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Brain–computer interface (BCI) operation: optimizing information transfer rates

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Abstract

People can learn to control mu (8–12 Hz) or beta (18–25 Hz) rhythm amplitude in the EEG recorded over sensorimotor cortex and use it to move a cursor to a target on a video screen. In the present version of the cursor movement task, vertical cursor movement is a linear function of mu or beta rhythm amplitude. At the same time the cursor moves horizontally from left to right at a fixed rate. A target occupies 50% (2-target task) to 20% (5-target task) of the right edge of the screen. The user's task is to move the cursor vertically so that it hits the target when it reaches the right edge. The goal of the present study was to optimize system performance. To accomplish this, we evaluated the impact on system performance of number of targets (i.e. 2–5) and trial duration (i.e. horizontal movement time from 1 to 4 s). Performance was measured as accuracy (percent of targets selected correctly) and also as bit rate (bits/min) (which incorporates, in addition to accuracy, speed and the number of possible targets). Accuracy declined as target number increased. At the same time, for six of eight users, four targets yielded the maximum bit rate. Accuracy increased as movement time increased. At the same time, the movement time with the highest bit rate varied across users from 2 to 4 s. These results indicate that task parameters such as target number and trial duration can markedly affect system performance. They also indicate that optimal parameter values vary across users. Selection of parameters suited both to the specific user and the requirements of the specific application is likely to be a key factor in maximizing the success of EEG-based communication and control.
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1. Introduction

Many people with severe motor disabilities require alternative methods for communication and control. Over the past decade, a number of studies have evaluated the possibility that scalp-recorded EEG activity might be the basis for a new augmentative communication interface (e.g. Farwell and Donchin, 1988; Sutter, 1992; Wolpaw et al., 1991; Birbaumer et al., 1999; Pfurtscheller et al., 1993; Kostov and Polak, 2000; reviewed in Wolpaw et al., 2002). EEG-based communication systems measure specific features of EEG activity and use the results as control signals. In some systems, these features are potentials evoked by stereotyped stimuli (Farwell and Donchin, 1988; Sutter, 1992). Other systems, such as our own, use EEG components that are spontaneous in the sense that they are not dependent on specific sensory events (Birbaumer et al., 1999; McFarland et al., 1993; Pfurtscheller et al., 1993; Wolpaw et al., 1986).

With our current EEG-based communication system, users learn over a series of training sessions to use EEG to move a cursor on a video screen (see McFarland et al., 1997a for full system description). During each trial, the user is presented with a target along the right edge of the screen and a cursor on the left edge (Fig. 1). The cursor moves across the screen at a steady rate, with its vertical movement controlled by EEG amplitude in a specific frequency band at one or several scalp locations. The user's task is to move the cursor to the height of the target so that it hits the target when it reaches the right edge. At present, cursor movement is usually controlled by the amplitude of mu rhythm activity, which is 8–12 Hz activity focused over sensorimotor cortex, or by the amplitude of higher frequency (e.g. 18–25 Hz) beta rhythm activity, also focused over sensorimotor cortex.

Effective brain–computer interface (BCI) operation has several requirements. First, the user must learn to control the EEG feature, such as mu-rhythm amplitude,

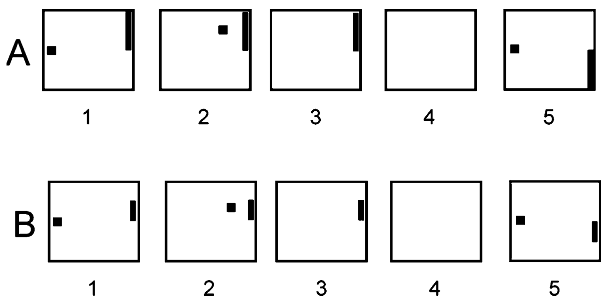

Fig. 1. The 2 (A) and 4 (B) target tasks. (1) one of the targets and the cursor are present on the screen, (2) the cursor begins to move across the screen with its vertical movement controlled by the user, (3) the target flashes when it is hit by the cursor, (4) the screen is blank for a brief interval, (5) the next trial begins. Note that on any given trial only one of two (A) or one of four (B) targets are present.

that determines vertical cursor movement. Second, signal processing must extract the EEG feature from background noise. For example, we use spatial filtering operations that improve the signal-to-noise ratio (McFarland et al., 1997b). Third, the system must translate this feature into cursor movement so that the user is able to reach each of the possible targets. In our system, cursor movement is a linear function of mu rhythm amplitude. This linear function has two parameters, an intercept and a slope. We use an adaptive algorithm to select values for these parameters that make all targets equally accessible to the user (McFarland et al., 1997a,b).

