Electroencephalographic(EEG)-based communication: EEG control versus system performance in humans

Hesham Sheikh*, Dennis J. McFarland, William A. Sarnacki, Jonathan R. Wolpaw

Laboratory of Nervous System Disorders, Wadsworth Center, New York State Department of Health and State University of New York, Empire State Plaza, Albany, NY 12201, USA

Abstract

People can learn to control electroencephalographic (EEG) sensorimotor rhythm amplitude so as to move a cursor to select among choices on a computer screen. We explored the dependence of system performance on EEG control. Users moved the cursor to reach a target at one of four possible locations. EEG control was measured as the correlation (r^2) between rhythm amplitude and target location. Performance was measured as accuracy (% of targets hit) and as information transfer rate (bits/trial). The relationship between EEG control and accuracy can be approximated by a linear function that is constant for all users. The results facilitate offline predictions of the effects on performance of using different EEG features or combinations of features to control cursor movement.
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Individuals with severe motor disabilities require alternative means of communication and control. All conventional augmentative communication and control technologies require some measure of muscle control (e.g. a power wheelchair with mouth controls). Thus, these technologies may not be useful to those with little or no muscle control. Such individuals could benefit from communication systems that do not depend on muscle control. Recent research in our laboratory and in others has focused on developing non-invasive brain–computer interface (BCI) systems (see Refs. [11,13,14] for review). These BCI systems allow people to use scalp-recorded electroencephalographic (EEG) activity to control a device such as a computer cursor.

Participants using the Wadsworth BCI learn to control the amplitude of 8–12 Hz mu and/or 18–24 Hz beta rhythms in the EEG recorded over sensorimotor cortex and use that control to move a cursor in one or two dimensions to select among choices on a computer screen [1,12,13]. With this system, people can answer questions [3] or spell words [8]. This EEG control does not depend on muscle activity [9], and thus provides participants with a new, non-muscular communication and control channel.

Our present work is focused on improving the speed and accuracy of BCI communication and control. In this effort, we collect comprehensive EEG data during online operation and analyze it offline to evaluate alternative EEG features or combinations of features. In these offline analyses, our principal goal is to predict whether and to what degree specific alternatives will improve speed and accuracy online. These predictions depend on knowledge of the online relationship between the user's control of specific EEG features (measured as the correlation (r^2) between the features and the location of the target (i.e. the location of the correct choice)) and system performance (measured as accuracy, or the percent of trials in which the target is hit). R^2 is a common index of prediction in statistical analysis. It is the proportion of variance in a dependent variable that is explained by a given statistical model (r^2 = explained sum of squares/total sum of squares) [15]. In the present case, we use the target location as the predictor, and r^2 is the proportion of the variance in the user's EEG feature that is accounted for by the target location. Thus, if the user has no EEG control r^2 will be 0, while if the user has perfect control, so that the EEG feature is completely determined by target location, r^2 will have its maximum value of 1.00.

To the extent that r^2 serves as a good predictor of system performance, it can be used in offline analyses of data previously collected to evaluate the potential online value of alternative EEG features. We sought to establish the validity

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* Corresponding author. Tel.: +1-518-474-7958 or +1-518-473-3631; fax: +1-518-486-4910.

E-mail addresses: sheikh@wadsworth.org (H. Sheikh), wolpaw@wadsworth.org (J.R. Wolpaw).

and usefulness of this approach by determining the actual relationship between r^2 and system performance in a number of representative users.

Four adults participated in this study. Users A, B, and C were men (aged 38, 29, and 40 years) and user D was a woman (aged 43 years). Two had no disabilities, while user C had a T7 spinal cord injury that confined him to a wheelchair and user D was deaf in her left ear. All users gave informed consent to the study, which had been reviewed and approved by the New York State Department of Health Institutional Review Board.

An initial session defined the scalp locations and EEG frequencies to be used for online cursor control (see below). The optimal locations and frequencies were user-specific and were continually monitored and periodically updated as previously described [1]. Prior to beginning this study, each user participated in ten 30 min sessions at the rate of two to three per week to develop EEG control and an additional four to 188 sessions devoted to a variety of studies.

