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Electroencephalographic (EEG) control of three-dimensional movement

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Abstract

Brain–computer interfaces (BCIs) can use brain signals from the scalp (EEG), the cortical surface (ECoG), or within the cortex to restore movement control to people who are paralyzed. Like muscle-based skills, BCIs' use requires activity-dependent adaptations in the brain that maintain stable relationships between the person's intent and the signals that convey it. This study shows that humans can learn over a series of training sessions to use EEG for three-dimensional control. The responsible EEG features are focused topographically on the scalp and spectrally in specific frequency bands. People acquire simultaneous control of three independent signals (one for each dimension) and reach targets in a virtual three-dimensional space. Such BCI control in humans has not been reported previously. The results suggest that with further development noninvasive EEG-based BCIs might control the complex movements of robotic arms or neuroprostheses.

S Online supplementary data available from stacks.iop.org/JNE/7/036007/mmedia

(Some figures in this article are in colour only in the electronic version)

1. Introduction

The adult CNS displays a large repertoire of adaptive behavior acquired through practice, usually referred to as skills. These skills are normally produced by muscles. In contrast, brain–computer interfaces (BCIs) enable people to communicate or to control devices by using brain signals rather than muscles. Thus, they can help people with devastating neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), brainstem stroke, cerebral palsy and spinal cord injury (Wolpaw and Birbaumer 2006).

Studies to date show that humans and animals can learn to use electroencephalographic activity (EEG) recorded from the scalp, electrocorticographic activity (ECoG) recorded from the cortical surface, or signals recorded within the cortex (neuronal action potentials or local field potentials (LFPs)) to control the movements of a cursor or other device in one or two dimensions (Wolpaw *et al* 1991, 2002, Chapin *et al* 1999, Fetz 1999, Serruya *et al* 2002, Taylor *et al* 2002, Carmena *et al* 2003, Andersen *et al* 2004, Wolpaw and McFarland 1994, 2004, Leuthardt *et al* 2004, Hochberg *et al* 2006, Schalk *et al* 2008, Velliste *et al* 2008, Ganguly and Carmena 2009). Three-dimensional (3D) control has been reported only for intracortical signals (i.e. neuronal action potentials) in monkeys (Taylor *et al* 2002, Velliste *et al* 2008).

Both actual movement and movement imagery are accompanied by changes in the amplitudes of certain EEG rhythms, specifically 8–12 Hz mu rhythms and 18–30 Hz beta rhythms. These changes are focused over sensorimotor cortex (Pfurtscheller *et al* 2008) in a manner consistent with the homuncular organization of this cortical region (Woolsey 1958). Thus, in our earlier demonstrations that people could learn to use EEG for two-dimensional (2D) movement control, we began the training process by using for control the mu- and/or beta-rhythms changes normally associated with left-hand or right-hand movement imagery (Wolpaw and McFarland 1994, 2004). In the present study, we extended this strategy to 3D control by beginning the training process from the mu- and/or beta-rhythm changes normally associated with left-hand, right-hand or foot movement imagery (Morash *et al*

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2008, Pfurtscheller *et al* 2008). The results show that EEG can support 3D movement control. Thus, they may accelerate the development of BCIs useful to people with severe motor disabilities.

2. Methods

The methodology is summarized here. Additional detail is available elsewhere (Wolpaw and McFarland 2004, McFarland *et al* 2006). The BCI users were four adults, one woman and three men, aged 29–59. One man (user 2) had a spinal cord injury (T7) and was confined to a wheelchair. Three had participated in earlier BCI studies (e.g., McFarland *et al* 2008), and one had no previous BCI experience. All gave informed consent for the study, which was reviewed and approved by the New York State Department of Health Institutional Review Board.

The BCI user sat in a reclining chair (or in his own wheelchair) facing a video screen and remained motionless. BCI operation and data collection were supported by the general-purpose BCI software platform BCI2000 (Schalk *et al* 2004) in conjunction with a 64-channel SA Instrumentation amplifier and a Data Translation DT-3003 64 channel A/D board. EEG was recorded from 64 scalp locations (Sharbrough *et al* 1991) by 9 mm tin electrodes embedded in a cap (Electro-cap International) and referenced to an electrode on the right ear, and was digitized at 160 Hz and stored for later analysis. Each user completed 2–3 sessions/week. A session comprised eight 3 min runs separated by 1 min breaks and each run averaged 14–25 trials.

