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EEG-Based Communication and Control: Speed–Accuracy Relationships

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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 our current EEG-based brain–computer interface (BCI) system, cursor movement is a linear function of mu or beta rhythm amplitude. In order to maximize the participant's control over the direction of cursor movement, the intercept in this equation is kept equal to the mean amplitude of recent performance. Selection of the optimal slope, or gain, which determines the magnitude of the individual cursor movements, is a more difficult problem. This study examined the relationship between gain and accuracy in a 1-dimensional EEG-based cursor movement task in which individuals select among 2 or more choices by holding the cursor at the desired choice for a fixed period of time (i.e., the dwell time). With 4 targets arranged in a vertical column on the screen, large gains favored the end targets whereas smaller gains favored the central targets. In addition, manipulating gain and dwell time within participants produces results that are in agreement with simulations based on a simple theoretical model of performance. Optimal performance occurs when correct selection of targets is uniform across position. Thus, it is desirable to remove any trend in the function relating accuracy to target position. We evaluated a controller that is designed to minimize the linear and quadratic trends in the accuracy with which participants hit the 4 targets. These results indicate that gain should be adjusted to the individual participants, and suggest that continual online gain adaptation could increase the speed and accuracy of EEG-based cursor control.

KEY WORDS: brain–computer interface; EEG; cursor control; mu rhythm; beta rhythm.

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 (Farwell & Donchin, 1988; McFarland, Neat, Read, Wolpaw, 1993; Pfurtscheller,

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Flotzinger, Kalcher, 1993; Sutter, 1992; Wolpaw, McFarland, Cacace, 1986). 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 visual stimuli (Farwell & 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 (McFarland et al., 1993; Pfurtscheller et al., 1993; Wolpaw et al., 1986).

With our current EEG-based communication system, participants learn over a series of training sessions to use EEG to move a cursor on a video screen (see McFarland, Lefkowicz, & Wolpaw, 1997, for full system description). During each trial, the participant is presented with a target somewhere on the periphery of the screen and a cursor in the center. His or her task is to move the cursor to the target. The cursor moves as a function of an EEG control signal, which is EEG amplitude in a specific frequency band at one or several scalp locations, until it either reaches the target (i.e., a hit) or reaches some other place on the periphery (i.e., a miss). 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.

Cursor movement is a linear function of the EEG control signal. In the simplest format, the participant controls vertical cursor movement to a target located at the top or bottom edge of the screen. The cursor position is updated 10 times per second according to Eq. (1). If ΔV is the cursor movement, S is the control signal, b is the gain, and a is the mean control signal for the user's previous performance,

$$\Delta V = b(S - a) \tag{1}$$

is the function that determines each cursor movement. The linear equation is presented in this form so that a and b can be defined independently of each other. If the user's control signal remains stable, so that a (i.e., the intercept) does not change, net cursor movement over many trials will be zero and top and bottom targets will be equally accessible. The value of b (i.e., the slope, or gain) determines the magnitude of the cursor movement for a given value of $(S - a)$.

Previous studies found that a, the intercept, is best defined by a simple running average of S for the most recent trials (Ramoser, Wolpaw, & Pfurtscheller, 1997). Selection of b, the gain, is a more difficult problem. In the past, we have assumed that gain should be low when participants are first learning EEG-based cursor control, and should rise as they acquire control. Our usual goal has been that the duration of cursor movement for a trial should be 5–10 s at the beginning of participant training, and fall to about 2 s (i.e., about 20 individual cursor movements) after training. We initially addressed this goal with an online algorithm that sought a specific trial length (McFarland et al., 1997). After each 3-min run, the system determined average trial duration. If it was shorter than criterion, b was increased by 10%, whereas if it was longer, b was decreased by 10%.

More recently, we have used a method in which the online algorithm seeks a value for the gain that results in a certain rate of cursor movement, measured in pixels/s. In the first version of this method, the algorithm increased (or decreased) b by a fixed amount (e.g., 10%) at the end of each run if the gain resulted in a rate of cursor movement in pixels/s that was less than (or greater than) criterion. This method was rather slow in approaching the desired movement rate (pixels per second). We are now using a method in which the algorithm periodically resets b to equal the desired rate (in pixels/s) divided by the standard deviation of S, the EEG control signal, for the same number of recent trials that are used to compute a, the intercept. We found that this method rapidly approaches a gain that produces the desired rate of cursor movement. At the same time, although we have an effective method for defining b so as to achieve any desired rate of cursor movement, we do not know what the most desirable rate of cursor movement actually is, nor whether it is the same for all participants.

This study investigated the relationship between gain and accuracy. We first conducted simulations of the effects of gain using a simple model of participant performance. We next evaluated the effects of gain with human volunteers. This allowed us to determine whether participants performance could be understood by the simple model and whether this model could be used to optimize performance. The experimental evaluation of gain effects took advantage of the fact that, because the standard deviation of the control signal does not depend on the concurrent value of the gain, i.e., b in Eq. (1), any desired pixels/s value can be used to compute a new value of b. Thus, it is possible to change the desired pixels/s value from trial to trial, and thereby evaluate the impact of gain on performance. Cursor speed is a function both of the slope and of the number of movements per second. We kept the update rate fixed at 10/s because variation of this parameter influences feedback delay and spectral resolution whereas the slope parameter does not.

