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The P300-based brain–computer interface (BCI): Effects of stimulus rate

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HIGHLIGHTS

- Accuracy of P300-based letter selection increases with slower flash rates.
- Optimal flash rate varies with the individual user.
- Feedback did not effect performance.

ABSTRACT

Objective: Brain-computer interface technology can restore communication and control to people who are severely paralyzed. We have developed a non-invasive BCI based on the P300 event-related potential that uses an 8×9 matrix of 72 items that flash in groups of 6. Stimulus presentation rate (i.e., flash rate) is one of several parameters that could affect the speed and accuracy of performance. We studied performance (i.e., accuracy and characters/min) on copy spelling as a function of flash rate.

Methods: In the first study of six BCI users, stimulus-on and stimulus-off times were equal and flash rate was 4, 8, 16, or 32 Hz. In the second study of five BCI users, flash rate was varied by changing either the stimulus-on or stimulus-off time.

Results: For all users, lower flash rates gave higher accuracy. The flash rate that gave the highest characters/min varied across users, ranging from 8 to 32 Hz. However, variations in stimulus-on and stimulus-off times did not themselves significantly affect accuracy.

Providing feedback did not affect results in either study suggesting that offline analyses should readily generalize to online performance. However there do appear to be session-specific effects that can influence the generalizability of classifier results.

Conclusions: The results show that stimulus presentation (i.e., flash) rate affects the accuracy and speed of P300 BCI performance.

Significance: These results extend the range over which slower flash rates increase the amplitude of the P300. Considering also presentation time, the optimal rate differs among users, and thus should be set empirically for each user. Optimal flash rate might also vary with other parameters such as the number of items in the matrix.

1. Introduction

Many people with severe motor disabilities require alternative methods for communication and control. Numerous studies over the past two decades show that scalp-recorded EEG activity can be the basis for non-muscular communication and control systems, commonly called brain-computer interfaces (BCIs) (e.g., Birbaumer et al., 1999; Farwell and Donchin, 1988; Pfurtscheller et al., 1993; Wolpaw et al., 1991; see Wolpaw et al., 2002 and Wolpaw, 2009 for reviews). EEG-based communication systems measure specific features of EEG activity and use them as control signals. Some BCI systems use features that are potentials evoked by stereotyped stimuli (Farwell and Donchin, 1988). Others use EEG components in the frequency domain that are spontaneous in the sense that they are not dependent on specific sensory events (e.g., Wolpaw and McFarland, 2004).

The P300-based matrix speller, originally described by Farwell and Donchin (1988), is a promising approach to providing communication to users with severe motor disabilities (Vaughan et al., 2006). As noted by Farwell and Donchin, (1988), the P300 occurs when a subject recognizes a rare target stimulus. Since the P300 signals

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the subjects' recognition of the target event without the requirement for an overt response it represents a useful signal for a BCI. Although the rate at which users communicate with P300-based BCIs is at present slow in comparison to muscle-based assistive devices, it does provide a useful alternative for those in whom severe paralysis prevents use of such conventional methods. Improving the P300-based speller so as to increase speed and accuracy would augment its value and expand the population of potential users.

The P300 potential itself has been the focus of many psychophysiological studies (see Polich, 2007 for a review). The rate of stimulus presentation is one of the parameters that has been shown to affect the magnitude of the P300 response (e.g., Hansen and Hillyard, 1984). This effect appears to be due to the time between target stimuli, with longer target-to-target times producing larger P300 responses (Croft et al., 2003; Gonsalvez and Polich, 2002).

This study examined the role of the stimulus rate (i.e., the flash rate) as a determinate of speed and accuracy for the P300 speller. We varied the flash rate in two experiments: the first varied flash rate and flash duration proportionately while the second varied them independently.

2. Experiment 1 methods

The BCI users were six adults (two women and four men, ages 27–62), all with previous P300-based BCI experience. One woman had ALS and required artificial ventilation and one man had ALS and was ambulatory. The study was approved by the New York State Department of Health Institutional Review Board and all the users provided informed consent. Each participated in eight sessions, four sessions without feedback (as to the item selected) followed by four with feedback. Weights (see below) for the feedback sessions were computed from the prior no-feedback sessions using data obtained with the same ISI (i.e., interval between each flash onset).