During recording, the user sat in a reclining chair 2 m from a video screen and was asked to remain motionless. EEG was recorded from 64 standard scalp electrodes distributed over the entire scalp [6]. All 64 channels were referenced to the right ear, amplified $20,000\times$ with a bandpass of 0.1–60 Hz, digitized at 160 Hz, and stored for offline analysis. To control the cursor online, the power in a 3 Hz wide band obtained from an autoregressive spectral analysis of the spatially filtered signals from one to three scalp locations over the sensorimotor cortex was used in a linear equation to determine cursor movement.

Fig. 1 shows the online protocol. Each trial began when a target (i.e. the correct choice) occupying 25% of the height of the screen appeared at one of four locations (i.e. top, mid-top, mid-bottom, bottom) spaced along the right edge of the screen. Target location was block-randomized. One second later, the cursor appeared in the middle of the left edge and moved steadily across the screen in 2 s. Its vertical movement was controlled by the user's EEG as described below. The trial ended when the cursor touched the right
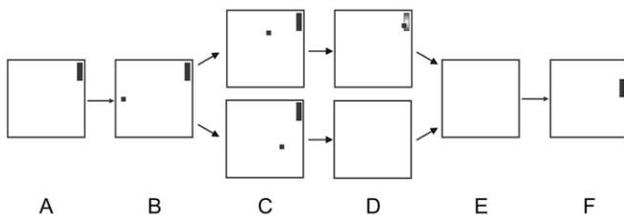
Fig. 1. Trial protocol. (A) A target occupying 25% of the right edge of the screen appears at one of four locations along the right edge of the screen. (B) One second later, the cursor appears in the middle of the left edge, and (C) moves steadily across the screen in 2 s with its vertical movement controlled by the user's EEG as described in the text. (D) The trial ends when the cursor touches the right edge of the screen. If it touches the target, the target flashes for 1 s as a reward and the computer registers a hit. If it touches one of the other three possible locations, the cursor and target disappear, and the computer registers a miss. (E) One second of blank screen precedes the beginning of the next trial (F).

edge of the screen. If it touched the target, the target flashed as a reward and the computer registered a hit. If it touched one of the other three locations, the cursor and the target disappeared and the computer registered a miss. The screen was blank for 1 s and then the next trial began.

During the 2 s in which the cursor moved steadily across the screen, its vertical movement was determined by the user's EEG as follows. Every 100 ms the most recent 200 ms of the spatially filtered EEG from one to three channels over the sensorimotor cortex [2] was analyzed by an autoregressive algorithm [1] to determine the amplitude (i.e. the square root of power) in a mu and/or beta rhythm frequency band. The one to three amplitudes were combined to give an EEG feature that was the independent variable in a linear equation that controlled vertical cursor movement (which thus occurred ten times/s). The slope and intercept of this equation were adjusted at the end of each trial as previously described [1,4,11].

Users completed two to three sessions per week. Each session comprised six or eight 3 min runs separated by 1 min breaks. Each run consisted of 32–35 trials. Users A and B contributed ten sessions, user C nine sessions, and user D six sessions. For all sessions, users A, B, C, and D achieved average accuracies of 70%, 73%, 70% and 38%, respectively (overall average accuracy 64%). With four choices, accuracy in the absence of any EEG control would be 25%. Thus, users A, B, and C displayed moderately good system performance, while user D's system performance, while better than chance, was poor.

EEG control was assessed by calculating r^2 values for each of the 3 min runs (32–35 trials) in each session. The mean power of all the 200 ms EEG segments in a trial was correlated with the target condition during that trial. Data were collected for 48–60 runs (six to ten sessions) for each user. R^2, the coefficient of determination, is the proportion of the variance of the amplitude accounted for by the target position [15]. It reflects the user's EEG control. System performance was measured both as accuracy, i.e. the % of trials in which the target was hit, and as bits/trial [10,11]. User control versus system performance was evaluated by regression analysis.

Fig. 2 illustrates typical EEG control with data from one session of user C. The top panel shows frequency spectra for the four target locations for the EEG channel that controlled cursor movement online. The main differences among the spectra occur in the mu rhythm band (centered at 13 Hz) and to a lesser extent in the beta band (centered at 27 Hz). The linear equation converted mu rhythm amplitude to vertical cursor movement. As Fig. 2 shows, mu rhythm amplitude varied appropriately with target position. The bottom panel shows r^2, the coefficient of determination [15], the proportion of the variance of the amplitude accounted for by the target position. As indicated above, this measure reflects the user's EEG control.

