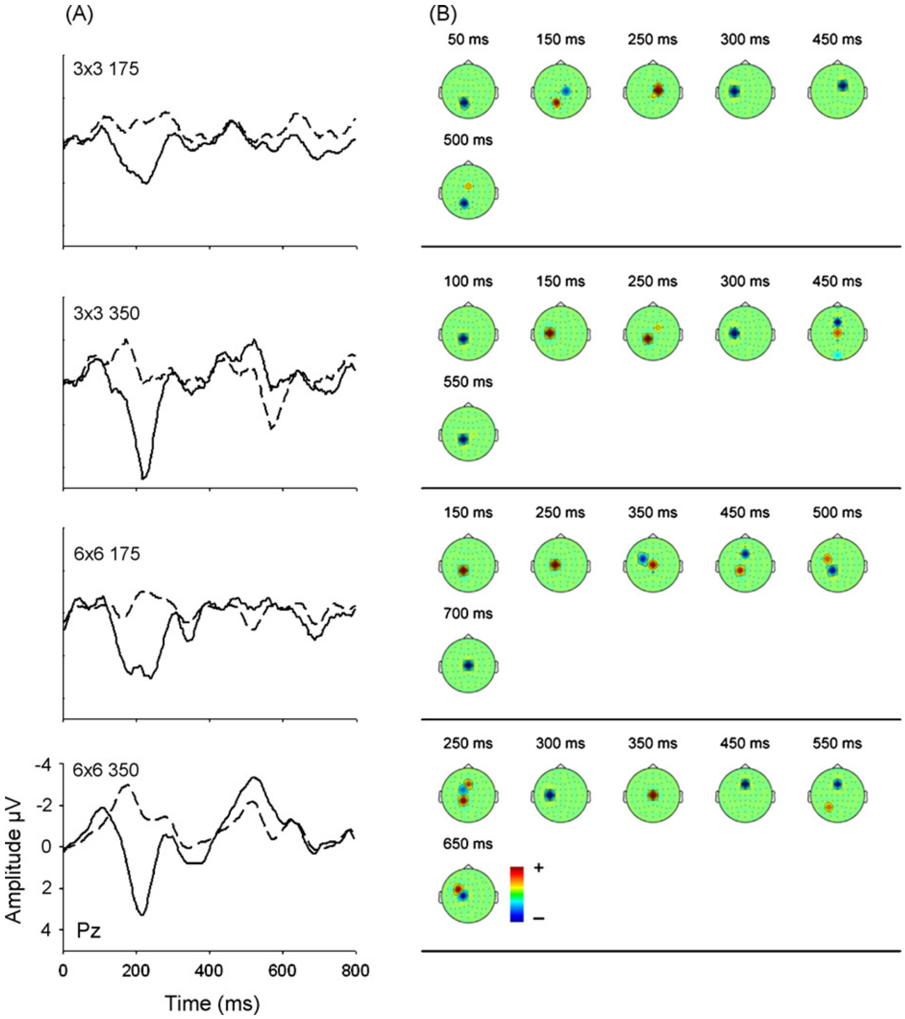


Fig. 6. (A) User 2's average waveforms for target (solid lines) and non-target responses (dashed lines) for each of the four conditions from electrode Pz. (B) Classification coefficients corresponding to each of the four experimental conditions. Positive values are shown in red and negative values are shown in blue. The time at which the coefficients are applied is noted above each topography, and the electrode location is noted in each topography.

(target or non-target), 16 time points beginning at time zero and separated by 50 ms were used as input. The factors of time (1–16), matrix (3 × 3 and 6 × 6), ISI (175 and 350-ms), and target (target and non-target) were entered into the analysis. Only two effects reached statistical significance. The time × target interaction showed that, across the 16 time points tested, the amplitude for the target items increases more than the amplitude for the non-target items ($F(15,60) = 2.39$, $P = 0.009$). The matrix × time × target interaction showed that, in addition to the difference between targets and non-targets across time, the 6 × 6 matrix target responses are largest, 3 × 3-matrix target responses are intermediate in size, and non-target responses for both matrices are smallest ($F(15,60) = 2.13$, $P = 0.020$). Fig. 7 shows both of these interactions. This result shows that there are significant amplitude differences between target and non-target stimuli, and the difference varies as a function of matrix size.