EEG was recorded with a cap (Electro-Cap international, Inc.) containing 16 scalp electrodes (F3, Fz, F4, T7, C3, Cz, C4, T8, CP3, CP4, P3, Pz, P4, PO7, Oz, PO8 after Sharbrough et al., 1991). All channels were referenced to the right mastoid and grounded to the left mastoid since we have found that these work well with ALS patients in their typical environment. The EEG was amplified with a g.USBamp (Guger Technologies), digitized at 512 Hz, filtered between 0.5 and 30 Hz, and stored. All aspects of data collection and experimental design were controlled by the BCI2000 general purpose software platform (Schalk et al., 2004).

The user sat 1.4 m from an LCD monitor (20" diagonal) and viewed a matrix display (see Fig. 1). The user's task was to focus attention on one character in the matrix (i.e., that target) and note the number of times it flashed. The word(s) to be spelled were presented above the matrix and the current target letter was specified at the end of the word in parenthesis and remained on until the next selection began. One-half second after the letter to be spelled was indicated, the letters of the matrix began to flash in groups of six. The letters comprising each group varied with each presentation (i.e., a given letter was not always presented with the same five other letters). Each letter flashed 10 times for each selection with the constraint that a given letter did not flash twice in succession (see Townsend et al., (2010) for a more complete description). In feedback sessions, the letter selected was presented for 3.5 s in the feedback line immediately below the target word(s). This line was blank during no-feedback sessions. Each session was composed of six runs in which the users spelled 5–9 characters from the sequence "The quick brown fox jumps over the lazy dog 17459". Flash rates of 4, 8, 16, and 32 Hz varied across runs within sessions. Flash rate values were counterbalanced across the character sequences and order of the run within a session. All users received the same order of flash rates so as not to confound individual differences with order of presentation. The duration of the flash was always half of the time between successive flash onsets. That is, when the flash rate was 4 Hz, the time between flash onsets was 250 ms and the flash duration was 125 ms, while when the flash rate was 32 Hz, the time between flash onsets was 31.25 ms and the flash duration was 15.625 ms.

Amplitudes and latencies of individual ERP components were evaluated at Pz separately for each user's target and non-target averages. The N200 component was defined as the most negative point between 80 and 240 ms. The P300 component was defined as the most positive point between 230 and 450 ms. The negative slow wave was defined as the most negative point between 400 and 800 ms.

Stepwise linear discriminant analysis, implemented in Matlab 7.0 using the Statistics toolbox STEPWISEFIT function, was used to determine coefficients for online classification (Krusienski et al., 2008). A subset of eight channels (Fz, Cz, P3, Pz, P4, PO7, Oz, PO8) and averages of 25 time points, collected over the first 800 ms post-stimulus, were used as features for classification (the data was low-pass filtered and then decimated). The selection of channels was based on a prior study (Krusienski et al., 2008) that indicated that these electrodes provided classification comparable to a full set of 64 electrodes. A reduced set is desirable since we wish to work toward a practical system that can be used on a routine basis in patients' homes. For each condition and subject there were a total of 450 target flashes and 4950 non-target flashes used to train classifiers. Additional analyses were performed with the SAS DISCRIM function in con-