For the first 1–4 sessions (i.e. 8–32 3-min runs totaling 24–96 min), the users practiced 1D control in each dimension of movement (i.e. vertical, horizontal and depth dimensions; 2–3 runs/session for each dimension). For the next 10–12 sessions (i.e. 80–96 runs totaling 4–5 h), they practiced 2D control with the three possible pairings of the three dimensions (i.e. 2–3 runs/session with each pairing). Finally, the users moved on to full 3D control, and each completed 21–42 sessions (i.e. 168–336 runs totaling 8–17 h) on the standard 3D task (figure 1). Performance on the 3D task improved steadily as each user gradually gained better control over the EEG features that controlled cursor movement, and as the iterative adaptive feature selection and weighting procedures (see below) progressively modified the set of EEG features used and adjusted their weights so as to vest control of cursor movement in those features that the user was best able to control. Training was continued until the progressive improvement over sessions was no longer clearly apparent (i.e. until performance began to asymptote).

To control each dimension of cursor movement (horizontal, vertical and depth), the digitized data from three or four electrodes over sensorimotor cortex of both hemispheres were re-referenced according to a large Laplacian transform (McFarland *et al* 1997). Every 50 ms, the frequency spectrum of the previous 400 ms segment from each electrode was computed by a 16th-order autoregressive algorithm (McFarland and Wolpaw 2008). The logarithms of the amplitudes in specific 3 Hz wide frequency bands

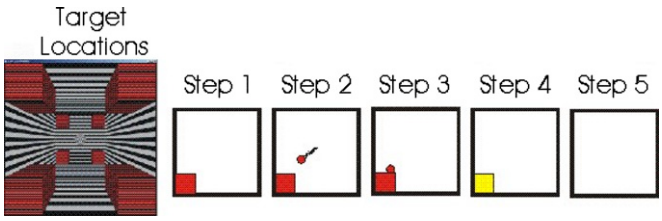

Figure 1. The 3D movement control format. The large screen image on the left shows the virtual 3D cube with the eight possible targets in the corners and the cursor in the center. The smaller screen images show the sequence of steps in one trial: (1) a target appears; (2) 1 s later the cursor appears and moves in three dimensions controlled by the user's EEG activity as described in the text; (3) the cursor reaches the target; (4) the target turns yellow for 1.5 s; (5) the screen is blank for 1 s and then the next trial begins. (Step 2 lasts up to 15 s. If the cursor does not reach the target in this time, the screen goes blank for 1.5 s prior to step 5.)

(center frequencies 10–31 Hz) were the EEG features that controlled cursor movements. One or more of these features comprised the control signal (i.e. the independent variable) in a linear equation that specified cursor movement in a particular dimension (McFarland *et al* 2006). That is, if ΔV was the vertical cursor movement, S_v was the control signal for vertical movement, b_v was the gain and a_v was the mean value of S_v for the user's previous performance,

$$\Delta V = b_v(S_v - a_v) \tag{1}$$

was the function that determined each vertical cursor movement. Similarly, if ΔH was the horizontal cursor movement,

$$\Delta H = b_h(S_h - a_h) \tag{2}$$

was the function that determined horizontal cursor movement. Finally, if ΔD was the cursor movement in depth,

$$\Delta D = b_d(S_d - a_d) \tag{3}$$

was the function that determined cursor movement in depth. Movements in each dimension occurred 20 times s^{-1}.

Initial feature selection was based on a preliminary screening in which the user imagined specific limb movements (Wolpaw and McFarland 1994). The user was asked to imagine left-hand, right-hand or foot movement. The features selected initially and at each of the periodic reevaluations came from electrodes located over sensorimotor cortex. Feature selection was then periodically updated between sessions by a stepwise multiple regression procedure (SAS Institute Inc.) (Wolpaw and McFarland 2004). Starting with no initial model terms, the feature that most reduced the residual variance (i.e. the variance not accounted for by target location), and did so with $p < 0.01$, was added to the model. Additional features were then added in the same fashion. After each new addition, a backward stepwise regression removed any variables for which p was >0.01. This process continued until no further features satisfied the addition/removal criteria.

The weights assigned to the selected features were determined by least-squares criteria according to the equation

$$(X'\ X)b = X'Y, \tag{4}$$

where X was an m by n matrix formed from the n observations of m features and Y was the vector of n values (i.e. target locations). Solving for b, the vector of feature weights gave

$$b = (X'X)^{-1}X'Y. \quad (5)$$

Following each of these periodic stepwise regression analyses, the features selected for each of the three linear equations were weighted according to its results. Then, after each trial, the weights assigned to these features were automatically adjusted by the LMS algorithm (Haykin 1996) so as to optimize for each dimension the correlation between target location and cursor position. This continual automatic adaptation used past performance to optimize the feature weights (Wolpaw and McFarland 2004).

For the online update of feature weights, a prediction error was computed for each control signal at the end of each trial:

$$e_t = p_t - o_t, \quad (6)$$

where p_t is the predicted target position on the current trial based on the current values of the features and o_t is the actual target position on the dimension in question. Then the weights were updated according to

$$w_{it} = e_t r w_{it-1}, \quad (7)$$

where w_{it} is the weight at the end of the current trial for the ith feature and r is a constant that determines the rate of adaptation.

