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Prediction of human voluntary movement before it occurs

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ABSTRACT

Objective: Human voluntary movement is associated with two changes in electroencephalography (EEG) that can be observed as early as 1.5 s prior to movement: slow DC potentials and frequency power shifts in the alpha and beta bands. Our goal was to determine whether and when we can reliably predict human natural movement BEFORE it occurs from EEG signals ONLINE IN REAL-TIME.
Methods: We developed a computational algorithm to support online prediction. Seven healthy volunteers participated in this study and performed wrist extensions at their own pace.
Results: The average online prediction time was 0.62 ± 0.25 s before actual movement monitored by EMG signals. There were also predictions that occurred without subsequent actual movements, where subjects often reported that they were thinking about making a movement.
Conclusion: Human voluntary movement can be predicted before movement occurs.
Significance: The successful prediction of human movement intention will provide further insight into how the brain prepares for movement, as well as the potential for direct cortical control of a device which may be faster than normal physical control.

1. Introduction

Much of human movement is considered volitional. Though the concept of the voluntariness has been considered within the scope of philosophy, many physiologists have now been studying it (Hallett, 2007). Kornhuber and Deecke recorded EEG signals associated with human self-paced voluntary finger movement (Kornhuber and Deecke, 1965) and identified a slow, negative DC potential occurring as early as 1.5 s before the production of the movement. The DC potential prior to human voluntary movement was named the Bereitschaft potential (BP), and the term movement-related cortical potential (MRCP) is a later developed term that refers to all the potentials related to movement. The BP itself can be spatiotemporally divided into two components; BP1 or early BP that starts from 1.5 s before voluntary movement, a slow negative slope maximized over the central-medial scalp; and BP2 or late BP that usually starts from 400 ms before voluntary movement and has a steeper negative slope lateralized over the primary motor area (Shibasaki and Hallett, 2006). Besides the slow DC potentials, frequency power changes are also associated with the production of human voluntary movement. Pfurtscheller et al. reported a short-lasting block/decrease of frequency power or event-related desynchronization (ERD) in the alpha band (8–12 Hz) (Pfurtscheller and Aranibar, 1979) and in the central beta band (16–24 Hz) (Pfurtscheller, 1981) beginning about 2 s before self-paced button pushing. Different from the DC potentials, the ERD in the alpha and beta bands starts bilaterally over primary motor areas. ERD in the beta band is largely contralateral before dominant hand movement, whereas it is bilateral before non-dominant hand movement (Bai et al., 2005). Thus, the evidence shows that the brain is activated as early as 1.5–2 s before the actual execution of voluntary movement. Therefore, we may potentially predict movement intention earlier than the actual movement if we can reliably detect the features from the pre-movement slow DC potentials or ERD from EEG signals.

Libet et al. performed a series of studies investigating human awareness of voluntary movement (Libet et al., 1983; Libet, 1990, 1991). Subjects were asked to make spontaneous voluntary movements and record the time when they felt the first awareness of the urge to move. EEG was recorded during this task and the BP was used to assess pre-movement cortical activity. The subject's perception of awareness of the intention to move occurred 500–800 ms following the onset of the movement-related cortical

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activity. This was interpreted to mean that initiation of a voluntary act may begin without conscious awareness.

Recent neural engineering efforts feature a rapid growth of interest in the development of a brain–computer interface (BCI) or brain–machine interface (BMI). BCI or BMI provides an alternative communication/control pathway so that paralyzed patients may control external devices from their brain directly. Using external assistive devices such as a wheelchair or robotic arms, patients may partly restore their motor function (Wolpaw, 2007). Conventional BCIs can utilize non-motor activities, such as the P300 related to attention (Donchin et al., 2000; Sellers and Donchin, 2006), or the steady state visual evoked potential (SSVEP) related to visual processes (Bin et al., 2008; Muller-Putz and Pfurtscheller, 2008). BCIs do not necessarily operate from single trials or single events; the P300 BCI obtains the potential by averaging over a number of trials. Previous motor-related BCIs use activity during physical movement or motor imagery ('thought' of limb movement) with or without feedback, and some used averaged activity from multiple movements (Mason and Birch, 2000; Pfurtscheller et al., 2006). A BCI may also rely on post-movement activity as developed in our group (Bai et al., 2008; Battapady et al., 2009; Huang et al., 2009; Bai et al., 2010), and Purtscheller's group (Pfurtscheller and Solis-Escalante, 2009). Since we now want to predict voluntary movement, only the activity associated with motor preparation before the movement can be used. Moreover, to predict in real-time we must use online data and perform calculations very rapidly. Though there were two papers related to offline or simulated online prediction of movements in single trials (Loukas and Brown, 2004; Morash et al., 2008), the prediction of movement online in real-time before movement occurs is a novel approach, which to our knowledge, has not been reported before.