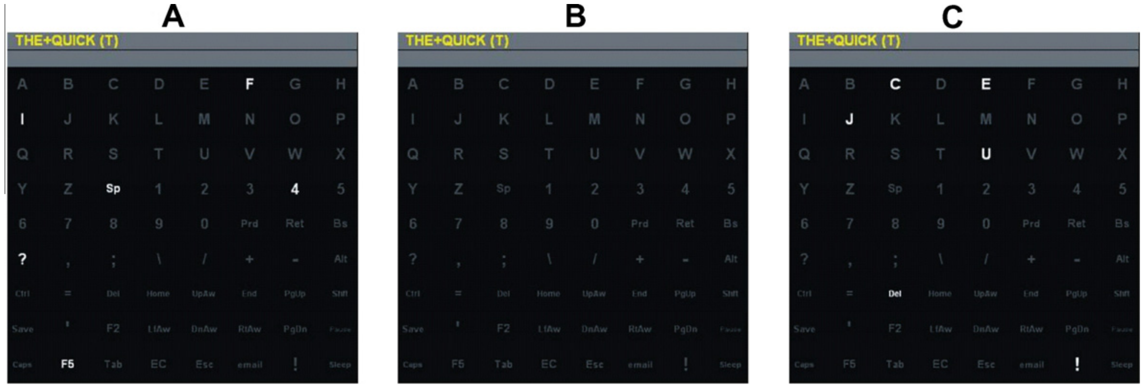

Fig. 1. The P300 Speller matrix. A. A group of six characters flashes. This is the on-period. B. No characters are highlighted. This is the off-period. One divided by the combined duration of the on- and offline periods in seconds is the flash rate. C. A new group of six characters flashes.

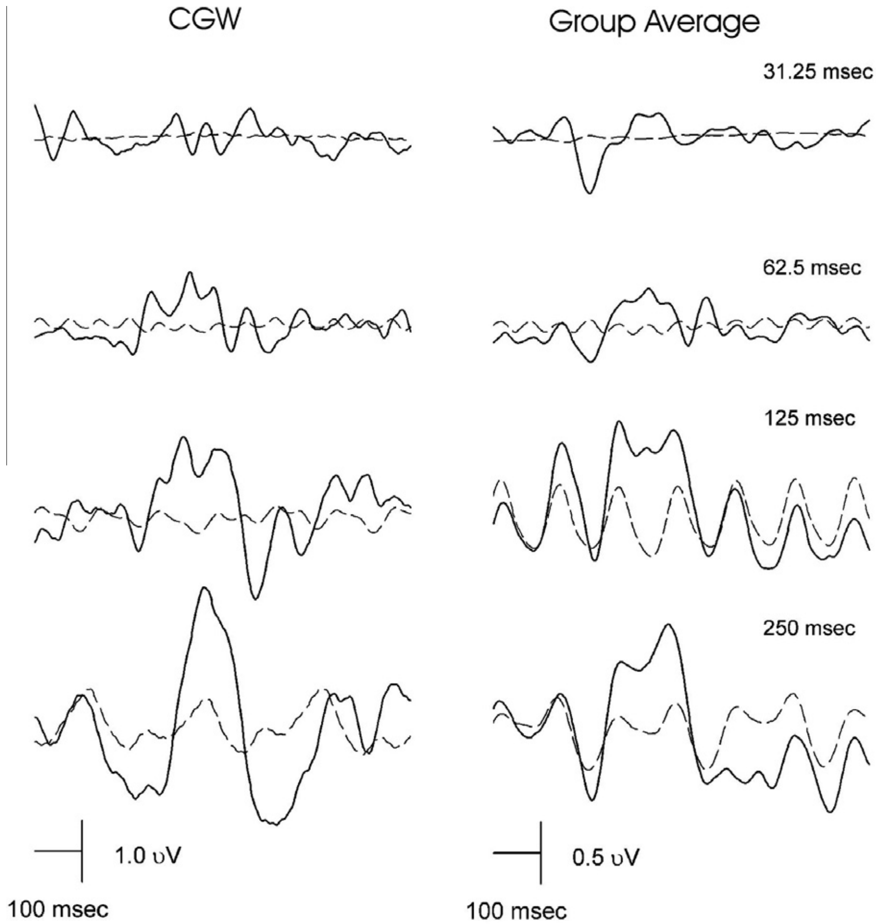

Fig. 2. Waveforms at Pz for the user with ALS on a respirator (left column) and the group average (right column) for each interstimulus interval. Average waveforms for targets are represented by the solid line and average waveforms for non-targets is represented by dashed lines.

junction with the CROSS-VALIDATE option, which classifies each observation in the data set using a discriminant function computed from all other observations in the data set, excluding the observation being classified (i.e., leave-one-out cross-validation). The individual observations were the 200 features associated with each specific flash of six letters.

3. Experiment 1 results

ERPs at Pz for each interstimulus interval for the most severely affected ALS user and for the group average are shown in Fig. 2. Average amplitudes and latencies for the N200, P300 and late negative slow wave are shown in Table 1. The interstimulus interval effect was highly significant for the P300 component ($df = 3/5$, $F = 18.01$, $p < 0.0001$) and the late negative slow wave ($df = 3/5$, $F = 16.33$, $p < 0.0001$). Both of these components showed near-linear increases in amplitude with larger interstimulus intervals. The effect of interstimulus interval on the N200 amplitude and all latency measures were not significant.