Two important task parameters might also affect BCI performance. One is the number of possible targets. A greater number of targets could increase system performance, since more targets provide more information. Alternatively, a greater number of targets could decrease system performance by decreasing accuracy. The other is the rapidity of horizontal cursor movement. Faster horizontal movement could increase performance by permitting a greater number of selections per unit time, or by decreasing accuracy, decrease performance. This study evaluated these two questions by varying target number and horizontal movement time systematically in a representative group of BCI users. We determined the effects of these variations on BCI performance, which was measured both as accuracy (i.e. the percent of targets hit) and as information transfer rate or bit rate (i.e. bits/min). Bit rate is a standard measure of communication systems that takes into account accuracy, the number of possible selections, and the time required to make each selection. As described in Pierce (1980), the number of bits transmitted per trial, or B, can be computed as:

$$B = \log_2 N + P \log_2 P + (1 - P)\log_2 [(1 - P)/(N - 1)] \tag{1}$$

where N is the number of possible targets, and P is the probability that the target is hit. Bit rate or bits/min, can then be computed by dividing B by the trial duration in min.

2. Experiment 1: effect of number of targets

BCI performance might be increased by increasing the number of targets since, according to Eq. (1), the number of bits transmitted per trial is a function of the number of alternatives. However, Eq. (1) also indicates that accuracy is important. If accuracy declines markedly as the number of targets increases, the result could be a reduction in bit rate. These relationships are illustrated in Fig. 2, which shows bits/trial as functions of accuracy for different numbers of targets. For example, Fig. 2 shows that an accuracy of 95% with 2-targets yields more bits/trial than an accuracy of 70% with 4-targets. Accordingly, Experiment 1 asked whether increasing the number of targets could increase bits/trial.

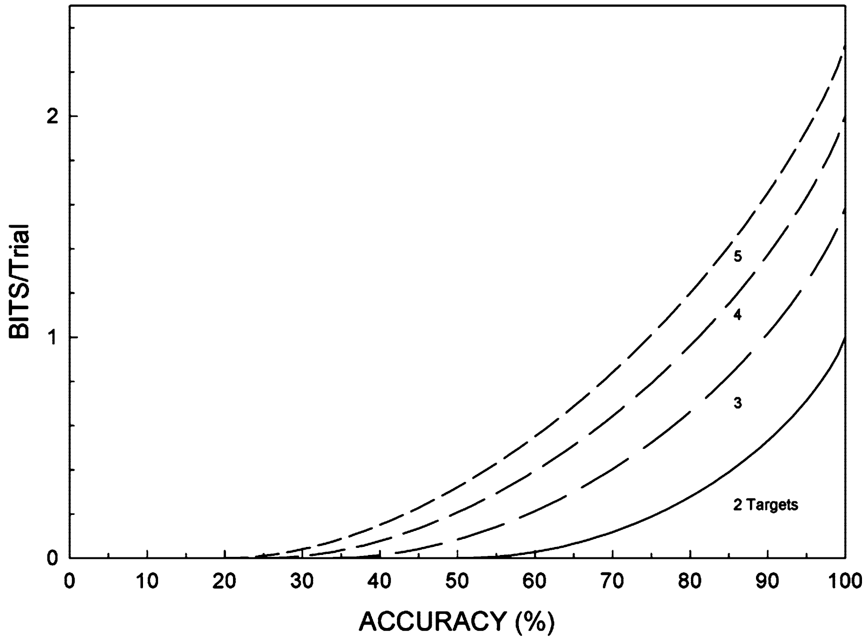

Fig. 2. Bits/trial as a function of accuracy (percent of targets hit) for different numbers of targets.

2.1. Method

2.1.1. Users

The BCI users were eight adults (three women and five men, ages 20–44). Six had no disabilities. One had a spinal injury at the level of C6 and another had cerebral palsy. Both of these latter two users were confined to wheelchairs. All gave informed consent for the study, which had been reviewed and approved by the New York State Department of Health Institutional Review Board. After an initial evaluation defined the frequencies and scalp locations of each person's spontaneous mu and beta rhythm activity, he or she learned EEG-based cursor control over several months (two to three sessions/week). Thus, these users had extensive experience with the present task prior to this study.