Waveforms from electrode Pz for all users and all conditions are shown in Fig. 8. The waveforms are averaged across all five sessions. In the 3 × 3 conditions, the solid curves represent one-third of the stimuli (i.e., the row and column containing the target) and in the 6 × 6 conditions the solid curves represent one-sixth of the stimuli. The figure illustrates the variability in the ERP response, across users and conditions.

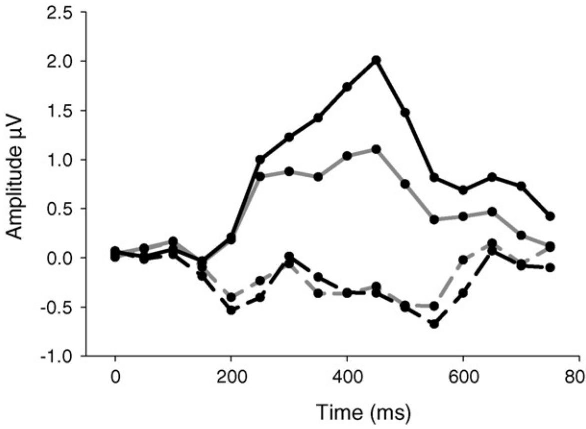


Fig. 7. Mean Pz amplitude in 16 50-ms steps, for all sessions of all users for the 3 × 3 (gray lines) and 6 × 6 (black lines) matrices for target (solid lines) and non-target (dashed lines) stimuli.

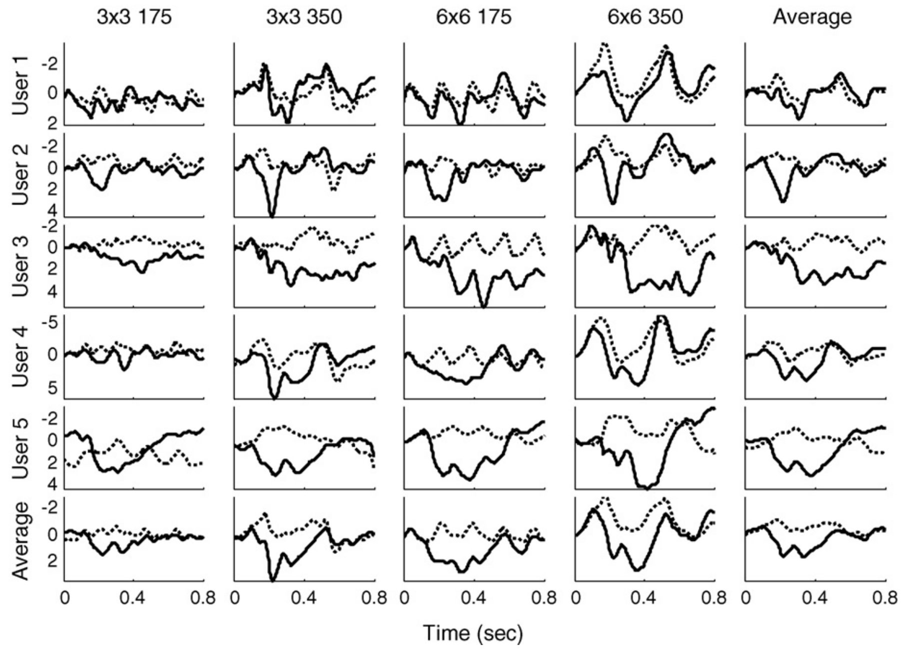


Fig. 8. Average waveforms of responses to target stimuli (solid lines) and non-target stimuli (dashed lines) from electrode Pz for each user for all four conditions for all five sessions.