For each subject and flash rate, data sets for the no-feedback (i.e., calibration) and feedback conditions were evaluated separately with SAS DISCRIM using the CROSS-VALIDATE option. Accuracy of classification as a function of flash rate and condition is shown in Fig. 3. An ANOVA revealed a significant effect for rate ($F(3,15) = 26.38$, $p < 0.0001$). Neither condition ($F(1,5) = 0.08$, $p < 0.7922$) nor the condition by rate interaction ($F(3,15) = 1.18$, $p < 0.3522$) had a significant effect. Accuracy increased with slower flash rates but did not depend on condition (i.e., on whether feedback was present).

We next analyzed the effects of flash rate on accuracy in the feedback sessions using data from individual runs within users. Accuracy for each user as a function of flash rate is shown in Fig. 4. ANOVA on these data revealed significant effects for rate ($F(3,15) = 30.32$, $p < 0.0001$), user ($F(5,25) = 15.61$, $p < 0.0001$), and the interaction between rate and user ($F(15,75) = 2.77$, $p < 0.0019$). Accuracy increased with slower flash rates for all six users, but there were marked differences across users.

The number of characters/min was computed for each run as the difference between the number correct and number wrong di-

Table 1
Amplitudes (microvolts) and latencies (milliseconds) of the N200, P300 and late negative slow waves at Pz. Values represent the averages over all users.

Interstimulus Interval (msec)	N200 amplitude	N200 latency	P300 amplitude	P300 latency	Slow Wave amplitude	Slow Wave latency
31.25	−0.524	168.5	0.454	329.3	−0.307	574.2
62.5	−0.519	154.3	0.798	346.2	−0.357	524.5
125	−0.722	150.7	1.249	309.0	−0.958	615.8
250	−0.869	163.5	1.529	300.8	−1.275	563.3

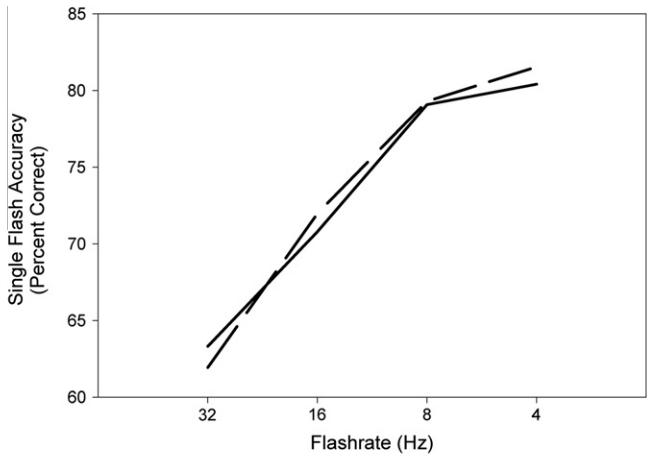

Fig. 3. Average classification accuracy for all users as a function of flash rate for calibration (no-feedback) (solid) and feedback (dashed) sessions.

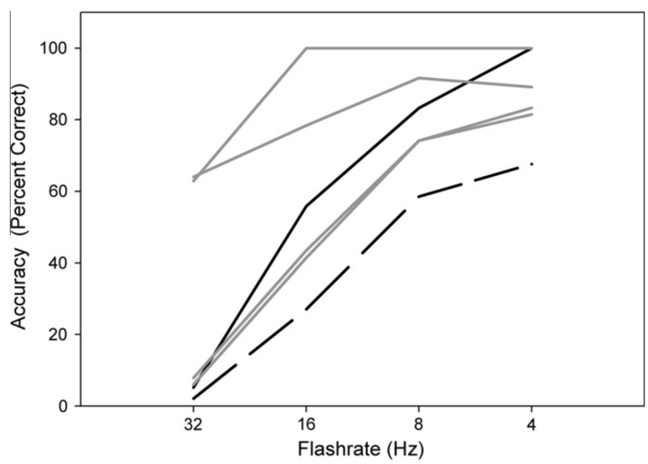

Fig. 4. Classification accuracy as a function of flash rate for individual users. The user with ALS who is on a respirator is represented by the solid black line, the user with ALS who is ambulatory is represented by the dashed black line, and all other users are represented by gray lines. Note that all users show increased accuracy with slower rates.