2.1.2. Procedure

The user sat in a reclining chair facing a 51 cm video screen 3 m away, and was asked to remain motionless during performance. Scalp electrodes recorded 64 channels of EEG (Sharbrough et al., 1991), each referenced to an electrode on the right ear (amplification 20 000; bandpass 1–60 Hz). A subset of channels were digitized at 196 Hz and used to control cursor movement online as described below. The spectral bin-channel combinations used as features for cursor control were initially selected by determining features that were most reactive to movement and imagery (McFarland et al., 2000). In addition, all 64 channels were digitized at 128

Hz and stored for later analysis. These analyses guided subsequent adjustments to the features used with the aim of optimizing performance. In all cases the frequencies selected were within the mu or beta frequency range and the channels used were over sensorimotor cortex.

The user controlled vertical cursor movement as the cursor moved horizontally across the screen at a fixed rate. Thus, as Fig. 1 shows, the cursor moved vertically under user control and horizontally under computer control. The user's task was to move the cursor vertically so as to intercept the target. The distance from the left edge to the right edge of the screen was 308 steps. The trial ended when the cursor touched the right edge and thereby hit or missed the target. To control vertical cursor movement, 1–3 EEG channels over the sensorimotor cortex of each hemisphere were derived from the digitized data according to either a common average reference method or a Laplacian transform (McFarland et al., 1997b). Every 100 ms, the most recent 200 ms segment from each channel was analyzed by an autoregressive algorithm (Marple, 1987), and the amplitude (i.e. square root of power) in a 3-Hz wide frequency band was calculated. The amplitudes of the 1–3 channels were combined to produce an EEG control signal according to our standard algorithm, in which cursor movement is a linear function of the EEG control signal. That is, if ΔV is the cursor movement, S is the control signal (i.e. a linear sum of the spectral band-channel combinations used as control features), b is the gain, and a is the mean control signal for the user's previous performance:

$$\Delta V = b(S - a) \tag{2}$$

was the function that determined each cursor movement. This form of the linear equation was used so that a and b could be defined independently of each other. The intercept a was set so that, if future performance was similar to previous performance, net cursor movement over all trials was zero (McFarland et al., 1997a,b). Thus, the intercept minimized directional bias, maximized the influence that the user's EEG control had on the direction (i.e. upward or downward) of cursor movement, and helped make all targets equally accessible. The slope (or gain) b determined the magnitude of the cursor movement for a given value of $(S-a)$. To ensure that all targets were equally accessible, the online algorithm adjusted the intercept and slope in Eq. (2) to eliminate any correlation between the probability that the target would be hit and the vertical location of the target (McFarland and Wolpaw, in press).

Each session consisted of eight 3 min runs separated by 1 min break, and each run consisted of 20–30 trials. As illustrated in Fig. 1, each trial consisted of a 1 s period between target appearance and cursor movement, a 2 s period during which cursor movement occurred, a 1.5 s post-movement reward time (i.e. the time during which the target flashed if hit or went blank if missed), and a 1 s inter-trial interval. After training on the 2-target task, the 3-, 4-, and 5-target tasks were gradually introduced over several sessions. While each target (consisting of a vertical bar as shown in Fig. 1) occupied 50% of the right edge of the screen in the 2-target task, it occupied 33% in the 3-target task, 25% in the 4-target task, and 20% in the 5-target task. Finally, to evaluate the effect of target number, each user completed four sessions in which each of the four different tasks (i.e. 2-, 3-, 4-, and 5-target versions) was used for two of the eight runs. Thus, each user was first familiarized with each task and then tested with a total of eight 3 min runs with each value of target number. In each session, each value of target number was presented once within a block of four runs, and over sessions the order of presentation was counterbalanced across run positions.

User control of the EEG was assessed by means of r^2, which is the proportion of the total variance in the dependent variable that is accounted for by the independent variable (Winer, 1962). It is a measure of the extent to which the EEG feature in question depends upon the target presented to the user (e.g. Wolpaw et al., 1991). Greenhoiuse–Geisser correction was applied to all P-values to correct for unequal covariances in all analyses with repeated measures (Winer, 1962).