We examined gain effects in a newly developed four-target version of the cursor movement task. The results obtained with this four-target task indicate that gain affects the relative accessibility of central and end targets. These findings have important implications for the design of the algorithm that supports EEG-based communication and control.

METHODS

Participants

Participants were five adults: four without disabilities (one women and three men, ages 33–58) and a 24-year-old man with cerebral palsy who is confined to a wheelchair and communicates with a touch-talker. 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 participant's spontaneous mu and beta rhythm activity, he or she learned EEG-based cursor control with a two-target task in ten 30-min sessions (2–3/week) and then participated for 10–69 additional sessions devoted to a variety of studies (e.g., this study, McFarland, McCane, & Wolpaw, 1998; Miner, McFarland, & Wolpaw, 1998). Over the course of each participant's participation, offline data evaluations led to adjustments in the electrode locations, frequency bands, and spatial filter used by the online algorithm that controlled cursor movement. The next section summarizes the online methodology used in this study. A comprehensive description of system configuration and operation is available elsewhere (McFarland et al., 1997).

Standard Session Format and System Operation

The participant 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 later. In addition, all 64 channels were digitized at 128 Hz and stored for later analysis.

In this study, the participants controlled one-dimensional (i.e., vertical) cursor movement. Cursor movement was controlled as follows. After digitization of the right-ear referenced EEG signals, 1–3 EEG channels over the sensorimotor cortex of each hemisphere were derived according to either a common average reference method or a Laplacian method (McFarland, McCane, David, & Wolpaw, 1997). Spatial filter selection was based upon the best offline analysis of results. Every 100 msec, the most recent 200-msec 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. This frequency band corresponded to the arch-shaped mu rhythm or the central beta rhythm, both of which are generated in sensorimotor cortex (Gastaut, 1952; Kuhlman, 1978; Pfurtscheller & Berghold, 1989). The 1–3 channel amplitudes were combined to produce an EEG control signal, which was used as the independent variable in a linear equation that defined a vertical cursor movement in units of cursor steps (i.e., Eq. (1) above). If the value was positive the movement was upward and if it was negative the movement was downward. (In one participant, the opposite was true; and, in this participant, the data were analyzed with respect to the sign of the control signal, rather than the direction of cursor movement.) Thus, every 100 msec, the cursor moved the defined number of steps up or down the screen. The intercept of the equation was set so that, if future performance was similar to previous performance, net cursor movement over all trials would be zero (McFarland et al., 1997). As a result, the intercept reduced bias in one direction or another and maximized the influence that the participant's EEG control had on the direction (i.e., upward or downward) of cursor movement.

Each session consisted of eight 3-min runs separated by 1-min breaks, and each run consisted of 20–30 trials. Each trial began with a 1-s period during which the screen was blank. All participants were initially trained on a two-target task, followed by a three-target task, and finally the four-target task. The four-target task is illustrated in Fig. 1. Four boxes were arranged in a vertical column. The correct target was highlighted, the cursor began in the center, and the participant's task was to move the cursor into the correct target and hold it there for a predetermined period of time (i.e., the dwell time, which was usually 2 s). If the cursor remained in the highlighted box for the required dwell time, that box flashed and a correct selection was registered. If the cursor remained in one of the other boxes for the required dwell time, the screen went blank and a miss was registered. The dwell time was reset if the cursor left any box. If the cursor movement computed by Eq. (1) resulted in movement outside the range of the targets, the cursor remained at the maximum or minimum value in that range (i.e., the top or bottom edge of the screen).

Evaluation of the Effects of Gain

For each trial of the four-target task, gain, i.e., b in Eq. (1), was defined as described in the Introduction: a chosen rate in pixels/s divided by the standard deviation of the control signal for the last four targets of each type. To evaluate the effects of gain, the chosen rate of cursor movement was varied either between 3-min blocks or on a trial-to-trial basis. With each participant, we evaluated cursor rate for three sessions of eight runs each. In