Our goal was to test whether we could reliably predict human voluntary movement BEFORE natural movement ONLINE IN REAL-TIME from scalp EEG signal; and further to determine when a reliable prediction can be made. The major technical challenge for this investigation is the low signal-to-noise ratio of single-trial EEG signals associated with movement preparation before movement occurs. The amplitude of the slow DC potentials of BP in EEG is about 8–10 μV, and the BP is generally only evident after averaging about 40–50 trials of repeated voluntary movements. Considering that the amplitude of spontaneous activity of EEG is in the range of 100 μV, the online detection of the small activity of BP is extremely difficult. In particular, it is more difficult to detect early activity of the BP1, which has an amplitude around 2–3 μV. In contrast to the DC potential, the ERD or power decrease in alpha and beta bands can sometimes be observed in a single-trial EEG signal. Though the ERD is maximal at movement onset and the amplitude of the early ERD (before movement) is usually smaller, the ERD might be a relatively better feature for real-time online prediction compared to the BP. For the prediction problem, the performance is determined both from the false positive rate (specificity) and false negative rate (sensitivity), and the trade-off between them. A reliable prediction, however, is in favor of a low false positive rate such that once we make a positive prediction an actual movement will occur shortly thereafter, whereas some misdetections of voluntary movement may be less important. Therefore, ideally the goal would be to reliably make prediction with a low false positive rate under a reasonable sensitivity or false negative rate.

BCIs are developed as an alternative pathway to restore communication or control in paralyzed patients who cannot make voluntary movement. The objective for this study is different from that of previous BCIs; we want to predict natural movements, not identify movement once it has already occurred. In the BCI context, this should make movement seem more natural. Success in this endeavor may also have applications in human physiology. For example, early prediction might help to understand when and how humans initiate voluntary movement, and to allow the development of new interventions to change or terminate some intended movements. Thus this work will extend the capacity of state-of-the-art BCIs.

2. Methods

2.1. Subjects

Seven healthy volunteers (Six males and one female; 22.6 ± 2.4 years old) participated in the study. All were right handed according to the Edinburgh inventory (Oldfield, 1971). The protocol was approved by the Institutional Review Board, and all subjects gave their written informed consent for the study.

2.2. Experimental protocol

Subjects were seated in a chair with the forearm supported by a pillow. They were asked to perform a self-paced voluntary movement task of wrist extension. They were specifically asked not to count time and were asked to make the movement whenever they wanted to. Furthermore, subjects were asked to keep all muscles, other than those in the performing hand relaxed. They were also asked to remain relaxed between any successive two movements. Eye movements, blinks, body adjustments, throat clearing, and other movements were to be avoided. A computer monitor that delivered visual information was placed about 1.5 m in front of the subjects.

The whole experimental procedure consisted of four sessions; each session was about 10–15 min with 5–10 min break between two consecutive sessions. The total duration including experiment setup (0.5–1 h) and the four test sessions was about 2–3 h. The fourth session was for other purposes and the data from that session are not included in this study. The three sessions were:

Session 1. Calibration session for modeling, to make a parametric prediction model from data associated with voluntary movements.
Session 2. Calibration session for validation, to validate the parametric prediction model and to determine an appropriate working point (i.e., threshold) under a targeted false positive rate (offline procedure).
Session 3. Online prediction, to predict subjects' movements while subjects performed voluntary movements under the parametric prediction model.

In all three sessions, subjects performed the same motor task of self-paced wrist extension with their right hand.

2.3. Visual paradigm

Calibration sessions (sessions 1 and 2): the visual paradigm for the two calibration sessions was the same. Subjects performed self-paced wrist extension, where EMG and EOG activities were monitored online continuously every 50 ms. Once EMG or EOG activity was detected by the computer program, the central box became green or red, and an event marker was made in the EEG records. The EMG signals were bipolarly derived, highpassed at 5 Hz and rectified before being sent to a threshold detector. The detection threshold for EMG signals was 25 μV. The EOG signals were bipolarly derived from diagonal electrodes placed above the left eye and below the right eye. The threshold for detection was set at 100 μV. For appropriate modeling, the dataset associated with the idle state or baseline state and dataset associated with the intention to move were required for constructing a parametric model for the prediction. As noted in the Section 1, evidence shows that human movement intention may start from 1.5 s before movement onset (Deecke, 1990; Cui et al., 2000; Bai et al., 2006). The data from 1.5 s before movement to EMG activity onset were extracted to model the active state during which subjects were intending to move, i.e., true positives. The data within 2 s after the central box turned off from green or red color were extracted for modeling the inactive state or idle state, i.e., true negatives. Because subjects were asked to move whenever they wanted to, it was possible that the time window for the active state overlapped with the inactive state time window. In order to avoid possible overlap, only the trials where the duration from central box turned off to next movement detected (from (a) to (b) or from (e) to (f) in Fig. 1) was larger than 5 s were used for the modeling. Though we asked the subjects to move instantly when they wanted, subjects reported that sometimes they were thinking about movement, i.e., planning to perform wrist extension, though they did not make the movement thereafter instantly. The trials for the modeling had at least 1.5 s of data between inactive and active windows, which might avoid the uncertainty for data modeling since it was difficult to determine which state the period should be. For both calibration sessions, the task was completed when 40 valid trials were obtained. Because some trials were excluded due to the shorter length between inactive and active windows, subjects performed more than 40 trials with actual repeated movement ranging from 50 to 60 times.