2.2. Results

We first confirmed that cursor movement was based on the user's EEG rather than non-EEG artifacts. Fig. 3 shows voltage spectra and topographies of r^2 from one of the participants averaged separately for 2-, 3-, 4-, and 5-target tasks. The voltage spectra show narrow-band modulation around 11 Hz, and to a lesser extent, around 24 Hz. Furthermore, the scalp topographies of r^2 are focused over central scalp locations indicating that control was based on modulation of the user's EEG. The other users in this study showed similar narrowly focused spectra and scalp topographies.

We measured BCI performance both as accuracy (i.e. percent of targets hit) and as information transfer rate, or bits/min (Eq. (1)). To evaluate the effect of target number on performance, we performed analysis of variance with number of targets as a within-users effect. Fig. 4 shows that accuracy decreased as target number increased ($df = 3/21$, $F = 42.51$, $P < 0.0001$) while bits/trial was highest for the 4-target task ($df = 3/21$, $F = 6.97$, $P < 0.0003$).

We also performed analysis of variance with bits/trial and user as factors and the interaction of target number, user, and session as the error term for the interaction of target number and user. This statistical model is conceptually similar to those employed in generalizability theory (Crocker and Algina, 1986). The effect of user was significant for both accuracy ($df = 7/49$, $F = 67.45$, $P < 0.0001$) and bits/trial ($df = 7/49$, $F = 70.0$, $P < 0.0001$). The interaction of target number and user was significant for bits/trial ($df = 21/147$, $F = 2.09$, $P < 0.0096$). Thus, the number of targets that gave the highest information transfer rate varied among users. Table 1 shows the data for each user. For six users, 4 targets gave the highest bit rate, while for one user 2 targets was optimal and for another, 5 gave the highest rate.

Finally, to assess the impact of task difficulty (i.e. target size) on the user's control of the EEG signal, we assessed that control by calculating as functions of number of targets the absolute values of the control signal for the top-most and bottom-most targets and r^2 (i.e. the proportion of the variance of the EEG signal for top and bottom targets accounted for by target position). We then performed analysis of variance with target number as a within-user effect. As Fig. 5 shows, while the absolute values of the control signal were not greatly affected by the number of