The objective of this feature selection and weighting process was to minimize, for each dimension, the squared difference between the actual target position and the cursor position predicted by the EEG control signals. Both the stepwise feature selection and online adaptive algorithms used these same criteria. In summary, to the extent that past performance predicted future performance, these procedures served to optimize for each dimension the correlation between target location and cursor movement (Wolpaw and McFarland 2004).

3. Results

Table 1 shows, for each user's final training sessions, the set of EEG features (specific frequency bands from specific scalp electrodes) that comprised the independent variable for each of the three linear equations that controlled the three movement dimensions. These feature sets were the result of the iterative adaptive interactions over the course of training between each user's control capacities and the feature selection and weighting procedures described in section 2.

As previously noted, each user completed 21–42 3D sessions, and 3D control gradually improved over these sessions. Figure 2 shows this gradual improvement (as percent of trials completed within 7 s) for each user. The data from the first 21 sessions, for which there were data from all four users, were evaluated by ANOVA. The effect of sessions was significant ($F = 3.84$, $p < 0.0001$), and thus confirmed that performance improved with continued practice. Performance improved as each user gradually gained better control over the EEG features that controlled cursor movement, and as the iterative adaptive feature selection and weighting procedures

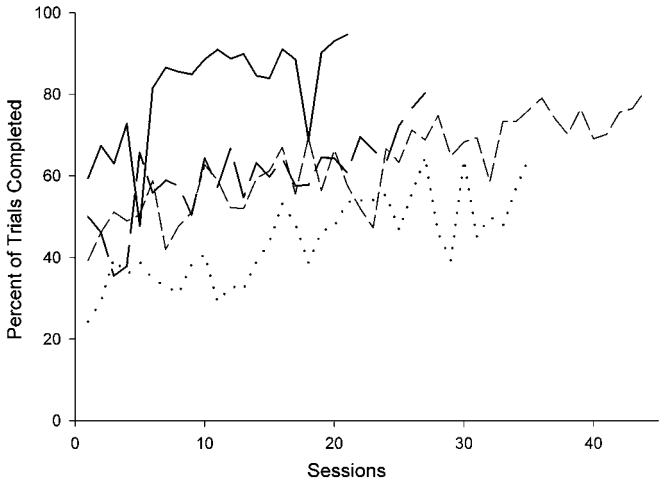

Figure 2. Percent of trials completed for each user as a function of sessions. User A is represented by the solid line, user B by the large dashed line, user C by the small dashed line and user D by the dotted line. Note each user's gradual improvement over sessions.

Table 1. The EEG features (specific frequency bands at specific scalp electrodes) that controlled vertical, horizontal and depth cursor movements for each user. For each feature, the scalp electrode (Sharbrough *et al* 1991) and the center frequency of the 3 Hz wide frequency band (in parenthesis) are given.

	Electrode (frequency)		
User	Vertical	Horizontal	Depth
1	Cz (26) CPz (26)	C4 (26)	C3 (26)
2	Cz (24)	C3 (12) C4 (12)	C4 (12)
3	Cz (19) Cz (31)	C3 (10) C4 (10)	C3 (10)
4	Cz (20) CPz (20) CPz (29)	C3 (23) C4 (23)	C3 (20) C3 (23)

(see section 2) periodically modified the set of EEG features used and adjusted their weights so as to vest control of cursor movement in those features that the user could best control. Figure 3 illustrates these progressive changes in user control and in the features used for control with data from one user at early, middle and late stages of training.

Using three consecutive 3D sessions at the end of training (336–608 trials from each user), we assessed EEG control and the cursor movement control that it provided. We assessed EEG control by spectral and topographical analyses of the correlations of the average values for each trial of the vertical, horizontal and depth control signals with the vertical, horizontal and depth locations of the target (Wolpaw and McFarland 1994, 2004). Table 2 gives, for each user, the correlation of each dimension's control signal with each of the three dimensions of target position. As table 2 shows, each control signal correlated strongly with its own dimension of target location and showed no or much lower correlations with the other two signals' dimensions of target location. Thus,