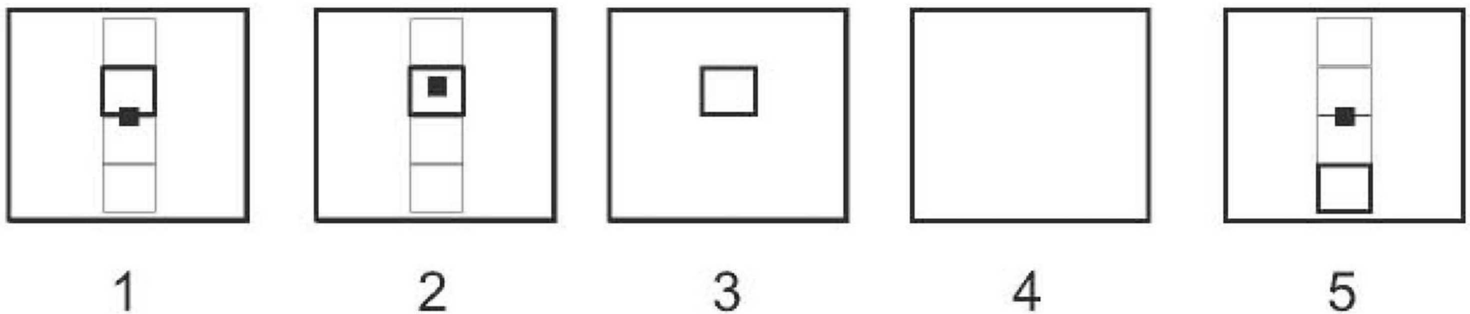

Fig. 1. The four-target task. (1) All four boxes appear with the correct box outlined in bold, (2) the cursor moves toward or away from the target, (3) if the cursor remains in the correct box for the required dwell time the correct target flashes, otherwise the screen goes blank, (4) the screen goes blank for a brief period between trials, and (5) the next set of targets appears.

an additional three sessions from each participant, dwell time was varied between 3-min blocks. The parameters that were evaluated on a between-run basis were presented in a counterbalanced order with respect to run number within a session.

Task Simulation

We developed a simple model of participant performance and used it to simulate results for the two-target and four-target tasks. We modeled task performance with the signal plus noise as input. This simulation assumed that a constant signal is corrupted by Gaussian noise. Our expectation was that these simulations would suggest a gain selection procedure that would help optimize actual performance.

The model calculated each simulated cursor movement, ΔM, as

$$\Delta M = T + e \tag{2}$$

where T is a function of the target and current cursor position that will move the cursor toward the center of the target (i.e., the cursor moves up by a constant amount when it is below the center of the target and down by a constant amount when it is above the center of the target), and e is a constant random process. The ratio of these is an index of the amount of control the participant has acquired (i.e., T/e is proportional to the signal-to-noise ratio and $T/(T+e)$ is r^2).

There are several factors to consider in predicting performance on the four-target task as gain changes. With reduced gain, the trial might last longer, more cursor movements might occur and, by the central limits theorem, error would be inversely proportional to the square root of the number of cursor movements. However, this is complicated by the dwell time required for selection. Higher gains may get the cursor to the target faster, but may also make it more difficult for the participant to keep the cursor in the target for the required dwell time.

Simulations were performed with a signal that was the sum of a movement toward the target and random (Gaussian) noise, i.e., as in Eq. (2) above. For each movement a constant movement toward the target was summed with a value derived from the random number generator "gasdev" (Press, Teukolsky, Vetterling, and Flannery, 1992). The amount of control could be expressed in terms of the variance due to the movement toward the target divided by the sum of this movement and the random noise (i.e., r^2). The constant movement was toward the center of the target box and the noise was sufficient to produce r^2 values of 0.100. This value of r^2 is within the range typically seen in participants (based on the data window used for each cursor movement, rather than a trial average). This simulated control signal was multiplied by a series of gain values. For each gain value, 10,000 trials were simulated.

Gain Controller

Simulations of the four-target task suggested that optimal performance will occur when the targets are equally accessible (and, as shown in the Results section below, actual participant performance matched the expectation). Thus, we designed and tested a gain controller that made the targets equally accessible. This controller adjusted the parameters *a* and *b* of Eq. (1). If the four possible targets in the task are ordered from top to bottom, the intercept, i.e., *a* in Eq. (1), controls the linear trend in accuracy, and the slope, i.e., *b* in Eq. (1), controls the quadratic trend. The gain controller operated at the end of each 3-min run. It decreased *b* by 1 pixel/s when the quadratic trend was positive and increased *b* by 1 pixel/s when the quadratic trend was negative. Thus, the controller was designed to gradually produce gain values that gave a quadratic trend of 0. A multiplier of the mean of the control signal, i.e., *a* in Eq. (1), was likewise adjusted to minimize the value of the linear trend in target accuracy. This adjustment factor started with an initial value of 1 and was changed by 0.01 per run based on the linear trend in target accuracy.

RESULTS

Simulated Data

Figure 2 shows the results of the simulation of the effects of three different gain values on accuracy for each target of the four-target task. These gains chosen are representative values from a series of 18 gain values that produce a continuously varying surface. It is