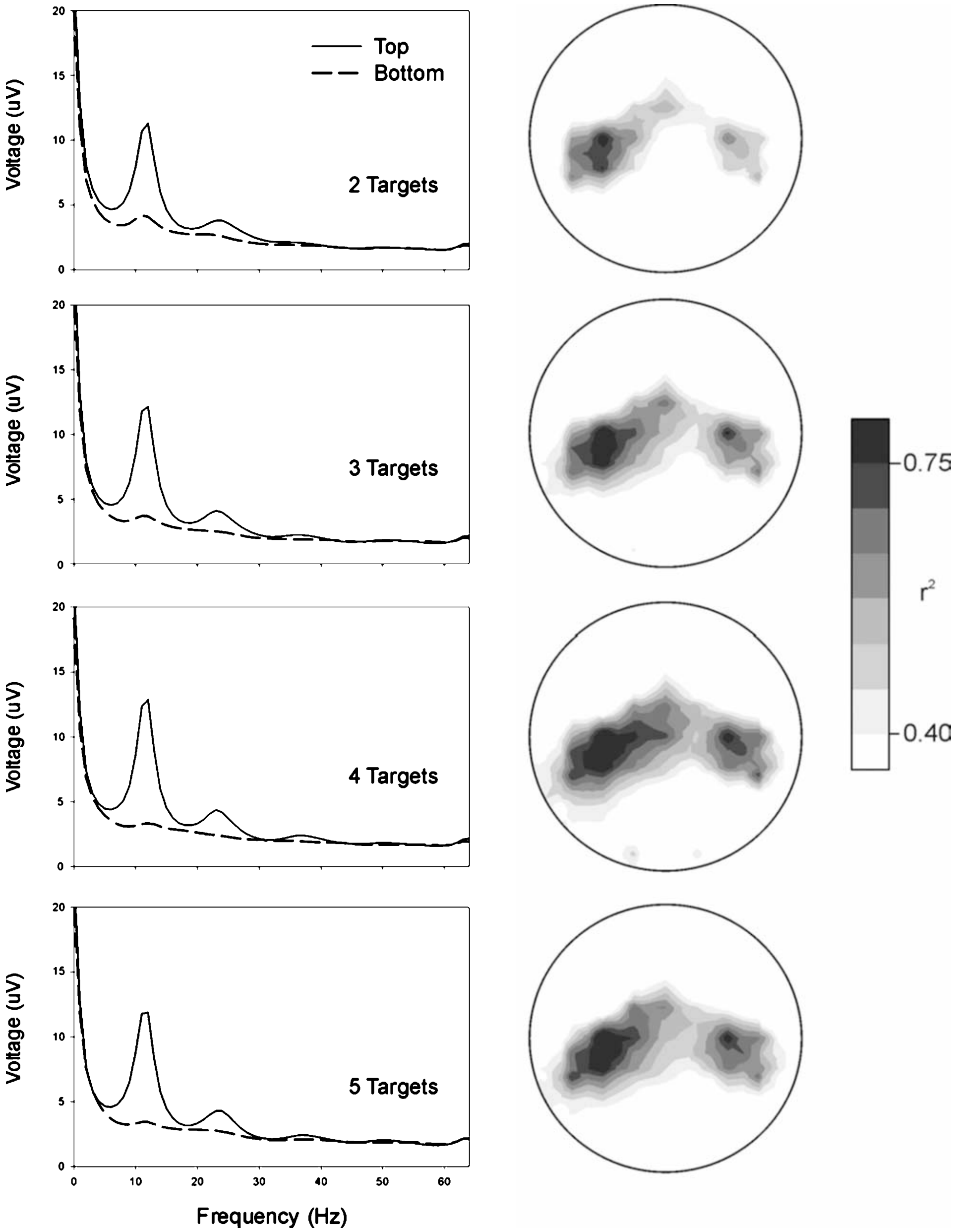

Fig. 3. Left: voltage spectra of the EEG control signal for top (solid) and bottom (dashed) targets from a single user during performance of the 2-, 3-, 4-, and 5-target tasks. The control signal for this subject was the sum of the 11 Hz bins from C3 and C4. Control is focused in narrow bands around 11 and 24 Hz. Right: topographies at 11 Hz of r^2 from the same user. Control is focused over central areas.

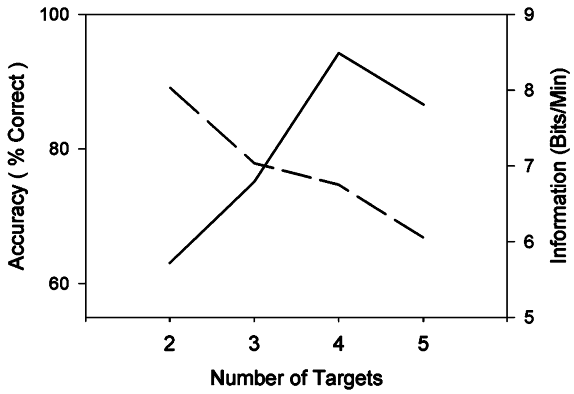

Fig. 4. Accuracy (dashed) and bits/min (solid) as functions of the number of targets averaged across all users.

Table 1
Mean (S.E.M.) bits/min as a function of number of targets for each user

User	Number of targets			
	2	3	4	5
1	8.85 (0.58)	13.02 (1.09)	17.09 (0.78)	15.93 (1.02)
2	6.47 (0.57)	6.99 (0.94)	7.78 (1.05)	8.40 (1.23)
3	8.76 (0.49)	10.27 (1.51)	11.82 (1.76)	10.37 (1.13)
4	6.35 (0.54)	8.13 (0.89)	10.98 (1.05)	9.05 (0.93)
5	0.70 (0.21)	0.81 (0.22)	1.75 (0.61)	1.62 (0.33)
6	7.20 (0.66)	6.81 (0.83)	6.89 (0.85)	5.96 (0.93)
7	4.08 (0.99)	4.03 (0.95)	7.32 (1.41)	7.24 (0.73)
8	3.38 (0.75)	4.28 (0.93)	4.30 (0.42)	3.89 (0.96)

targets, the mean r^2 value was highest for the 4-target task (df = 3/21, F = 5.68, $P <$ 0.0085).

2.3. Discussion

EMG artifacts produce broad-banded modulation involving higher frequencies (Goncharova et al., 2000), eye movements and eye blinks produce broad-banded modulation in lower frequencies (McFarland et al., 1997a,b), and the topographies of EMG, eye movements, or eyeblinks are focused over the edges of the montage (Goncharova et al., 2000). Thus, the spectra and topographies shown in Fig. 3 indicate EEG-based control appropriately focused in frequency and space, as found in previous studies (e.g. Wolpaw et al., 1991, 2000).