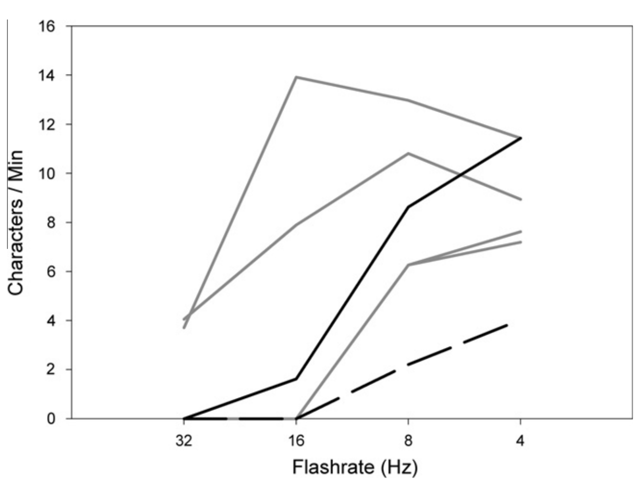

Fig. 5. Characters/min as a function of flash rate for individual users. The user with ALS who is on a respirator is represented by the solid black line, user with ALS who is ambulatory is represented by the dashed black line. All other users are represented by gray lines. Note that the flash rate that gives the maximum characters/min varies across the users.

vided by the total time in minutes. Townsend et al. (2010) showed that if the probability of making an error is q, then the number of trials required to make N selections given error correction which itself is prone to error is $N/(1-2q)$. Using their formula to determine accuracy adjusted for error correction involves taking the reciprocal of this with N set to a value of 1. This reduces to $1-2q$, which is equivalent to $p-q$ (given that p is $1-q$, the probability of a correct response). These data are shown in Fig. 5. ANOVA on these data with rate and users as factors and interactions of the factors in question with separate runs as error terms showed significant effects for rate ($F(3,15) = 4.24$, $p < 0.0234$) and for the rate by user interaction ($F(15,75) = 2.66$, $p < 0.0028$). The main effect of users was marginally significant ($F(5,25) = 2.50$, $p < 0.0576$). The maximum characters/min differed across users. Similar effects were obtained in an analysis of bit-rate.

We then asked whether the effects of flash rate on the P300 waveforms were qualitative (i.e., changing the waveform) or simply quantitative (i.e., changing magnitude). To evaluate this in each user, we compared for the test data obtained with each flash rate, the classifications produced by the weights obtained from the training sets obtained with the different flash rates. The results are shown in Table 2. An analysis of variance on this data indicated that the main effects of training set rate ($df = 3/15$, $F = 11.23$, $p < 0.0004$) and test set rate ($df = 3/15$, $F = 25.89$, $p < 0.0001$), as well as the training X test set rate interaction ($df = 9/45$, $F = 27.66$, $p < 0.0001$), were significant. The significant interaction reflects the fact that classification of a given test set was optimal when the set was classified with weights obtained from the training set that had the same flash rate. Thus, it appeared that flash rate did have a qualitative effect on the waveforms.

We used a leave-one-out cross validation procedure to assess the effects of feedback. Thus, we felt it important to evaluate the potential effect of this algorithm on the results. For each user, we examined classification error rates for weights obtained with data at the 4 Hz rate. We compared three methods: leave-one-out cross validation; resubstitution (i.e., classification of the same data used for generating the weights); and generalization to new data sessions. We evaluated weights obtained from the no-feedback data set and generalized to the feedback data as well as weights obtained from the feedback data set and generalized to no-feedback data. The mean results for all users are shown in Fig. 6A. Analysis of variance indicated that only the main effect of method was significant ($df = 2/9$, $F = 31.56$, $p < 0.0001$), condition (i.e., feedback or no-feedback) did not have a significant effect. As Fig. 6A shows, resubstitution gave the lowest error rate, cross validation was intermediate, and generalization to new data produced the highest error rate. Post-hoc Newman-Keuls tests indicated that the difference between resubstitution and cross validation ($p < 0.05$) and the difference between cross validation and generalization ($p < 0.05$) were both significant. This suggests two possible effects. The difference between resubstitution and cross validation was probably due to overfitting for resubstitution that was not present for cross-validation. This is in accord with the rational for using crossvalidation (Mosier, 1951). The difference between cross validation and generalization to new data may be due to sampling of data from different sessions. That is, there may be some differences in the statistics of the data acquired in different sessions. Most important, this evaluation indicated that our finding that condition (i.e., feedback/no-feedback) did not affect classification was not simply an artifact of our assessment method.