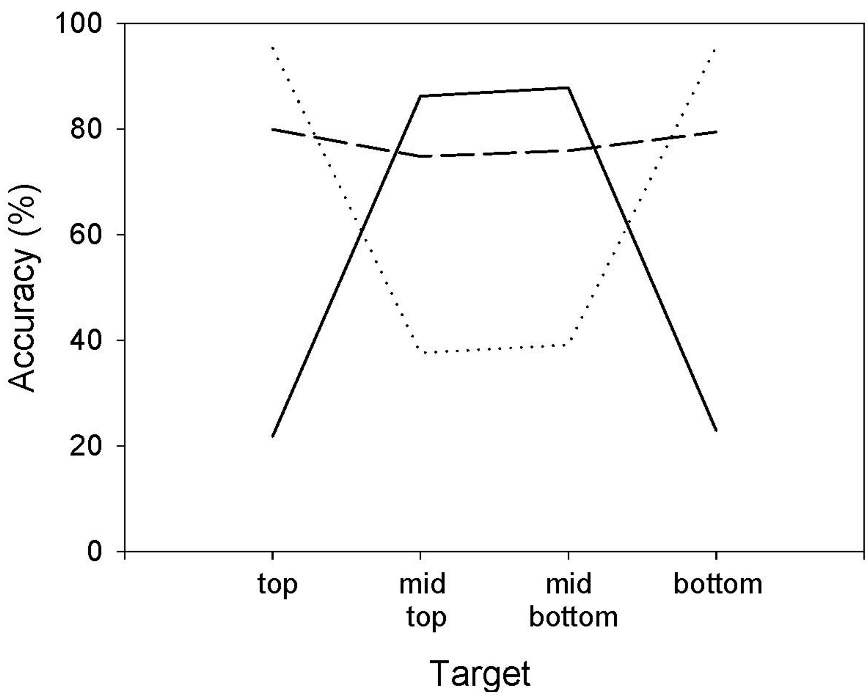

Fig. 2. Simulation of the effects of gain on performance for individual targets. Each point represents 2500 simulated trials. The control signal was produced by a constant movement toward the center of the correct target combined with a Gaussian noise (see text). The gain is expressed as a multiplier of the control signal. Solid line represents a gain of 5 (arbitrary units), the dashed line represents a gain of 10, and the dotted line represents a gain of 15. A low gain favors central targets whereas a high gain favors end targets.

apparent that a low gain favors the middle targets, a high gain favors the end targets, and an intermediate gain produces nearly equal accuracy for all targets. As shown in Fig. 2, optimal overall accuracy is associated with intermediate gain (i.e., when targets are equally accessible).

Actual Data

Figure 3 shows the average percent correct for five participants for each target at two gain values. These results represent the average of all data collected during gain testing. The results agree with the simulation in showing that low gain favors the central targets whereas high gain favors the end targets. It is notable, however, that the values we selected for empirical evaluation actually represent intermediate and high levels of gain. An analysis of variance of accuracy indicated that there was a significant interaction between gain and target ($F = 43.25$, $p < .0001$), whereas there was no significant effect or interactions involving presentation mode (between-run vs. between-trial variation of gain). In addition, there was a significant interaction between gain and participant ($F = 6.55$, $p < .0122$) and between gain by target by participant ($F = 2.22$, $p < .05$). Figure 4(A) shows the

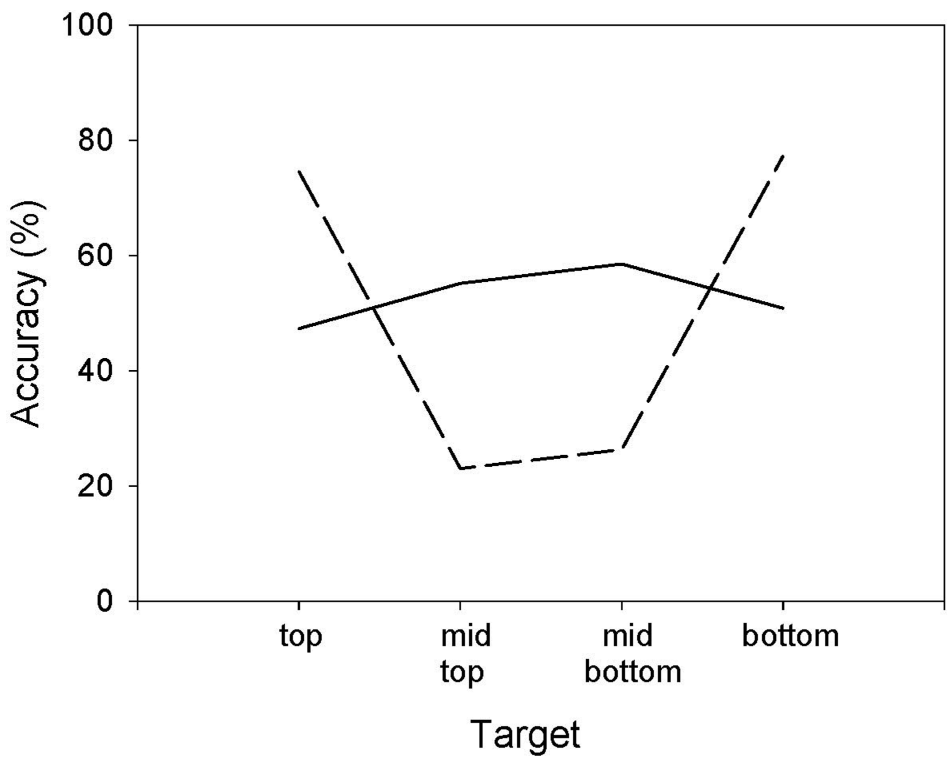

Fig. 3. The effects of gain on performance for individual targets. Each point represents the mean of data from five participants from three sessions each. The solid line represents a cursor movement rate of 45 pixels per second and the dashed line represents a cursor movement rate of 90 pixels per second. A low rate favors central targets whereas a higher rate favors end targets.