## 4. Discussion

This study demonstrates several important points. First, a previously untested matrix containing only nine items can yield very high classification rates despite the increased probability with which the attended item is presented. Second, classification accuracy is stable over the course of five experimental sessions. Third, matrix size and ISI affect classification; and matrix size and stimulus class (i.e., target versus not-target) affect waveform morphology. Fourth, a shorter ISI yields higher classification rates. Fifth, individual differences in the EEG response play a large role in classification performance, as shown by significantly higher accuracy when user specific coefficients were compared to general coefficients. Sixth, the relationship between accuracy and bits/min must be considered when a BCI system is being calibrated for a given user.

### *4.1. Effects of matrix size*

Research on the P300 event-related potential has demonstrated that the amplitude of the P300 response increases as the probability of the presentation of a target item decreases (Duncan-Johnson and Donchin, 1977). This result has been replicated within the context of a matrix speller (Allison and Pineda, 2003), and in the current study. The current study expands this finding to demonstrate that the probability manipulation does not compromise classification accuracy (at least for the two matrix sizes that were tested).

This finding has important implications for future instantiations of the P300-BCI that may offer different matrix sizes to perform a variety of different tasks. In such cases, flexibility of matrix size can be a major asset. For example, one might want to change the matrix size if visual impairments or other deficits prevent a potential user from using a BCI. In other cases, a different matrix size might produce a substantial increase in accuracy (see User 1, Table 3). Although use of a matrix smaller than 6 × ~~6~~ would necessitate more than one choice to select one character from the entire English alphabet, the increase in accuracy might outweigh the additional time required for an additional selection (see Section 4.3 below for further discussion).

### *4.2. Effects of inter stimulus interval*

The present study found that the shorter ISI yielded the highest classification accuracy. This result is consistent with the ISI effects reported by Meinicke et al. (2002). Farwell and Donchin (1988) reported higher accuracy rates with a longer ISI. The reason for the inconsistency is unclear. Nonetheless, the current findings and the Meinicke et al. (2002) findings are encouraging because they indicate that a faster display produces higher classification accuracy and faster communication. For practical purposes, it appears to be worthwhile to test multiple ISI values and thereby determine the optimal value for each user.

### *4.3. Speed, accuracy, and bits/min*

Although bit rate (bits/min) is an objective measure of information transfer, the importance of accuracy for effective BCI-based communication should not be overlooked (Wolpaw et al., 2000, 2002). We performed a simulation to examine the relationship between bits/character and the number of selections required to produce an accurately selected series of 10 characters using error correction, as a function of accuracy (using a 6 × ~~6~~ matrix). The results of the simulation,

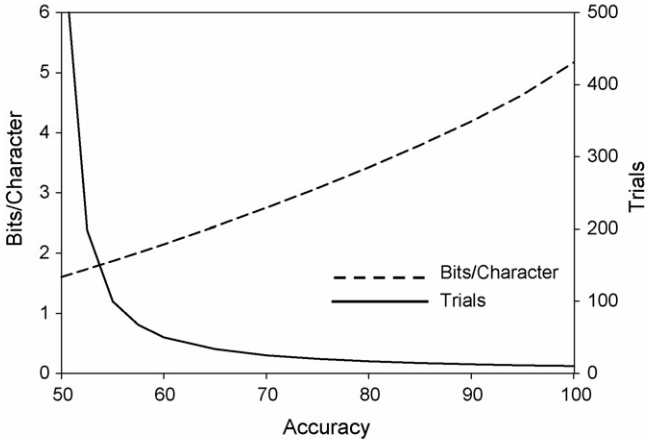


Fig. 9. Results of a simulation examining bits/character selection (dashed line) and selections needed to correctly complete a 10-character sequence with error correction (solid line) vs. selection accuracy for the 6 × ~~6~~ matrix.

based on 10,000 trials, are presented in Fig. 9 (bits/selection (left axis) and number of selections (right axis)).