To evaluate the possible role of changes in data statistics across sessions, this analysis was repeated with data sets that were concatenated across sessions and then reformed by random sampling (i.e., by forming two new data sets from observations randomized across sessions). Fig. 6B shows the results. The effects of method were again significant ($df = 2/10$, $F = 41.82$, $p < 0.0001$). The differ-

Table 2
Accuracy (proportion of correct classifications) for the test (feedback condition) data for each stimulus rate as a function of the stimulus rate of the training (no-feedback condition) data used to parameterize the classification algorithm. Training rates are associated with the rows and test rates are associated with the columns. Note that for each test rate (columns), the highest accuracy occurs at the same training rate as that used in testing (in bold).

Stimulus Rate for Training Data (Hz)	Stimulus Rate for Test Data				
	32 Hz	16 Hz	8 Hz	4 Hz	Mean
32	**0.6211**	0.6469	0.6539	0.6257	0.6359
16	0.5898	**0.6881**	0.7224	0.7120	0.6781
8	0.5643	0.6590	**0.7625**	0.7698	0.6889
4	0.5320	0.6047	0.7184	**0.7861**	0.6603
Mean	0.5768	0.6487	0.7143	0.7234	–

ence between resubstitution and crossvalidation was significant ($p < 0.01$), but the difference between crossvalidation and generalization was not. Indeed, cross validation and generalization produced nearly identical results. This suggests that the significant difference found between cross validation and generalization when session identity was maintained was due to sampling of sessions with different statistics.

4. Experiment 2 methods

The BCI users were four men and one woman, ages 26–55, without previous BCI experience except for the man with ALS from the first study. The study was approved by the New York State Department of Health Institutional Review Board and each user gave informed consent.

The methods of Experiment 2 were the same as those of experiment 1 with the following exceptions. There were five conditions consisting of flashes with either 27 ms on and 27 ms off, 82 ms on and 27 ms off, 191 ms on and 27 ms off, 27 ms on and 82 ms off, and 27 ms on and 191 ms off. Thus the second and fourth conditions flashed at the same overall rate (9.17 Hz) but differed in on and off times. Likewise the third and fifth conditions flashed at the same overall rate (4.56 Hz) but differed in terms of on and off times.