The results of this experiment indicate that bits/min, i.e. the amount of information transmitted per unit time, depends on the number of possible targets,

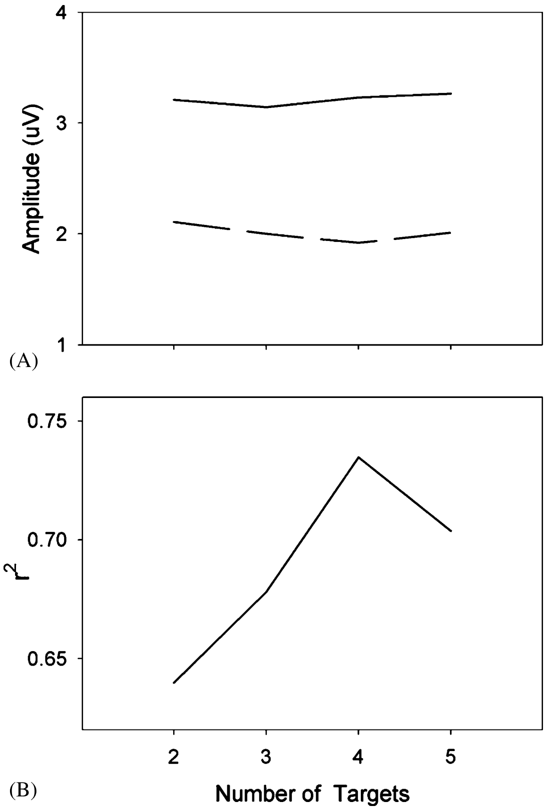

Fig. 5. (A) Amplitudes of the control signal for top (solid) and bottom (dashed) targets as functions of the number of targets averaged across all users. (B) Value of r^2 of the control signal for top vs. bottom targets as a function of the number of targets averaged across all users.

and that, for seven of the eight users tested in this study, the simplest version of the task, the 2-target version, did not give the highest value. At the same time, the effect of target number appears to vary among users. Improvement with higher target number probably requires a certain level of user EEG control. If a user's accuracy is low for the 2-target task, it seems unlikely that increasing the number of targets, which makes the task more demanding, will improve the bit rate. On the other hand, for a user with good EEG control, bit rate may be limited by the 2-target task, which allows a maximum rate of 1 bit/trial.

As Fig. 5 shows, user control of the EEG signal, measured as r^2 for the top versus bottom target comparison, increased as target size decreased from 50% (2-target task) to 25% (4-target task). Thus, users appeared to respond to increasing task difficulty by producing better control (at least up to the 4-target level). This result suggests that the effect of increasing target number on bits/trial cannot necessarily be predicted from performance on the 2-target task, and also suggests that user training might benefit from exposure to greater numbers of targets.

The accuracies reported here for the 4-target one-dimensional task are higher than those previously reported for a 4-target two-dimensional task (Wolpaw and McFarland, 1994). However, the BCI system used in the present study has online features that were not available at the time of the two-dimensional study (e.g. Laplacian and common average spatial filters (McFarland et al., 1997a,b), continual automatic intercept and slope adaptation (McFarland and Wolpaw, in press)). Thus, while results to date are better for one-dimensional EEG control, two (or more)-dimensional control (e.g. of mouse-like devices) may ultimately provide considerably higher information transfer rates.

3. Experiment 2: effect of trial duration

BCI performance, measured as information transfer rate, might also be increased by decreasing the duration of each trial and thereby increasing bit rate, or bits/min. However, in many control situations, accuracy decreases as speed increases (Fitts, 1954). The goal of Experiment 2 was to define for our current BCI system and standard task (Fig. 1) the relationship between trial duration, accuracy, and bit rate.

3.1. Method

3.1.1. Users

Users were seven adults (three women and four men, ages 20–44) all of whom also participated in Experiment 1. Six had no disabilities. One had a spinal cord injury at the level of C6 and was confined to a wheelchair. All gave informed consent for the study, which had been reviewed and approved by the New York State Department of Health Institutional Review Board.