Fig. 9 demonstrates some important points. First, while accuracy levels less than 60% provide substantial bits/selection, the time needed to produce useful communication might be unacceptable. For example, with 53% accuracy using the 6 × ~~6~~ matrix 175-ms ISI condition, it would take approximately 190 selections, or 1.2 h to produce a 10 item series of characters, with a corresponding bit rate of 1.7 bits/selection. Thus, accuracy is of paramount importance for determining the effectiveness of a practical BCI. As the figure clearly demonstrates, bit rate increases in a relatively linear fashion across the range of accuracy, but the number of trials to completion is very sensitive to accuracy. For example, with an accuracy of 95%, approximately 10.5 selections are required to complete a 10-item sequence, with a corresponding bit rate of 4.7 bits/selection. In contrast, with an accuracy of 80%, approximately 17 selections are required to complete a 10-item sequence, with a corresponding bit rate of 3.4 bits/selection. Thus, with a 15% decrease in accuracy (from 95% to 80%), the bit rate decreases by 29% (from 4.7 to 3.4) and the time to complete the 10-item sequence increases by 70%.

### 4.4. The ERP response and classification coefficients

The relationship between the ERP waveform from any given channel and the classification coefficients is complex. This is because as many as 1392 spatiotemporal features, distributed among up to 29 channels, are provided as input to the SWDA analysis. Thus, the relationship between a set of coefficients and the ERP responses cannot be captured by examination of any single channel, or even a subset of a few channel locations. Moreover, even if only a few channel locations were used to derive the classification coefficients, the relationship between the selected time × ~~c~~hannel locations and a waveform at a given location would not be easily ascertained due to factors such as response variability, component overlap, and suppressor variables (e.g., Krus and Wilkinson, 1986; MacKinnon et al., 2000). For example, Fig. 6A shows that the Pz waveforms are very similar in each of the four conditions. However, information that discriminates between target and non-target responses (i.e., the selected classification coefficients) is distributed among many channels, and at many time points located outside of the P300 window (see Fig. 6B). This additional information may benefit the SWDA analysis by providing baseline correction and/or suppressor variables.

### 4.5. Waveform differences

The results suggest that P300 responses elicited within the current paradigm differ across conditions in several respects. Many factors affect the amplitude, latency, and scalp distribution of P300 responses (see Fabiani et al., 1987, for a review). Importantly for current purposes, both matrix size and stimulus class affect waveform morphology (as measured at electrode Pz). The larger matrix size produces larger P300 amplitudes for the target stimuli because of the reduced probability of occurrence (Duncan-Johnson and Donchin, 1977; Allison and Pineda, 2003). Similarly, target stimuli produce P300 responses and non-target items do not, as is the case in typical oddball paradigm experiments (Fabiani et al., 1987; Pritchard, 1981). The results of the waveform analysis suggest that the P300 Speller paradigm does in fact operate as a true oddball paradigm because the waveform results are consistent with predictions based on previous studies that manipulate target probability using a typical oddball paradigm.

### 4.6. Classification across multiple sessions

Only one previous study has examined how classification changes across multiple sessions in a P300-BCI (Sellers and Donchin, 2006). Using a four-choice sequential oddball task that included auditory and visual stimuli, the study found that the main effect of sessions was not significant, over the course of 10 sessions. The current study, using a matrix style visual display, also shows no significant change in user performance over five sessions in the online analysis. Moreover, we have recently shown (Krusienski et al., 2005) that classification coefficients derived from data collected up to one year prior to a subsequent session can classify with near perfect accuracy. Thus, a user's performance appears to be quite consistent over time.

### 4.7. Conclusions

All five users in this study were able to use a P300-BCI. Averaging each user's most accurate condition resulted in mean accuracy of 88%. Overall, accuracy was higher in the 175-ms ISI condition than in the 350-ms ISI condition and accuracy was higher in the 3 × ~~3~~ matrix condition than in the 6 × ~~6~~ matrix condition. However, both matrix sizes produced acceptable levels of accuracy. This result has important implications for the development of future applications that will employ a menu-driven matrix system. It shows that it is feasible to present a user with matrices of sizes that vary according to different functions (e.g., word processing, answering direct questions, environmental controls, sending e-mail, etc.). Moreover, the consistency of a user's performance over time indicates that, although it is necessary to optimize BCI system parameters to achieve the best performance for each individual user, it may not be necessary to continually optimize these parameters over the ensuing time of use. Furthermore, P300-BCI communication appears to remain effective over sessions. This has important implications for the feasibility of eventually providing severely disabled users with BCIs that they can use in their homes.

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