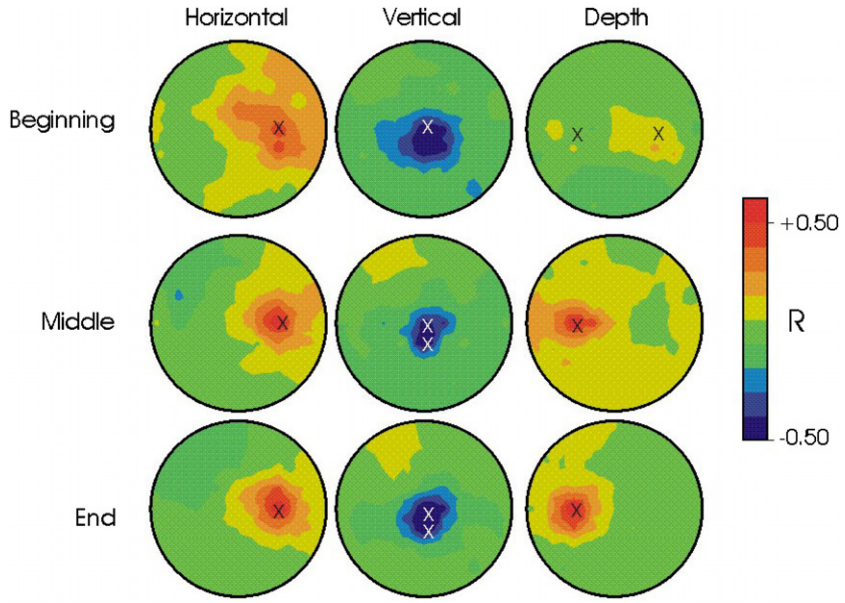

Figure 3. Topographies for user 1 at the beginning (sessions 1–3), middle (sessions 10–12) and end (sessions 19–21) of 3D training, for the correlations at each of the 64 electrodes between the spectral amplitude of the EEG and each dimension of target location. For each dimension of target location, the topography is for the 3 Hz frequency band centered at 26 Hz that provided that dimension's online control signal (i.e. table 1). (The correlations are shown as R rather than R^2 to distinguish negative and positive correlations.) 'X' indicates the locations of the electrodes that provided the frequency-band amplitudes that were used online. Note the changes over time in the topographies and magnitudes of control and in the electrodes used for control. The progressive improvement in performance summarized in figure 2 is accounted for by the increases in the user's control in the horizontal and depth dimensions, together with the adaptive algorithm's modifications in the electrodes used for control in the vertical and depth dimensions.

Table 2. Correlations (as R^2) of the vertical, horizontal and depth control signals (S_V, S_H, S_D) with their appropriate (highlighted) and inappropriate dimensions of target location (V, H, D). Each control signal is correlated exclusively or most strongly with its own dimension of target location.

	Vertical signal (S_V)			Horizontal signal (S_H)			Depth signal (S_D)		
User	$\boldsymbol{S_V}$**–***V*	S_V–H	S_V–D	$\boldsymbol{S_H}$**–***H*	S_H–V	S_H–D	$\boldsymbol{S_D}$**–***D*	S_D–V	S_D–H
1	**0.39**	0.01	0.00	**0.50**	0.00	0.00	**0.57**	0.00	0.00
2	**0.29**	0.01	0.14	**0.37**	0.00	0.16	**0.16**	0.00	0.00
3	**0.37**	0.03	0.28	**0.47**	0.09	0.04	**0.15**	0.04	0.01
4	**0.20**	0.00	0.03	**0.09**	0.00	0.01	**0.09**	0.00	0.00

users developed three independent control signals: one for each movement dimension.

Across the four users, performance did not correlate with amount of 3D training. User 1, who achieved the best control (table 2), had the least number of 3D training sessions (21 sessions, or 8.4 h). User 4, who achieved the least control, had 29 3D sessions (11.6 h), while users 2 and 3 had 26 and 42 (10.4 and 16.8 h), respectively. (User 2 was the person with a spinal cord injury.) Nor did performance correlate clearly with total amount of BCI training (i.e. including participation in previous studies). Users 1–4 had total BCI experience of 102, 367, 115 and 57 h, respectively. While the least successful user had the least experience, the most successful user had less experience than user 2 or 3. The differences in performance evident in table 2 may reflect inter-user differences in the prominence of sensorimotor rhythms in the scalp-recorded EEG (i.e. differences in signal-to-noise ratio) and/or in the effectiveness of the interactive adaptations in the algorithm and the brain over the course of training. Further improvements of the user-specific adaptations in the feature extraction and translation procedures might enable more users to achieve good performance.