Online prediction sessions (session 3): The positive prediction of movement and the detection of eye movement-related artifacts would turn on the light of the central box in the prediction sessions. The online prediction process was initiated after the central box was turned off, i.e., 3 s after the detection of the previous movement or 1 s after the detection of eye movement-related artifacts. Because the timing of movement or the timing of the event was not known when doing online prediction, the time from the start of prediction to event/movement was not the same in each trial. Further, because online prediction involves heavy computation, the interval between consecutive two predictions was set at 100 ms in order to avoid exhaustion of computer resources. The computer made predictions every 100 ms according to the power features estimated from 1 s time window as described in detail in Section 2.5.3.1.

2.4. Data acquisition

EEG was measured from 27 (tin) surface electrodes (F3, F7, C3A, C1, C3, C5, T3, C3P, P3, T5, F4, F8, C4A, C2, C4, C6, T4, C4P, P4, T6, FPZ, FZ, FCZ, CZ, CZP, PZ and OZ) according to the international 10–20 system (Jasper and Andrews, 1938), mounted on an elastic cap (Electro-Cap International, Inc., Eaton, OH, USA). The distance between two adjacent electrodes was approximately 2.5 cm. Bipolar recordings of the diagonal electrooculogram (EOG) was obtained. Two electrodes were placed side by side on the area nearly 3 cm below the elbow of the right arm to record electromyogram (EMG). Total duration of preparation included time to obtain informed consent, paradigm explanation, setting up the electrodes and preparations of hardware and software took about 30 min to 1 h. Signals from all channels were amplified (g.tec GmgH, Schiedlberg, Austria), filtered (DC-100 Hz), and digitized (sampling frequency, 256 Hz).

The digital signal was then sent to a HP PC workstation equipped with a 2.33 GHz Xeon CPU and was online processed using a homemade MATLAB (MathWorks, Natick, MA) Toolbox: brain–computer interface to virtual reality or BCI2VR (Bai et al., 2007, 2008). The BCI2VR programs provided both the visual stimulus/paradigm, as well as online processing of the EEG signal. The signal for the prediction was extracted following the timer set in MATLAB program.

2.5. Computational methods for online prediction

The online signal processing to predict movement consisted of three steps: spatial filtering, temporal filtering, and feature extraction and prediction.

2.5.1. Spatial filtering

Surface Laplacian derivation (SLD) was employed; the EEG signal from each electrode was referenced to the averaged potentials from the nearest four orthogonal electrodes (Hjorth, 1975). Through SLD, the EEG feature of local synchrony, i.e., frequency power changes, was enhanced (Pfurtscheller, 1988).

2.5.2. Temporal filtering

A data window of 1 s was retrieved from SLD filtered signals at each prediction interval, assuming that the EEG signal in a 1 s time window was stationary. The Welch method with a Hamming window was employed for power spectral density (PSD) estimation in order to reduce estimation variance and side-lobe effect (Welch, 1967); the data in the selected time window was segmented and periodograms from all segments were averaged to obtain a smoothed estimation. A 4 Hz frequency resolution or segment length of 256/4 = 64 under 50% overlapping, was used in Welch-based PSD estimation.

2.5.3. Feature extraction and prediction

Prediction was made by comparing a pre-determined threshold at each prediction interval. The best features, parametric model and threshold (working point) was determined from the data obtained from the calibration session for modeling.