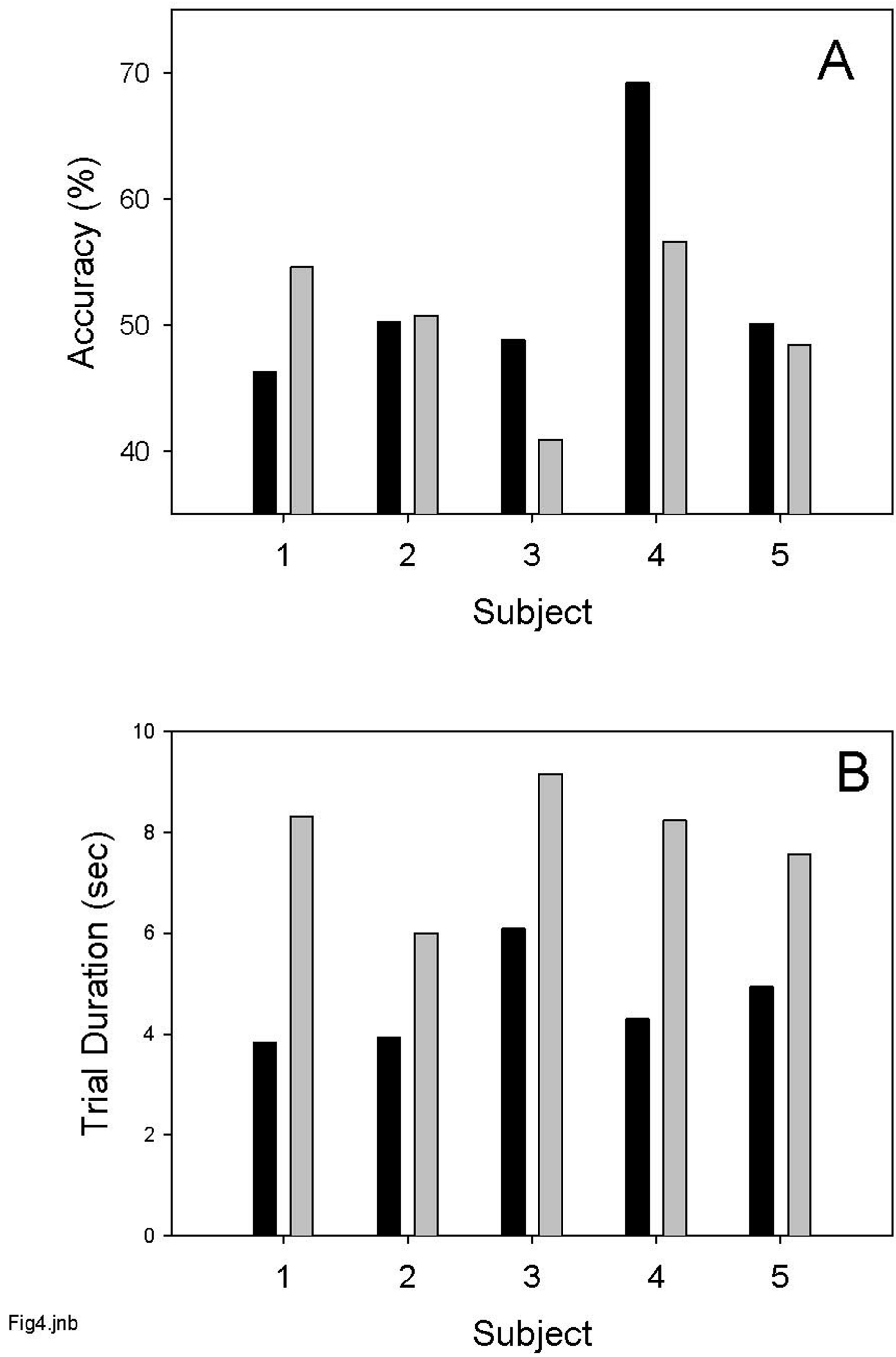

Fig. 4. Effects of gain on four-target performance of individual participants for accuracy (A) and trial duration (B). The solid bars represent a cursor movement rate of 45 pixels per second and the gray bars represent a cursor movement rate of 90 pixels per second. The optimal gain differs among individuals.

gain by participant interaction for percent correct. It shows that the optimal gain differed across participants. Figure 4(B) shows the mean trial duration for each participant. Larger cursor movements uniformly produced longer trial durations ($F = 54.63$, $p < .0018$). This seemingly paradoxical effect is due to the fact that larger cursor movements made it more likely that the cursor would move out of the box before the required dwell time was achieved.