To determine whether the users were controlling the three dimensions simultaneously or sequentially (e.g., moving up, then right, then forward), we evaluated for the first 0.5 s of each trial the individual movements in each of the three dimensions (which occurred every 50 ms) to determine whether a correct movement (i.e. toward the target) in one dimension affected the probability that the simultaneous movements in the other two dimensions were correct. If the users were controlling the dimensions sequentially (i.e. one at a time), the probability that a correct movement in one dimension was accompanied by correct movements in the other two dimensions would be less than that predicted by simply multiplying the fractions of all vertical, horizontal and depth movements that were correct together. This was not the case: the actual probabilities of simultaneous correct movements were 145%, 164%, 151% and 181% of their expected values for users 1–4, respectively. The fact that these probabilities were greater than 100% of expectation indicates that the users were not simply controlling

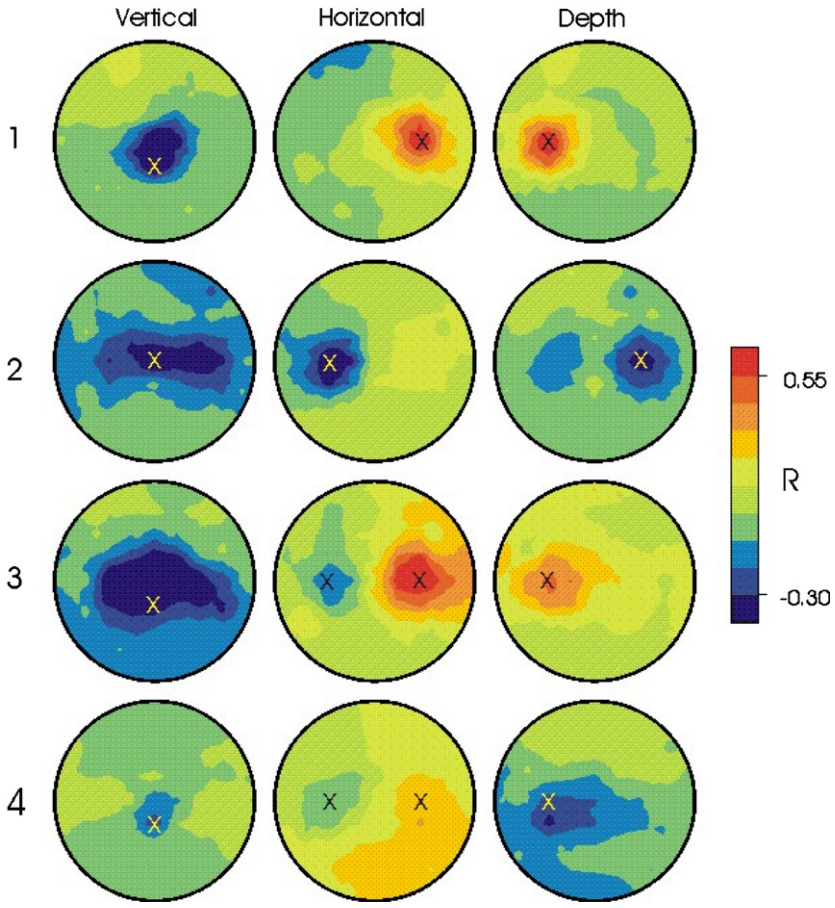

Figure 4. Topographies (nose at top) for each user (1–4) of the correlations for each of the 64 electrodes between the spectral amplitude of the EEG and each dimension of target location. For each dimension of target location, the topography is for the frequency band that made the largest contribution to that dimension's online control signal. (The correlations are shown as R rather than R^2 to distinguish negative and positive correlations.) 'X' indicates the locations of the electrodes that provided the frequency-band amplitudes that were used online. The center frequencies of the 3 Hz frequency bands of each user's topographies are given in table 1. While the correlations are all focused over sensorimotor cortex, they differ markedly across users as a result of inter-user differences in the course of the iterative adaptive interaction between user and system that occurs during training (see section 2). For example, user 1 controlled the three movement dimensions with 26 Hz activity from three different scalp electrodes, while user 3 controlled vertical movement with the left–right difference in 10 Hz activity, horizontal movement with 19 Hz and 31 Hz activity at the vertex, and depth movement with 10 Hz activity on the left.

one dimension at a time; they were controlling the three dimensions simultaneously.

Figure 4 shows, for each user, the topographies (nose at top) of the correlations for each of the 64 electrodes between the spectral amplitude of the EEG and each dimension of target location. For each dimension of target location, the topography is for the frequency band that made the largest contribution to that dimension's online control signal. 'X' indicates the locations of the electrodes that provided the frequency-band amplitudes that were used online. Table 1 gives the frequencies of the topographies. While the correlations are all focused over sensorimotor cortex, they differ markedly across users as a result of the iterative adaptive interactions during training between the brain and the feature selection and weighting procedures.

Figure 5 shows user 1's control in more detail. Figure 5(A) shows the topographies of the correlations of 26 Hz activity (table 1) with the three dimensions, with the electrode(s) that controlled each dimension marked. Figure 5(B) shows the spectra for the correlations (as R^2) between activity at the electrode that made the largest (or only) contribution to the control signal for that dimension and the target location in that dimension. Each feature correlates strongly with its appropriate dimension of target location and not with the other dimensions. Figure 5(C) shows single EEG traces from electrodes used in the vertical, horizontal and depth control signals for trials in which the target was at the top or bottom, right or left, or back or front of the cube, respectively (figure 1). They illustrate the strong EEG feature control the user employed to move the cursor to the target.