2.5.3.1. Feature extraction. The frequency power by PSD estimation was categorized into active (intended to move) and inactive (idle) state from the dataset obtained from the calibration session for modeling (Session 1). There were 40 samples for each of the two states. Because we did not expect relevant activities in the delta, theta and gamma band, only alpha and beta band (8–30 Hz) activities were extracted for modeling. Assuming that cortical activity associated with movement intention occurs over the motor cortex, we reduced the channel number from 27 to 14, which covered both left and right motor areas. Therefore, the total number of features was 6 (frequency bins) × 14 (channels) = 84 features. The 84

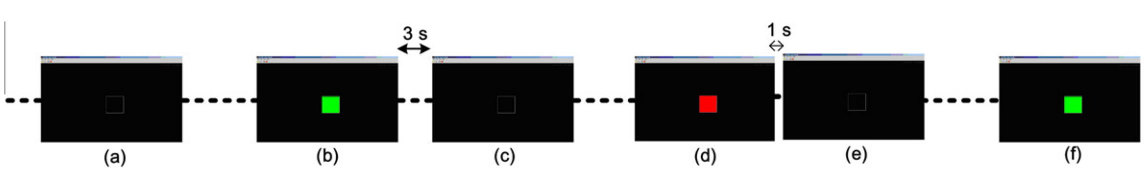

Fig. 1. Screen shot of visual paradigm provided in each of four sessions. The computer continuously monitored the rectified bipolar EMG activity every 50 ms; once the EMG activity was larger than a pre-set threshold, the central box turned into a green color as in (b) and (f), and after 3 s, the central box disappeared as shown in (a) and (c); once blink or eye movement activity was detected from EOG signal, the central box turned red (d) to remind subjects that there were excessive eye movement artifacts, and after 1 s, the central box disappeared as shown in (e). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.)

features were ranked by the Bhattacharyya distance. The Bhattacharyya distance provides an index of feature separability for binary classification, which is proportional to the inter-class mean difference divided by intra-class variance (Chatterjee et al., 2007). Because higher dimensionality of features might cause overfitting problem during modeling (may lose generalization), the best four features with the highest Bhattacharyya distance value were determined for the modeling and the prediction.

2.5.3.2. Modeling. A multivariate linear classifier of Mahalanobis linear distance (MLD) classifier was modeled from the four best-selected features. The Mahalanobis linear distance, which computed a pooled covariance matrix averaged from individual covariance matrices in two task conditions (Marques, 2001), was measured. In order to obtain a minimal false positive rate, the working point or threshold was determined from the model validation instead of using the hyper-planes leaning along the regressions as the discriminant boundaries.

2.5.4. Determining a working point/threshold

Based on the model determined from the dataset from the calibration session for modeling, a working point was determined offline from the validation of the model using the dataset from the calibration session for validation. The interval for prediction offline validation was 100 ms, the same as the online prediction. The range of Mahalanobis linear distance values for active state samples was divided into 200 prediction levels, and based on the 200 levels, a receiver operating characteristic (ROC) curve was created. Assuming that human movement intention starts from 1.5 s before movement, any prediction earlier than 1.5 s before movement onset was taken as an ambiguous prediction, and any prediction within 1.5 s before movement to movement onset was taken as a true positive, i.e., only the predictions made between 1.5 s before movement to movement onset were considered as successful or true predictions. In order to make reliable predictions with minimal false positives, the working point/threshold was determined from the level with 10% false positive rate.

2.6. Neurophysiological data analysis

Offline data analysis was performed in order to investigate the neurophysiology following human voluntary movement. The two datasets from the calibration session for modeling were used for the analysis. Data processing was performed offline using the same MATLAB Toolbox of BCI2VR. Epoching was done with windows of −4.096 to 2.048 s with respect to EMG onset. Any epochs contaminated with face muscle artifacts were rejected manually. Eye movement-related artifacts were removed using an auto-regressive model with exogenous input (ARX model), in which the diagonal EOG signal was used as the exogenous input (Cerutti et al., 1988). Approximately 40 artifact-free epochs in each subject were obtained. The time–frequency representation was calculated with an interval of 100 ms under 1 s time window. The Welch-based PSD was estimated on each of time window; FFT length was 64 (0.25 s) with a band width of 4 Hz, where Hamming window and 50% overlapping was adopted. The time–frequency data were obtained by averaging the log power spectrum across epochs and baseline was taken from −4.096 to −2.048 s with respect to movement onset. The MRCP was obtained by epoch averaging corresponding to movement onset. The MRCP was created after a linear phase10 Hz low-pass filter.

2.7. MRCP and ERD preceding human voluntary movement

The MRCP and ERD were calculated from the dataset recorded in experiment Session 1, i.e., the calibration session for modeling. The data for subjects 2, 4 and 5 are illustrated in Fig. 2. The epochs were back averaged with respect to movement onset, i.e., the time ‘0’. MRCP and ERD activities preceding movement onset were observed in all subjects. Early negative component of the MRCP (BP1) in subject 2 presented more than 2 s before movement onset, where a recognizable MRCP in subject 4 was only found about 1 s before movement onset. The amplitude of the early MRCP component was as small as 2–3 μV, though the later MRCP component (BP2) had larger amplitude about 8–10 μV. Similar to the MRCP, early ERD activity (blue color) was observed in the entire beta band from 16 to 30 Hz. The early onset of ERD activity was different among subjects, where subject 2 had an earlier onset about 2 s before movement. In contrast to the MRCP distribution over central-medial area, the ERD activity lateralized contralateral to the hand moved and developed bilaterally at movement onset. The ERD activity was also maximized at movement onset, which was more than 5 dB power decrease, or more than 56% reduction in rhythmic amplitude. Similar to the MRCP, subject 2 had earlier ERD onset about 2 s before movement, where steady ERD activity presented only 1 s before movement in subject 4. The post-motor activity of event-related synchronization (ERS) was observed in all subjects, which was maximized about 1 s after movement (red color).