3.1.2. Procedure

The general experimental procedure for this task was the same as that described above for Experiment 1. We used the 4-target task, since Experiment 1 showed that it usually provided the best information transfer rate. In Experiment 1, the cursor moved from left to right across the screen in 2 s. In this experiment we used 1-, 2-, 3-, and 4-s movement times. The durations of the other components of the trial illustrated in Fig. 1, the time between target appearance and the beginning of cursor movement (1 s), the post-movement reward time (1.5 s), and the inter-trial time (1 s), remained fixed. Thus, total trial duration varied from 4.5 s for the 1 s movement time trial to 7.5 s for the 4 s movement time trial. After a warm-up session in which variation in movement time was introduced, each user completed four sessions in which each of the four trial durations was used for two of the eight 3 min runs. Thus, each user had a total of eight runs with each value of trial duration. In each session, each trial duration was used once within a block of four runs, and over sessions the order of presentation was counterbalanced across run positions.

3.2. Results

To evaluate the effect of trial duration on BCI performance (measured as accuracy and as bits/min), we performed analysis of variance with movement time as a within-users effect. As shown in Fig. 6, accuracy increased with trial duration (or movement time) (df = 3/18, F = 101.92, $P < 0.0001$), while bit rate was greatest when movement time was 3 s (df = 3/18, F = 37.42, $P < 0.0001$).

We also performed analysis of variance on bits/min with trial duration and user as factors and the interaction of trial duration, user, and session as the error term for the interaction of trial duration and user. The interaction of trial duration and user was significant (df = 18/126, F = 1.95, $P < 0.0352$), indicating that the optimal trial duration varied among users. Table 2 shows these data.

Finally, to assess the impact of trial duration on the user's control of the EEG signal, we computed r^2 for top and bottom targets for each trial duration separately. For each condition we computed r^2 based on the average for each trial and also based on each 200 ms analysis interval. Analysis of variance indicated that the effects of analysis interval (df = 1/6, F = 831.13, $P < 0.001$) and the interaction between analysis interval and trial duration (df = 3/18, F = 151.49, $P < 0.0001$) were both significant. As shown in Fig. 7, the r^2 associated with the entire trial increased with increasing trial duration. This is to be expected, since more 200 ms intervals were averaged as trial duration increased. In contrast, the r^2 associated with individual 200 m epochs decreased as trial duration increased. This indicates that, for a given time period, users displayed less control during longer trials.

3.3. Discussion

The data of this experiment show a clear increase in accuracy with longer trial durations, and are consistent with those obtained with conventional motor tasks (e.g. Mottet et al., 1994; Szeto et al., 1993). On the other hand, they contrast to those of a previous study (McFarland and Wolpaw, in press) in which the user's task was

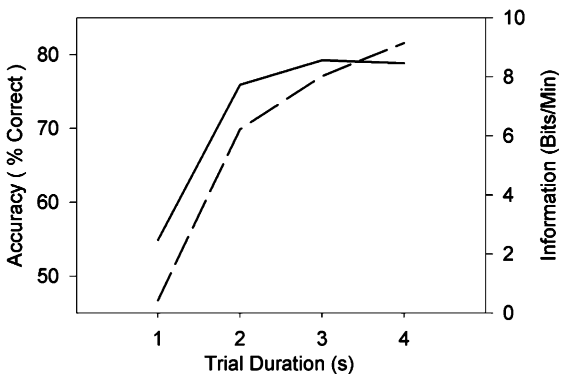

Fig. 6. Accuracy (dashed) and bits/min (solid) as functions of movement time averaged across all users.

Table 2
Mean (S.E.M.) bits/min as a function of movement time for each user

User	Movement time (s)			
	1	2	3	4
1	6.31 (0.96)	14.07 (0.65)	12.48 (1.09)	12.43 (0.34)
2	1.77 (0.24)	5.21 (0.87)	6.55 (1.44)	5.76 (0.77)
3	1.99 (0.41)	10.06 (1.35)	11.31 (1.34)	10.75 (0.86)
4	2.20 (0.45)	8.70 (0.79)	10.68 (0.73)	9.97 (0.79)
6	3.29 (0.70)	9.00 (1.18)	8.28 (1.47)	7.90 (0.49)
7	0.95 (0.32)	4.97 (0.81)	6.16 (0.99)	6.82 (0.88)
8	0.80 (0.30)	2.10 (0.58)	4.49 (1.28)	5.58 (1.20)