The EEG control summarized in table 2 and illustrated in figures 4 and 5 gave each user 3D movement control. Users 1–4 reached the target within the time allowed in 93%, 78%, 76% and 56% of the trials, respectively, and their median movement times for these completed trials were 1.6, 2.9, 3.2 and 4.9 s, respectively. Furthermore, the first of the eight possible target locations reached by the cursor correlated strongly with the actual target location ($P < 0.0001$ by χ^2 for each user), indicating that movement was not random. Supplementary videos S1 and S3

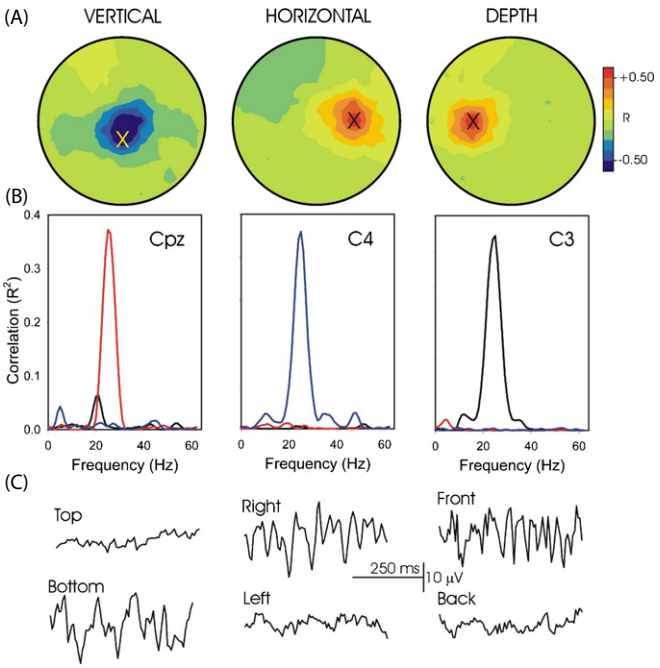

Figure 5. Topographical and spectral properties of EEG control for user 1. In this user, movement in each dimension was controlled by 26 Hz activity from specific scalp electrodes (table 1). (A) Scalp topographies (nose at top) of the correlations of the 26 Hz frequency band with the vertical, horizontal and depth target locations, respectively. The electrode(s) that controlled each dimension of movement are marked. (The correlations are shown as R rather than R^2 in order to distinguish negative and positive correlations.) (B) Spectra for the correlations (shown as R^2) of the activity at the scalp electrode that made the largest (or only) contribution to the control signal for each dimension of cursor movement with the three dimensions of target location. The correlations with the vertical, horizontal and depth dimensions are red, blue and black lines, respectively. It is clear that activity at the electrode that provided each control signal correlated strongly with its appropriate dimension of target location and did not correlate with the other dimensions. Furthermore, the correlation was focused in the appropriate (i.e. in this case, 26 Hz) frequency band. (C) Samples of EEG activity from single trials. The traces are single 400 ms epochs of Laplacian-derived EEG from one electrode. On the left are traces from scalp electrode CPz (the major source of the vertical control signal) for trials in which the target was at the top or bottom of the cube. In the middle are traces from electrode C4 (the source of the horizontal control signal) for trials in which the target was on the right or left side of the cube. On the right are traces from electrode C3 (the source of the depth control signal) for trials in which the target was at the front or back of the cube. They illustrate the strong 26 Hz control that the user employed to move the cursor to the target.

(available at stacks.iop.org/JNE/7/036007/mmedia) show the average trajectory to each target for users 1 and 3, respectively. Supplementary videos S2 and S4 (available at stacks.iop.org/JNE/7/036007/mmedia) show real-time performance for users 1 and 3, respectively. While both users have 3D control (i.e. table 2), user 1's performance is clearly superior.

An ancillary study started the cursor from locations other than the center of the cube (i.e. near the corner opposite the target). In spite of the variable starting points and the greater distance to the target, the percent of targets reached did not differ significantly from the percent reached with the standard (center start) format ($p > 0.25$ by ANOVA).

We also evaluated forearm and calf EMG activity during performance. EMG activity was usually well below 10% of MVC throughout and uncorrelated with target location. In the few instances in which EMG did correlate with target location in a particular dimension, the correlation of the EEG control signal with target location remained significant after the effect of the EMG correlation was removed. The results confirmed previous data (e.g., Vaughan *et al* 1998, Wolpaw and McFarland 2004) indicating that EEG-based cursor control does not depend on covert contractions of muscle groups strongly represented in the sensorimotor cortex areas that produce the EEG features used for control.