Evaluation of a Gain Controller

Simulated Data

One goal of a gain-control algorithm is to make all targets equally accessible. Both the simulated and actual data indicate that gain affects the shape of the function that relates accuracy to target position. This effect of gain can be described by the quadratic trend (Winer, 1971) in the accuracy–target position function. Figure 5 shows overall accuracy and the quadratic trend of accuracy across target position for various values of the gain parameter (data from the previous simulation shown in Fig. 2). The quadratic trend is negative when accuracy is greatest for central targets and is positive when accuracy is greatest for end targets. Because the empirical results (Fig. 3) were in close agreement with the simulations (Fig. 2), it seemed reasonable to design a gain controller based on the simulated results displayed in Fig. 5, which indicate that optimal gain is achieved when the

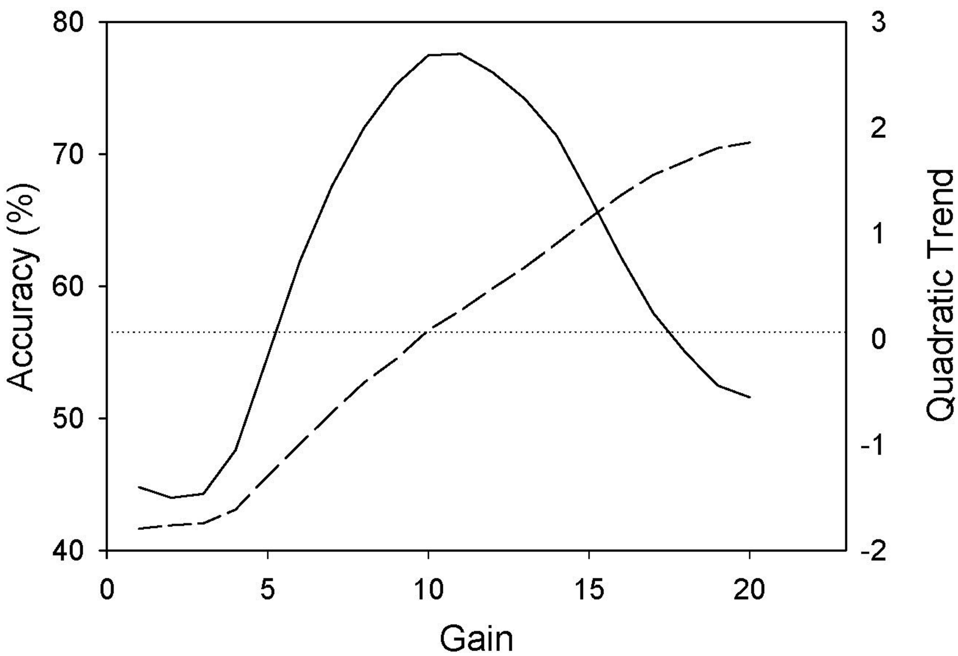

Fig. 5. Simulation of gain effects on overall accuracy and the orthogonal quadratic trend across targets. Each point represents 10,000 simulated trials. The solid line is overall accuracy (%), the dashed line is the quadratic trend across the target positions, and the dotted line is the 0 value for the quadratic trend. Optimal performance is achieved when the quadratic trend is near 0.

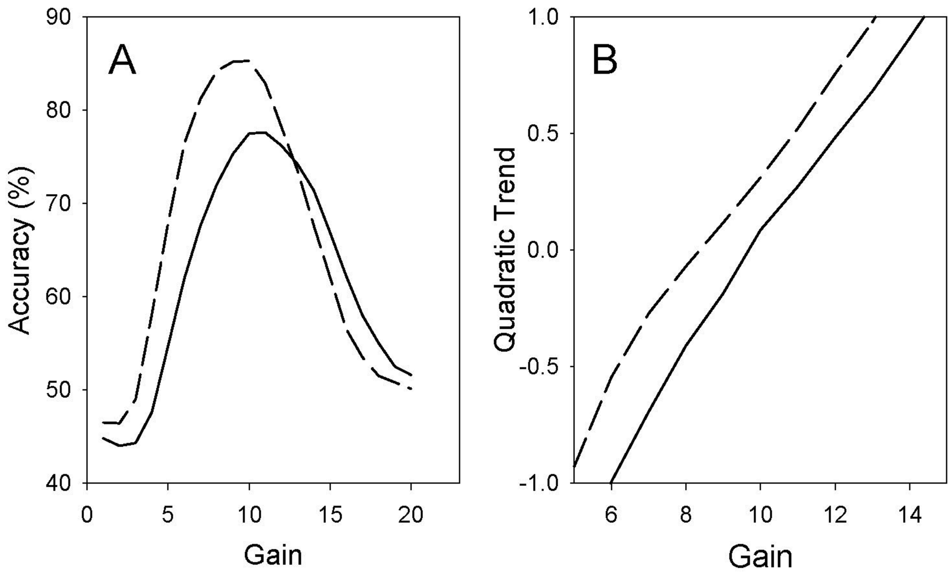

Fig. 6. Simulation of the effects of dwell time and gain on accuracy and the orthogonal quadratic trend across targets. Each point represents 10,000 simulated trials. The solid line represents a dwell time of 2 s and the dashed line represents a dwell time of 2.8 s. Maximum performance is greater for the longer dwell time. In addition, dwell time affects the optimal gain and the quadratic trend.

orthogonal quadratic trend is near 0. Thus, as indicated in the Methods section, we designed a controller that sought to minimize this trend.