2.8. Feature selection from separability index

The feature selection and parametric modeling was made from session 1 dataset for each subject. Bhattacharyya distance was investigated on each frequency feature on each EEG channel. Each trial of voluntary movement provided a pair of samples for active state during which subjects intended to move (from 1.5 s before movement to movement onset) and idle or baseline state during which subjects were at rest, which was at least 3 s before movement onset. Features with higher Bhattacharyya distance values illustrated in Fig. 3 (red color) were activities from channels over contralateral left motor areas (C1, C3 and C3P) in beta band, where the best band and spatial location were slightly different among subjects. The spatial and spectral patterns shown by Bhattacharyya distance were consistent with the ERD patterns illustrated in Fig. 2, that larger ERD in beta band over left hemisphere provided better separability indexed by higher Bhattacharyya distance values. The best four channel-band features with highest Bhattacharyya distance values were selected to construct a multivariate MLD model for the prediction.

3. Results

3.1. Determining a working point from model validation

A screen shot from the home-made Matlab program is illustrated in Fig. 4. The programmed Matlab window provided a toolbar that allowed the investigator to adjust the threshold to change the working point manually. The prediction model was created from the data samples of active state during movement preparation and idle state recorded in Session 1. The upper left plot in Fig. 4 provided the ROC curve of true positive rates and false positive rates from 200 discrimination threshold values. When increasing threshold, the working point was moved to the left and the false positive rate was decreased. However, the true positive rate or sensitivity was also decreased. Though the working point at the upper left corner provided optimal balance of true positive rate and false positive rate, the false positive rate was more important to achieve a reliable prediction of movement, where the miss-prediction was allowable and in secondary priority. As the movement prediction was made continuously online in real-time, the ROC curve from the calibration model was not accurate enough to rep-