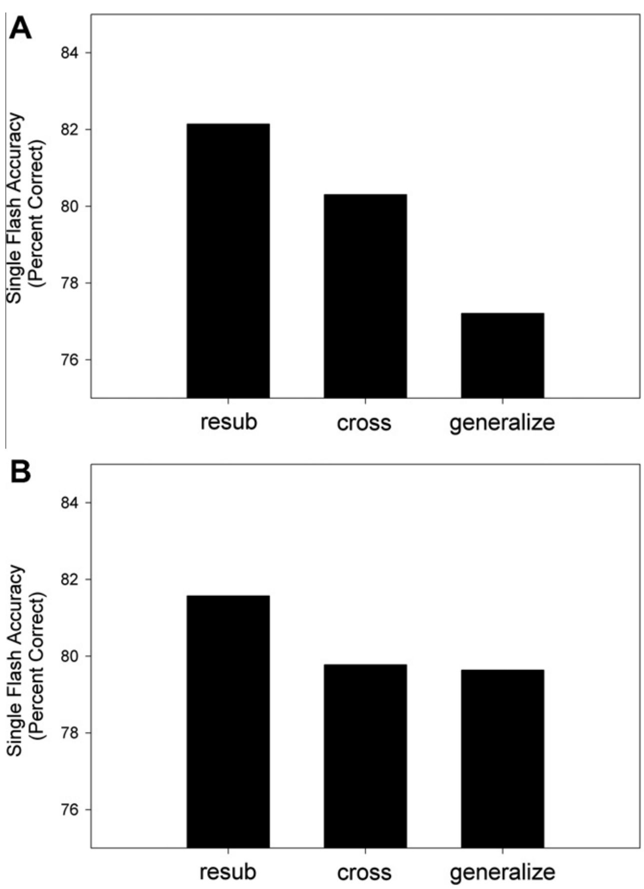

Fig. 6. Classification rate evaluated: on the training data (resub), by leave-one-out cross-validation (cross), and on a new data set (generalize). In A, the identity of the separate sessions' data sets is maintained. In B, the individual observations have been randomized across data sets. Note that resubstitution (resub) always results in lower classification error. Generalization to a new data set results in greater classification error when the identity of the sessions is maintained but not when observations are randomized, indicating that the statistics of the data vary across sessions.

5. Experiment 2 results

An ANOVA on accuracy during the feedback sessions indicated that both the main effect of user ($F(4,16) = 23.33$, $p < 0.0001$) and the time x user interaction ($F(8,32) = 5.95$, $p < 0.0001$) were significant. Rate did not have a significant effect on this measure, presumably due to a ceiling effect.

In order to avoid this ceiling effect (i.e., insensitivity of the analysis due to near perfect performance in most conditions), we used the SAS cross-validate option to calculate the single-flash classification accuracy (i.e., the accuracy for determining whether the group of items in a single flash included or did not include the target). Fig. 7 shows the results. An ANOVA on these data included three levels of time between flash onsets (54, 109, and 218 ms), two levels of stimulus proportion condition (flash or inter-flash interval lengthened), and two levels of feedback condition (no feedback or feedback). Only the effects of rate were significant ($F(2,8) = 86.31$, $p < 0.0001$).

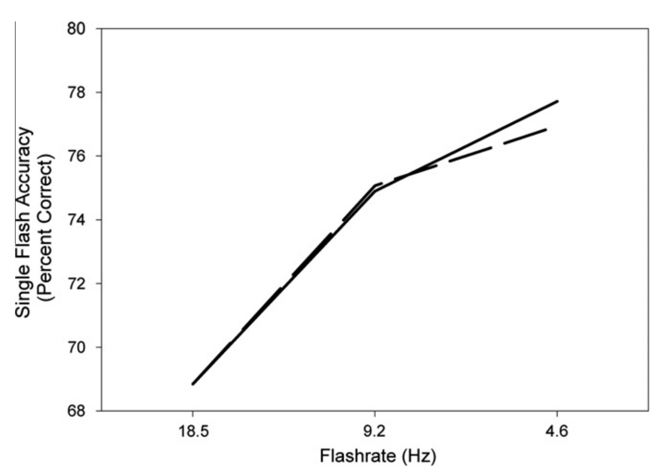

Fig. 7. The accuracy for single-flash classification as a function of the interval between the onset of successive flashes for calibration (no feedback) (solid) and feedback (dashed) sessions in Experiment 2.

6. Discussion

The present results show that the accuracy of a P300-based BCI spelling application increases as flash rate decreases. This finding is consistent with previous basic research on the P300 showing that the magnitude of the response increases with longer interstimulus intervals (ISIs) (e.g., Gonsalvez and Polich, 2002; Hansen and Hillyard, 1984). However, like most P300-BCI studies, the present study employed a range of ISI values that were much faster than those used in conventional P300 studies. For example, the Gonsalvez and Polich (2002) study used ISI values of 1,2 and 4 s. A previous BCI study using the P300 matrix speller evaluated a different range of flash rates (as well as different matrix sizes) and did not find consistent effects of flash rate on accuracy (Sellers et al., 2006). This study is difficult to compare with the present one due to differences in the size of the matrix and the earlier study's use of the row-column presentation format. Using target-to-target interval (probably the most important parameter) for comparison, the present study had an average target-to-target interval range of 750–5882 ms, while Sellers et al. (2006) had an average interval range of 1052–4167 ms. Thus, the somewhat wider range evaluated in the present study may help to account for its finding that flash rate had a significant effect.