4. Discussion

The results show that people can learn to use scalp-recorded EEG activity to control three movement dimensions simultaneously and independently (table 2). This control develops through training as the user gradually acquires better control of the EEG features that control movement, and as the BCI system gradually focuses on those features that the user can best control. Thus, 3D control is basically a skill (i.e. an ability acquired through practice (Brown 1993)) that user and system master together. Users did not have greater difficulty acquiring control of the second or third dimension than they did acquiring control of the first dimension. They did need further practice to control three dimensions simultaneously. As training proceeded and performance improved, users reported that the motor imagery they initially employed became less important and cursor control became more automatic. In this characteristic, the skill of EEG-based 3D movement control resembles conventional motor skills, in which training leads to automaticity and to performance that is less dependent on attention (Moors and de Houwer 2006).

Given this understanding of 3D control as a skill acquired through practice, appropriate modifications in the training protocol might be expected to facilitate learning and improve final performance. For example, table 2 indicates that several users were less successful in controlling cursor movement in the depth dimension than in the horizontal and vertical dimensions. This difference could be due in part to the fact that the depth dimension was less salient in the display that we used (i.e. figure 1, videos 2 and 4 available at stacks.iop.org/JNE/7/036007/mmedia). Thus, adding binocular cues for depth (e.g. through a stereoscopic display) might facilitate the user's acquisition of depth control.

This demonstration of EEG-based 3D movement control has practical implications. It suggests that, with further development, EEG-based BCI systems might prove capable of restoring movement control to people who are paralyzed.

4.1. The factors important for movement control

The factors that determine the control possible with EEG, ECoG and intracortical BCI methods are as yet unknown.

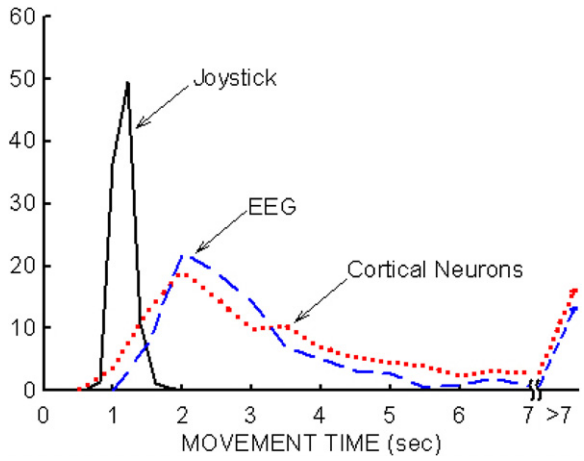

Figure 6. Distributions of target-acquisition times (i.e. time from target appearance to target hit) on a 2D center-out cursor-movement task for joystick control, EEG-based BCI control, and cortical neuron-based BCI control. The EEG-based and neuron-based BCIs perform similarly, and both are slower than and much less consistent than the joystick. For both BCIs in a substantial number of trials, the target is not reached even in the 7 s allowed. Such inconsistent performance is typical of movement control by present-day BCIs, regardless of what brain signals they use. (The joystick data and neuron-based BCI data are from Hochberg *et al* (2006). The EEG-based BCI data are from Wolpaw and McFarland (2004).)

Many efforts to develop BCI multidimensional movement control have started from the assumption that high-resolution signals are essential, and thus they have used intracortical electrodes to record neuronal action potentials or local field potentials (Serruya *et al* 2002, Taylor *et al* 2002, Carmena *et al* 2003, Ganguly and Carmena 2009, Andersen *et al* 2004, Hochberg *et al* 2006, Velliste *et al* 2008). Intracortical methods provide the highest resolution signals. At the same time, they face difficulties in ensuring stable long-term function (Otto *et al* 2008), and the information available from neurons may have inherent limitations (Rokni *et al* 2007). Furthermore, by demonstrating EEG-based 3D control in humans, the present study adds to recent evidence suggesting that signal resolution may not be the critical limiting factor.

Figure 6 shows the distributions of target-acquisition times for two studies of center-out 2D control in humans, one using a cortical neuron-based BCI (Hochberg *et al* 2006) and one using an EEG-based BCI (Wolpaw and McFarland 2004). The figure also includes the distribution of times for conventional muscle-based joystick control. The two BCIs studies had similar protocols, and they yielded nearly identical distributions of target-acquisition times. Both are slower and far less consistent than joystick control. Even after the considerable BCI training provided in each study, performance remains inconsistent. Such inconsistency is typical of BCI studies (e.g., compare supplementary videos 1 and 8 of Hochberg *et al* (2006)), including the present one. Indeed, the most striking feature of the comparison in figure 6 is the close similarity of the two BCI distributions. This similarity is remarkable, given that one BCI used single-neuron activity recorded within the cortex while the other used EEG recorded from the scalp. It suggests that their inconsistency was not related to signal resolution (which was high for the neuronal BCI and low for the EEG BCI), but rather reflects another factor that similarly limits both high-resolution and low-resolution BCI methods.