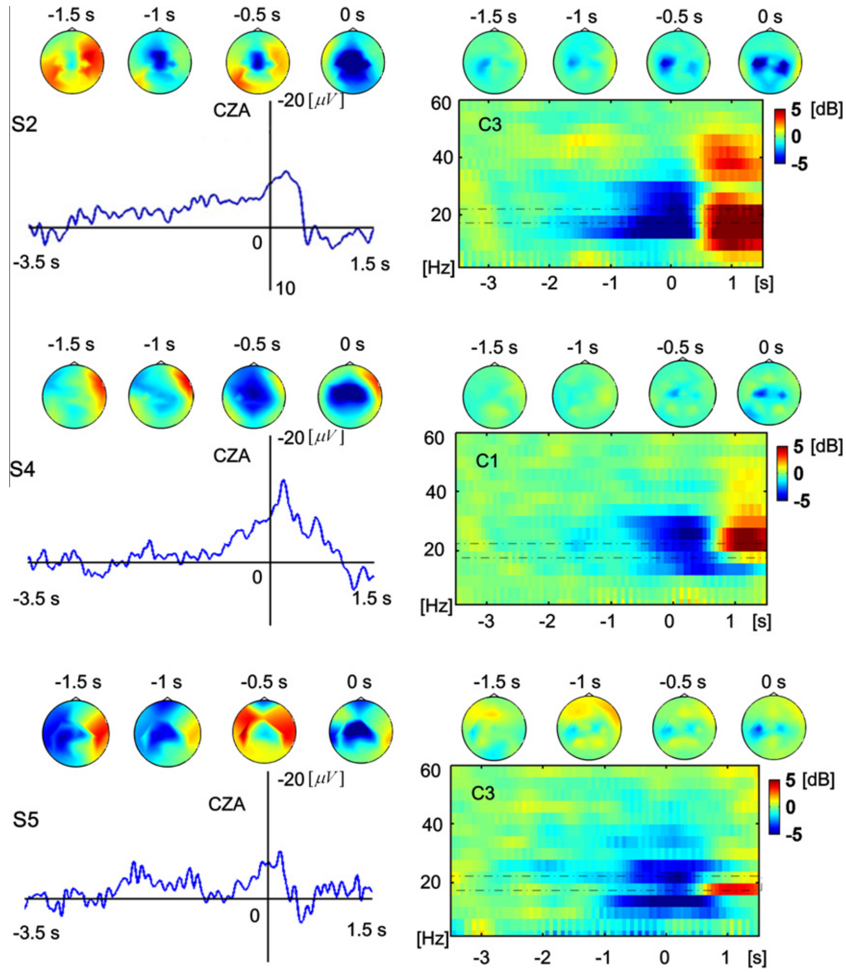

Fig. 2. Small negative potentials of MRCPs (the left column) presented as early as 1.5 s before movement onset, which was maximized over central-medial area (supplementary motor area). ERD or power decrease presented by blue color in the right column was also observed about 1.5 s before movement onset. In contrast to the spatial distribution of MRCPs, ERD developed over the left motor area contralateral to the moving right hand. The ERD presented from low beta to high beta bands (16–30 Hz), which was maximized at movement onset. The alpha ERD in 8–12 Hz was less distinguishable than beta ERD. The frequency band for the topographic plot of ERD is 18–22 Hz indicated by dash-dot line in time–frequency plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.)

resent an actual online prediction when considering data variance. Further, the data between the windows of idle state and active intention state was not taken into account in the calibration modeling. A validation procedure was performed to simulate the actual online continuous prediction. The ROC curve for the validation result was provided in the lower left plot. Instead of using false positive rate in the ROC curve for the calibration model, the prediction made earlier than 1.5 s before movement was treated as ambiguous prediction because it belonged to neither active intention state nor idle state (or difficult to determine whether it was idle state or not). The ROC curves from calibration (upper) and validation (lower) were different; for example, at the depicted working point, the false positive rate from calibration was 0 with true positive rate of 0.1, where for validation, the rate of ambiguous prediction was about 0.02 with the rate of true prediction was about 0.35. The prediction time with respect to movement onset from the continuous prediction in validation procedure is illustrated in the lower right plot. Most of predictions were made within 1.5 s before movement. There was one ambiguous prediction, which was made about 2.8 s before movement. The histogram for the EMG onsets with respect to the start of the continuous prediction, i.e., the central box indicating movement or blink was turned off, is shown in the upper right plot. The distribution of the EMG onsets was random showing that the subjects voluntarily determined when to move instead of time-locked to visual paradigm. Further, the EMG onset with respect to the start of the prediction was at least more than 1.5 s showing that the prediction started from idle state.

3.2. Online prediction of human voluntary movement

The online prediction of human voluntary movement was performed in session 3: subjects made voluntary movement when they wanted. The paradigm for Session 3 was the same as the paradigm provided in Sessions 1 and 2 for model calibration and validation. The computer continuously predicted whether subjects intended to move according to the calibration model, and a prediction marker was saved once the model output was larger than the pre-set threshold (working point). Sometimes there was a movement and sometimes there was no movement after a positive prediction was made from EEG signal. The online prediction was stopped until the start of the next trial after a movement was detected or prediction was made. The computer also continuously detected movement from the EMG signal and made a marker once movement was detected. The prediction time with respect to movement onset was calculated offline from prediction markers and EMG markers. The average prediction time for each subject is shown in Table 1 for those predictions where there were

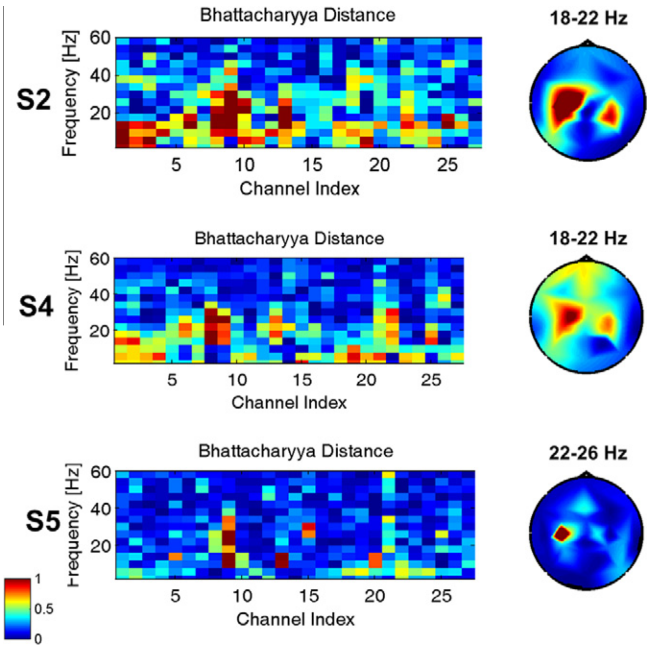

Fig. 3. Feature selection was determined from Bhattacharyya distance; a feature with higher value (in red) providing higher separability between active state that subject intended to move and idle/baseline state at rest. The channel index 1–27 corresponds to electrodes F3, F7, C3A, C1, C3, C5, T3, C3P, P3, T5, F4, F8, C4A, C2, C4, C6, T4, C4P, P4, T6, FPZ, FZ, FCZ, CZ, CZP, PZ and OZ. Features in beta band over left motor area provided best separability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.)

movements. The histogram for all the predictions made before movement for all subjects is illustrated in Fig. 5.