Martens et al. (2009) studied a P300 matrix speller with a constant flash rate of 6 Hz. In an analysis of variation in the pattern of targets and non-targets, they found better classification with longer target-to-target intervals. They suggested that two factors might have contributed to this effect: overlap of waveforms with shorter intervals (Woldorff, 1993); and refractory effects (Noguchi et al., 2004).

The presence or absence of feedback did not appear to modify P300 classification accuracy. This seems somewhat surprising since feedback might be expected to have multiple positive effects on performance (Salmoni et al., 1984). These include effects on learning as well as short term motivational effects. Nonetheless, in neither experiment did accuracy for sessions with feedback differ from that in sessions without feedback. In the paradigm used here, even when feedback is provided, there is a substantial delay between the stimuli and the feedback. Since multiple targets are presented at random intervals, the minimum delay between the last target and feedback would be 800 ms., but even with the fastest rate, the could be as great as 4550 ms. Smith and Smith (1987) suggest that the ideal human–machine system should provide instantaneous feedback. Thus, the P300 matrix speller may not provide knowledge of results soon enough to facilitate user performance. Alternatively, the processes involved in the generation of the P300 may not be readily influenced by feedback.

The lack of a feedback effect observed in the present study, combined with the apparent effectiveness of cross-validation, suggests that offline studies of P300 BCI data may generalize well to online usage. One possible consideration is that there appears to be some variation in the statistics of the data across sessions. This variation may not be systematic given that the four calibration (i.e., no feedback) sessions preceded the four feedback sessions but did not differ in accuracy. Rather this inter-session variation might be due to slight differences in recording factors, such as the exact positioning of the electrodes or electrode impedances. Inter-session differences in the user (e.g., in level of alertness) might also contribute. To the degree that these effects are simply random, classification might be improved by using more sessions from each user for calibration.

Slower flash rates consistently increased accuracy for all the subjects in this study. However, there were marked individual differences in the optimal flashrate when the number of characters per min. was considered. Individual differences could be due to any of several factors. For example, P300 varies with age, physical fitness, and neuropsychological factors (Pontifex et al., 2009; Polich, 2007). The present results suggest that individual differences in the P300 might well be characterized in terms of a function that relates accuracy to target-to-target interval. The intercept and slope of this function might also characterize P300 association with other individual differences. These could conceivably relate to a more general factor, such as speed of information processing (Sheppard and Vernon, 2008).

Bianchi et al. (2010) have suggested that, in addition to cognitive potentials, early visual components are involved in the performance of typical P300-BCI classifiers. In fact, it may be misleading to refer to the flashing visual matrix paradigm as a P300 paradigm since features from the entire 0–800 ms interval may be involved in classifier performance. Whether or not it is desirable to include early visual responses is debatable however given that patients who could most benefit from the use of BCI technology may have compromised eye movement control (Wolpaw et al., 2002). The results of the present study suggest that longer ISI values benefit late components most (see Table 1). These include not only the P300 component, but also a late slow negative wave. The preferential effect of ISI on late cognitive components might explain the dramatic improvement of our most severely impaired ALS user (see Fig. 2).

The P300-based matrix speller represents a promising approach to providing basic communication to users with severe motor disabilities (Vaughan et al., 2006). This paradigm requires some amount of time to highlight the alternatives a sufficient number of times to provide accurate classification. Optimization of the parameters used online can speed this process. While considerable attention has been devoted to comparing alternative classification algorithms (Lotte et al., 2007), it appears that different alternatives often produce comparable results (Krusienski et al., 2006). Customizing the features used for classification (i.e., channels and time points) may be more important for improving accuracy (Krusienski et al., 2008). The present study shows that the stimulus rate is also an important factor that should be adjusted for individual users. Rate might also interact with other factors, such as the number of items in the matrix and the number of items flashed simultaneously. These variables affect the target-to-target interval, which may be a critical underlying factor for determining the strength of the P300 response.

7. Summary

The accuracy of the P300 matrix speller increased as stimulus rate decreased. While this was true in all subjects, the form of the relationship, and the rate that maximized characters/min, varied across individuals. The fundamental factor accounting for these results may be the change in average target-to-target interval caused by change in stimulus rate. The presence or absence of feedback of the classification result for each trial did not affect the results although there was evidence of non-stationarities between sessions.

Acknowledgements

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