Movement control has been traditionally viewed as highly localized (e.g., Woolsey 1958). However, recent work indicates that movements are controlled by distributed cortical networks that include not only primary motor cortex, but other areas as well (e.g., premotor, prefrontal) (Dum and Strick 2002, 2005, Aflalo and Graziano 2006, Meier *et al* 2008, Ledberg *et al* 2007). These networks appear to function through synchronous oscillations in their constituent parts (Bullmore and Sporns 2009, Salinas and Sejnowski 2001, Sejnowski and Paulsen 2006, Zhang *et al* 2008). This new understanding suggests that present-day BCI movement control may be limited and inconsistent (e.g., figure 6) in large part because it relies only on signals from a single cortical area. Neuron-based control has typically focused on neurons from a few cubic mm of cortex, and has begun by using the neuronal activity observed during actual movements (e.g., Andersen *et al* 2004, Hochberg *et al* 2006, Velliste *et al* 2008). Similarly, EEG-based control has focused on rhythms recorded over sensorimotor cortex, and has begun by using the rhythm changes observed during movement imagery (e.g., McFarland *et al* 2008, Wolpaw and McFarland 1994, 2004).

This new understanding of the highly distributed nature of motor control suggests that the performance of BCIs, whether they use EEG, ECoG or intracortical signals, might possibly be improved by extracting signal features from multiple cortical areas and using adaptive algorithms similar to that of the present study to combine them to control movements. Employing signals from multiple areas might allow BCI operation to more closely mimic normal neuromuscular movement control. We speculate that, by eliminating the limit that may be imposed on BCIs that use only one area, this approach might allow the control capacities of the different signal types to be more fully realized and could produce more reliable performance. Furthermore, identification of the combinations of areas that perform best could illuminate the interactions most critical for movement control.

4.2. Development of BCIs to restore movement control

The primary goal of BCI research is to restore communication and control to people with severe motor disabilities. This study advances the goal in two ways. First, its demonstration of EEG-based 3D control suggests that BCIs capable of controlling neuroprostheses, robotic arms or comparable devices might not require surgical implantation of recording electrodes. This work complements and extends the recent demonstration that an EEG-based BCI can control a sequential movement-selection (i.e. reach-and-grasp) action (McFarland *et al* 2008).

Second, the present demonstration that EEG can support 3D movement control should facilitate evaluation of the hypothesis that consistency can be improved by using signals from multiple cortical areas. The inconsistency of the movement control provided by current BCIs, regardless

of which signals they use, is probably the single greatest impediment to their practical use. Unless and until BCI-based movement control becomes consistent, it will remain a laboratory curiosity, with little value to people who need to operate neuroprostheses or robotic devices in their daily lives. Because EEG is noninvasive, BCI research studies can readily record EEG from multiple areas and explore the usefulness of their various combinations. Furthermore, by doing this they might also suggest promising combinations of areas for exploration with high-resolution invasive methods. By demonstrating the potential of EEG-based BCIs, the present results show that EEG is a valid avenue for studying the value of combining signals from different areas, and they thereby encourage such studies.

Efforts to realize the clinical potential of EEG-based movement control must also address other important issues. These include the achievement of continuous sequential control, such as the ability to move to a location, to stay there while performing another action, to immediately move to another location, etc. Also important for practical applications will be development of improved training methods and better adaptive algorithms to enable most users to attain, and maintain, good control after relatively brief training. As hypothesized above, algorithms that use features from additional brain areas and/or measures of cross-channel relationships might possibly provide more reliable control (Varela *et al* 2001). Such expanded algorithms will need to incorporate better methods for identifying the most useful signal features from among a large feature set on the basis of relatively limited bodies of data (i.e. better regularization methods). In real-time BCI applications, the data most useful for selecting signal features are those from very recent performance, and these data are necessarily limited in amount. With such limited data, an algorithm that lacks effective regularization tends to overfit the data from a user's recent performance and thus provides parameter values that are not appropriate for future performance (i.e. they do not generalize well). While the present study used stepwise regression methods to select features, alternative procedures (e.g., Tibshirani 1996, Farquhar 2009, van Gerven 2009) might prove more effective.

5. Conclusions

By demonstrating that an EEG-based BCI can support 3D movement, this study shows that high signal resolution is not essential for complex movement control and suggests that other factors are more important. We hypothesize that combinations of signals from multiple cortical areas might produce more consistent performance. With further development, it may eventually become possible for people with severe neuromuscular disorders to operate devices such as a robotic arm, a motorized wheelchair or a neuroprosthesis with brain signals recorded from the scalp.

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