Figure 6 shows the results of a simulation of the effects of gain for two different dwell times. The dwell time affects the optimal gain value and accuracy as illustrated in Fig. 6(A). This simulation suggests that longer dwell times are associated with greater accuracy and lower optimal gain. Fig. 6(B) shows that the quadratic trend for various gain values also depends on the dwell time.

Actual Data

As Fig. 7(A) shows, use of the controller during a between-run manipulation of dwell time resulted in effects on performance consistent with the simulations. Accuracy was greater with longer dwell time. However, longer dwell time was also associated with longer trial duration. To determine the effect of dwell time on information transmission, we computed bits, or B, according to the formula,

$$B = \log_2 N + P \log_2 P + (1 - p) \log_2[(1 - P)/(N - 1)] \quad (3)$$

As derived from Pierce (1980) and originally from Shannon and Weaver (1964). Here B is bits, N is the number of possible targets (four in the present case), and P is the probability that the target will be hit (i.e., accuracy). Bit rate is computed by dividing B by the trial duration in seconds. Other BCI researchers have used alternative metrics, but these don't take the number of targets into account (e.g., Levine et al., 2000). Analysis of the metric

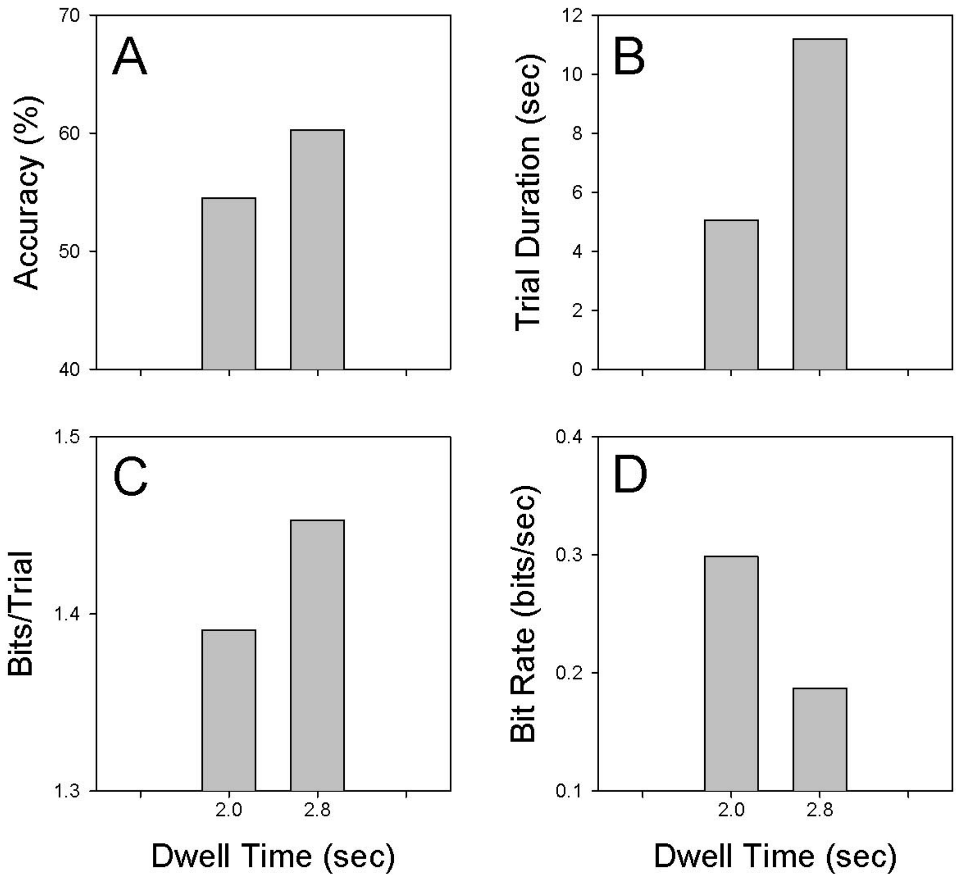

Fig. 7. Effects of dwell time on performance. Each value represents the mean of data from five participants (three sessions each). (A) shows that accuracy is greater for the longer dwell time [consistent with simulation results in Fig. 6(A). (B) shows that the trial duration increases with longer dwell times. The combination of these effects results in longer dwell times and more information (bits) per trial (C), but a lower bit rate (D).

derived from Eq. (3) showed that the additional time required by the longer dwell time reduced the information transfer rate (Fig. 7(D)). Figure 8 shows the output of the adaptive gain controller averaged over all participants for each of the two dwell times. The gain selected by the controller during this experiment was lower for the longer dwell time. This was consistent with the results of the simulation (Fig. 6).