Table 1
Online prediction of human voluntary movements.

Subjects	No. of total movements	No. of total predictions	No. of true predictions[a]	Average time of true predictions (s)[b]
S1	18	8	6	0.384
S2	30	13	9	0.429
S3	20	7	4	1.029
S4	57	29	26	0.497
S5	40	13	10	0.724
S6	40	14	10	0.433
S7	30	12	10	0.846

[a] The prediction made from 1.5 s before movement to movement onset.
[b] The relative time before movement onset.

Subjects 1 and 3 had a smaller number of moves than the other subjects due to a technical problem during the experiments; the computer crashed several times. Among all the subjects, predictions preceding movement were made 40 ± 7% of total moves. The true positive predictions, made within 1.5 s before movement onset, were about 75 ± 10% of total predictions; this was to equivalent to the number of trials in Sessions 3 that had a positive prediction before movement onset (each trial had no more than one positive prediction). The highest true positive prediction rate about 90% was achieved in subject 4, whereas subject 3 had the lowest true positive prediction rate about 57%. For the predictions made within 1.5 s window before movement onset, the average prediction time for all the subjects was 0.62 ± 0.25 s before movement. For all predictions made before movement, the average prediction time for all the subjects was 0.90 ± 1.0 s. A small number of predictions made 3 s before movement as shown in Fig. 5 produced a large variance of 1.0 s.

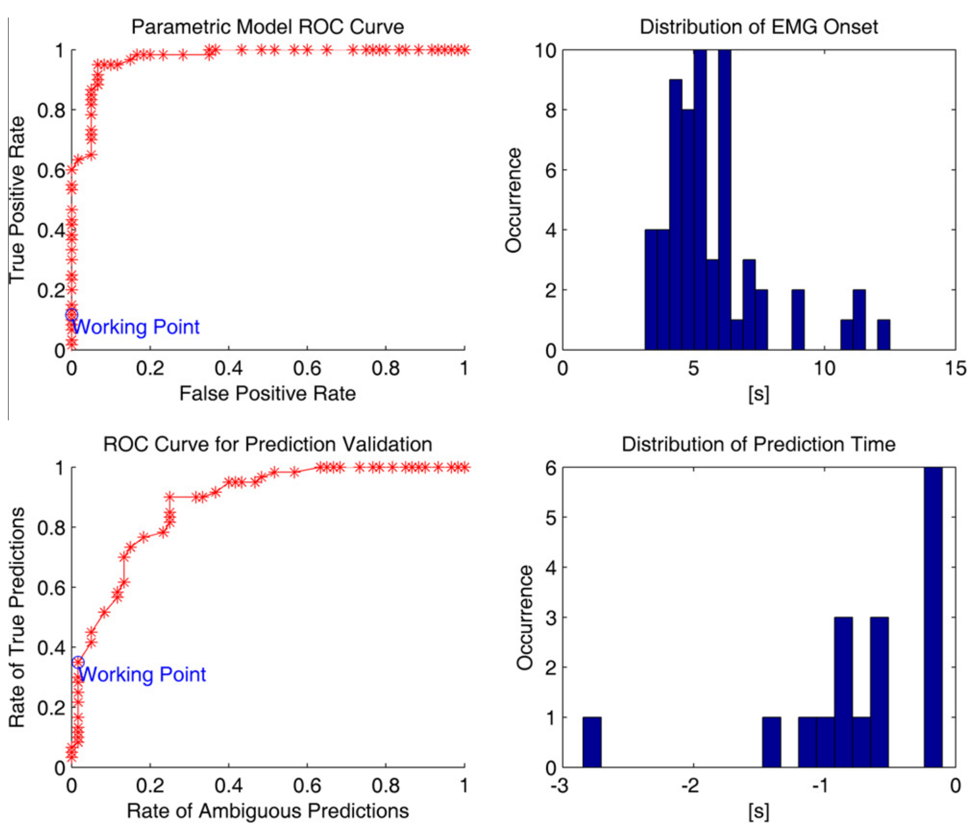

Fig. 4. Screen shot from validation procedure for Subject 2 to determine a working point in order to reduce false positive predictions or ambiguous predictions that were made earlier than a desired time window from 1.5 s before movement to movement onset. See detail in the text.