Fig. 3 presents the dependence of system performance on EEG control for the runs of each user. Accuracy is strongly
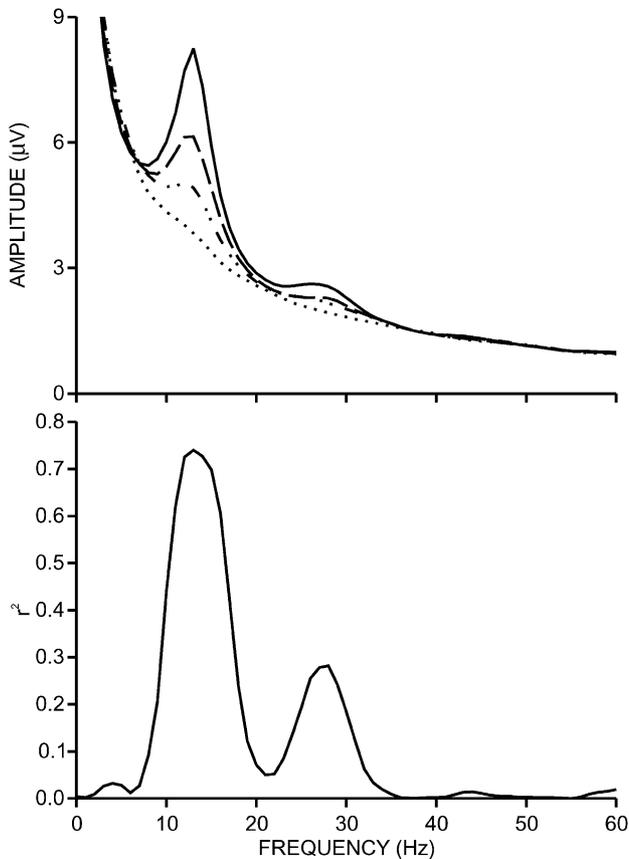
Fig. 2. Spectral focus of control from a user C session. (Top) Voltage spectra for top (solid), mid-top (dashed), mid-bottom (dashed-dotted) and bottom (dotted) targets for scalp locations that control online cursor movement (see text). (Bottom) Corresponding r^2 spectrum. EEG control is focused in the mu rhythm band (13 Hz) and to a lesser extent in the beta rhythm band (27 Hz).

correlated with EEG control: a highly significant linear correlation is present in each user.

To identify factors that determine the relationship between EEG control and system performance, we subjected the data shown in Fig. 3 to a multiple regression analysis. In this analysis the dependent variable was accuracy and the independent variables were the linear effect due to r^2 (i.e. to EEG control), the quadratic effect due to r^2, the user, and the interaction between r^2 and user. The linear effect of r^2 was significant ($r = 0.82$, $P < 0.0001$), but the quadratic effect was not ($r = 0.01$, $P = 0.64$). The effect of user was significant ($r = 0.33$, $P < 0.0001$), but the interaction of r^2 with user was not ($r = 0.04$, $P = 0.66$). The user effect simply indicates that system performance varied across users. At the same time, the lack of significant interaction between r^2 and user indicates that the slope of the linear regressions shown in Fig. 3 does not differ significantly across users. That is, a single slope accounts for the data of all four users; the prediction of performance from r^2 is not significantly improved by using a different slope for each user. It is also worth noting that the combined r for all data considered was

greater (i.e. $r = 0.88$, $P < 0.0001$) than r values obtained for any one user. This is due to the fact that the total body of data includes a greater range of values (for both r^2 and accuracy) than do the data of any one user, and it thus reflects the well-known effect of range restriction on correlation. At the same time, this equation for the combined data ($y = 0.6x + 0.3$) deviates from that expected from a simple linear relationship between r^2 and performance (i.e. $y = 0.75x + 0.25$). This difference probably reflects the effect of the dynamic factors such as those discussed below (e.g. spontaneous variation in user control).