DISCUSSION

This study examined the relationship between gain and accuracy in a one-dimensional cursor movement task. With four targets, large gains favored the end targets whereas smaller gains favored the central targets. In addition, the results of manipulating gain and dwell time within participants produces results that are in agreement with simulations based on a simple theoretical model of performance.

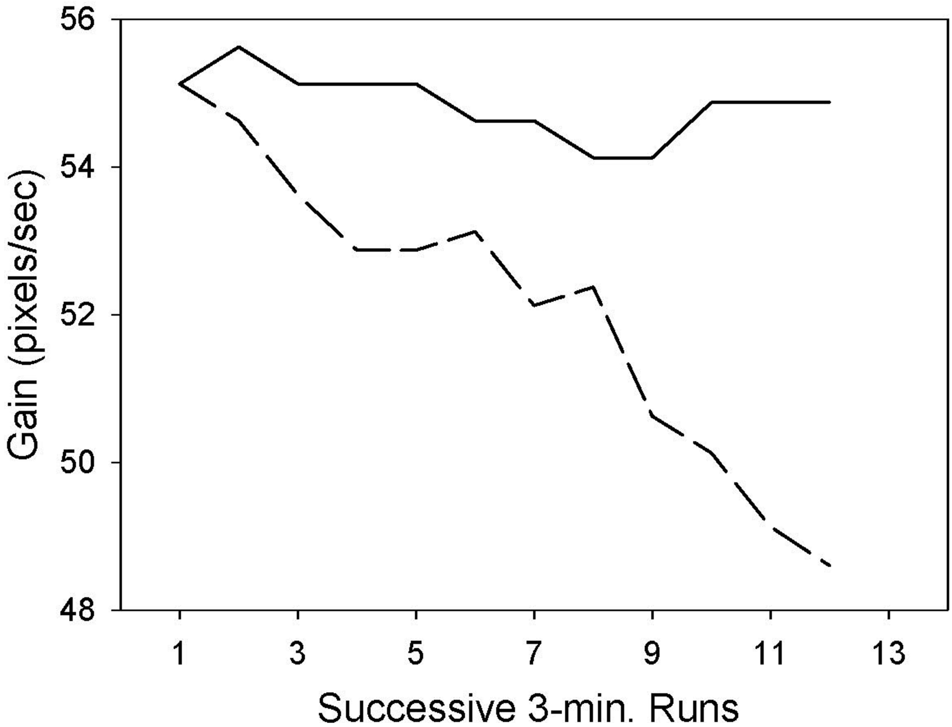

Fig. 8. Adaptation of the gain controller in five participants (three sessions each). The solid line represents a dwell time of 2 s and the dashed line a dwell time of 2.8 s. As predicted from the simulation shown in Fig. 6, the gain controller gradually reduced gains for the longer dwell time.

In general, most BCI studies do not examine parameters like gain in real-time experiments. We compared varying gain on single trials with varying gain between 3-min runs. Similar results were obtained. Varying parameters such as gain can be done between participants, between sessions, between 3-min runs, or between trials. The advantage of shorter intervals is that the data show less variability within conditions. We chose this approach despite the fact that it is technically more difficult to accomplish. However, it is obvious that this strategy will not work for all parameters one might wish to investigate.

The results of manipulating the cursor movement rate and dwell time within participants agree with simulations based on a simple model of performance. Together they suggest the utility of a controller that minimizes the linear and quadratic trends in the accuracy with which participants hit the four targets. This design makes the targets equally accessible and optimizes performance. The linear trend is associated with the intercept, a in Eq. (1), of the cursor control function and the quadratic trend is associated with the slope (b). In general, optimal performance appears to be associated with equal accessibility of targets. Thus, a gain controller similar to that developed here may help to optimize performance in other situations with a single control dimension and more than two possible targets.

Although not demonstrated formally, our initial experience with the four-target task used in this study indicated that performance would suffer greatly if reasonable gain values were not used. A skilled operator can make this type of adjustment. An automatic method such as that presented here frees the operator to attend to other details. In addition, to be useful for routine communication, BCI systems must ultimately not depend on the constant attention of a skilled operator. Additional considerations could be built into a gain controller that take into account the content presented in the targets (e.g., Perelmouter & Birbaumer, 2000). However, the equal probability case provides a reasonable initial approximation and is particularly appropriate for training purposes.

More generally, the present results show that it is possible to evaluate a simple model of BCI performance with empirical data. Although a complex model of human EEG may be necessary in certain cases, the present results suggest that a simple model captures relevant dynamics. This might be the case because gain effects are primarily related to the nature of the task rather than the dynamics of the user. The results also demonstrate the importance of considering individual differences in BCI performance and thus provide a motivation for designing adaptive systems. The adaptive controller used in this study makes the targets equally accessible to the user. This is important for two reasons. First of all, it optimizes current performance. Perhaps more importantly, it insures that the user can hit all of the targets. It is less likely that the user will learn the necessary skills if it is not possible (or probable) to select a given target. One of the most important aspects of user training is to allow the task to be solved.

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