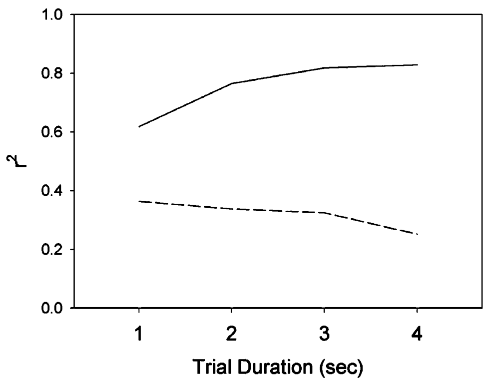

Fig. 7. Average r^2 as a function of trial duration for individual 200 ms epochs and for the average of entire trials. As trial duration increases, 200 ms epoch control decreases and whole trial control increases.

to move the cursor into a target box and hold it there for a fixed period of time (e.g. 2 s) to select the target. In that task, trial duration was affected by the user's control of cursor movement, and higher gain (i.e. slope in Eq. (2)) might increase trial duration by making it difficult for the user to stay within the target box. The task used in the present study does not have this complicating factor. Horizontal cursor movement is fixed and determines trial duration. Vertical cursor movement, which is under user control, determines target selection, but does not affect trial duration.

Longer movement times mean that more segments of EEG determine whether the cursor hits the target when it reaches the right edge of the screen. This tends to increase the signal-to-noise ratio and thus tends to increase accuracy. However, the signal-to-noise ratio for each individual 200 ms epoch actually decreases with longer trial durations. In addition, longer trial durations tend to decrease bit rate since time is the denominator of this rate measure. In sum, the trial duration that provides the highest bit rate must be determined empirically. Furthermore, the result may vary across users.

4. General discussion

The present results demonstrate the importance of appropriate selection of task parameters such as number of targets and trial duration. In the first experiment, increasing target number increased information transfer rate or bits/min, but only to a point (i.e. the 4-target task). With further increase, the decline in accuracy with more targets more than offset the greater maximum bits/trial allowed by more targets. In the second experiment, shortening trial duration by decreasing movement time usually increased bit rate, but again only to a point (i.e. 3 s movement time). With further shortening, the decline in accuracy more than offset the increase in bit rate provided by performing more trials in a given time. Both experiments also show that these task parameters should be individually adjusted for each user, and suggest that they should be continually evaluated as user training proceeds. For example, early in training when user control is relatively poor, fewer targets (e.g. 2) and longer movement times may be appropriate, while later in training more targets and shorter movement times may substantially improve information transfer rate. The results provide additional insight. In the first experiment, as target number increased and target size necessarily decreased, users responded by increasing EEG control (as shown by the increase in r^2 values shown in Fig. 4). For example, r^2 was higher with the 4-target task, in which the target occupied only 25% of the right edge of the screen, than with the 2-target task, in which it occupied 50%. In the second experiment, EEG control decreased with longer trial durations. These findings could help guide development of better methods for training users to operate EEG-based BCI systems.

The present results illustrate the necessity for actual online evaluation of the effects of task parameter selection on BCI performance. The results could not have been predicted from offline data analyses. Offline analyses and simulations can be helpful in guiding development of BCI systems, but they cannot confidently predict the effects of particular changes on actual online performance (e.g. Donchin et al., 2000). While making inferences about online performance from offline analyses has been a common practice in BCI research and development, inferences are simply inferences, and may be misleading. Properly designed, statistically valid, online comparisons of alternatives are essential.

These results are based on a small sample of subjects over a limited range of conditions. The optimal number of targets or trial duration may vary considerably with different degrees of cursor control or with different EEG features. We have not yet compared on-line the potential of various EEG features (e.g. different combinations of frequencies and locations) so the range of possible performances is unknown. Nonetheless the observation that the task parameters need to be optimized for individual subjects probably has considerable generality.

Finally, as the present results illustrate, current BCI systems provide relatively low information rates. Thus, they may be useful primarily for those with the most severe motor disabilities, those who cannot use conventional augmentative communication and control devices because they lack even the minimal neuromuscular control required. Wider application of BCI technology depends on further increase in information transfer rate. As the present study shows, appropriate user-specific selection of task parameters can contribute to such increase. Each improvement that increases information transfer rate should increase the population that could benefit from this new technology.

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