The results indicate that the r^2 value of the EEG feature that controls cursor movement online is a good predictor of system performance. When performance is measured as accuracy, the relationship is linear (at least for the r^2 range covered by the present data) and similar across users. Thus, the r^2 values of alternative EEG features, which can be calculated offline from stored data, should furnish useful estimates of the online performance levels that these features are likely to provide. As Fig. 3 illustrates, these estimates are not perfect; accuracy may vary substantially from run to run even without a change in r^2. This variation may reflect intra-run variations in the user's EEG control and/or inter-run differences in the effectiveness of the automated online adaptations that modify the slope and intercept of the linear equation in response to spontaneous changes in the EEG features [11]. Such variations may affect accuracy and r^2 differently since accuracy is based on single-trial events while r^2 is based on the statistics of the entire run. These factors may also contribute to the fact that the performance provided by a given value of r^2 is higher for users A–C than for user D.
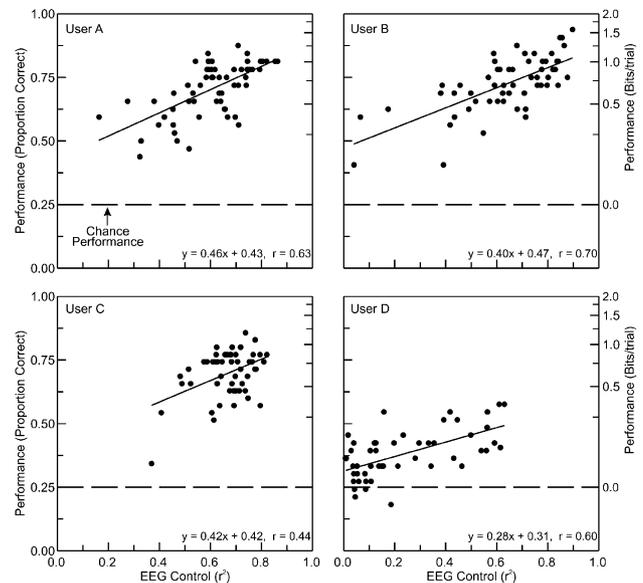
Fig. 3. EEG control (r^2) versus performance (accuracy and bit rate) for the EEG feature that controlled the cursor online. Linear regression lines with equations and r values are shown. Performance improves as EEG control improves.

Offline analyses based on r^2 calculations (or alternatively, on discriminant analysis) are more straightforward and efficient than those that depend on simulations of online performance. The difference is particularly marked for analyses aimed at predicting the online usefulness of combinations of EEG features, for in such cases simulations require extensive systematic evaluations of representative sets of weights for the different features and for the parameters used in the equations that translate these combinations of features into cursor movement.

At the same time, because online performance reflects the continuous interaction of the system and the user, an offline analysis can only predict the online effects of a given change in the system (such as use of a different or an additional EEG feature). As a result, the predictions derived from offline analyses must be tested online. Online evaluations are usually time-consuming and labor-intensive, much more so than offline analyses. Thus, the primary value of offline analyses is that they can indicate which alternatives are likely to be most successful and can thereby substantially reduce the number of online evaluations that are necessary.

In an earlier study, we used offline r^2 analysis to compare the potential value of EEG features derived by different spatial filters [2]. The analysis predicted that a common average reference (CAR) filter or a Laplacian filter with a specific electrode spacing would provide better online performance, and these predictions have proved correct. Furthermore, we routinely use r^2 analyses to determine for each new user the frequency band and scalp location of the EEG feature that controls cursor movement. The present study provides formal support for these uses of offline r^2 analysis.

Current work is employing r^2 analyses to identify combinations of different EEG features that are likely to improve performance. One recent study shows that, when cursor movement is controlled by mu or beta rhythm amplitudes, errors are accompanied by production of an error potential in the time-domain that might be used to improve performance [5]. Preliminary results of a second study suggest that mu or beta rhythm amplitudes can also be combined with another newly-defined time domain EEG feature to improve performance [7].

Fig. 3 illustrates another important consideration for efforts aimed at improving BCI performance. Relatively modest improvement in r^2, while it may produce only correspondingly modest improvement in accuracy, can yield a substantial improvement in bit rate, the amount of information transmitted per trial [10,11]. For example, for user A in Fig. 3, an r^2 increase from 0.60 to 0.80 increases accuracy by 13% (from 71% to 80%) while it increases bit rate by 44%. Thus, relatively small improvements in user EEG control can produce large improvements in information transfer rate, which is a standard measure of the performance of a communication system.

Acknowledgements

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