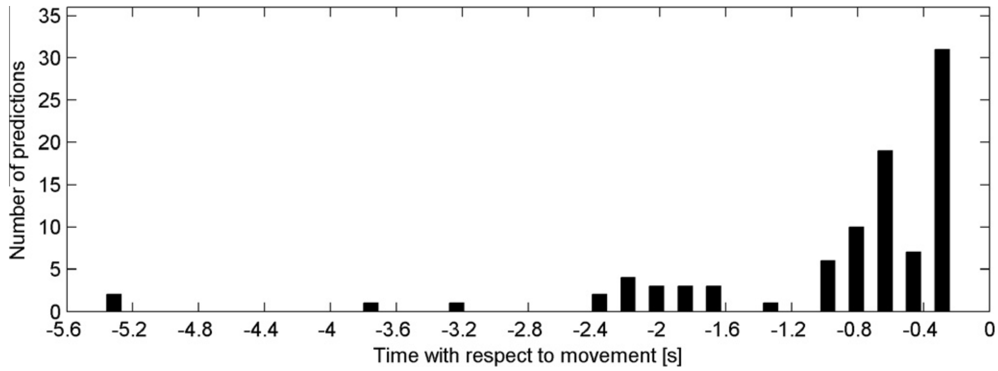

Fig. 5. Histogram of the predictions made proceeding movements from all subjects. Movement onset is at 0. Around 80% were true positive predictions that were made in the time window from 1.5 s to movement onset. The predictions made earlier than 1.5 s before movement were ambiguous predictions.

4. Discussion

4.1. The prediction of human voluntary movement

We have successfully demonstrated that human voluntary movement intention can be predicted online in real-time with a small false positive rate. With our method, the prediction is made about 0.62 s before voluntary movement onset. In this study, we attempted to make reliable predictions with minimal false positive rate so that once a prediction was made, it was very likely that subjects would produce a subsequent voluntary movement. The best online prediction was made in subject 4; there were 26 true positive predictions out of 29 total predictions, or about 90% successful prediction rate.

We presumed that true positive predictions are the predictions made within the 1.5 s time window before movement. According to this presumption, we modeled the active intention from 1.5 s before movement to movement onset. We determined the 1.5 s window from the early onset of MRCP as well as ERD, although the time of the start of human voluntary movement is very difficult to determine (Haggard et al., 2002), and in particular, when the initiation of the voluntary movement may be unconscious (Libet et al., 1983). Though we set a 1.5 s time window, we found that most of the predictions were made close to movement onset (within 0.6 s before movement, see Fig. 5).

It is difficult to interpret the ambiguous predictions that were made earlier than 1.5 s before movement onset. At least some of the predictions were made when subjects were merely planning to move their wrists. However, the subjects did not produce the movement at the time, although we asked the subjects to make the movement instantly whenever they wanted. This consideration is supported from subjective feedback after experiments; subjects often reported that they actually were wondering or thinking about movement when computer made positive predictions.

4.2. Computational methods for prediction

In this study, we employed a simple feature selection method from separability indexing. This feature ranking method using Bhattacharyya distance runs very fast because of the small computational load. The selected features were spatially and spectrally consistent with the well-established physiology associated with human motor control. Though this selection method supported a good classification, it does not provide an optimal selection of multiple features. We have explored more computational intensive methods using a genetic algorithm (Raymer et al., 2000). Though the features selected by the two methods were different, the prediction accuracy for these two methods was comparable. We determined to use the simpler method because of its faster calculation time.

The linear classification method of MLD classifier was adopted in the prediction. Similar to the feature selection methods, we also explored more computation intensive nonlinear methods of neural network (Bishop, 1995; Nabney, 2004), and support vector machine with linear and nonlinear kernel functions (Vapnik, 1998; Fan et al., 2005). In our offline exploration, the prediction performance from the nonlinear methods had no significant improvement beyond the simple linear method, though we had taken much effort to tune the hyper-parameters in the nonlinear methods to avoid the overfitting problem (Bai et al., 2007). According to the general recommendation for BCI algorithm (Muller et al., 2003), we adopted the simple linear classifier, which provided comparable prediction performance to computational intensive methods.

We may also predict human natural movement from brain signals other than EEG. Loukas and Brown performed a simulation study to predict human intention from the recorded local field potential activity in the subthalamic nucleus, in which they demonstrated a high potential of accurate prediction before actual movement (Loukas and Brown, 2004). Though their study was not a real online prediction in real-time, it suggests that a more accurate prediction might be possible when an invasive signal with better signal-to-noise ratio is available.

A previous study (Morash et al., 2008) answered the question about the prediction of what limb subjects wanted to move from signals associated with a cued movement paradigm, whereas we wanted to predict self-paced voluntary movement (without cue) before movement in this study. The major differences are: (1) the timing of movement was known in the previous study, whereas the timing of the movement was not known when the prediction of the forthcoming movement was made online; (2) the previous work was done offline whereas the prediction of movement in this study was performed online in real-time; and (3) the previous classification of intention to move different limbs was established on the motor physiology of different spatial distribution of ERD in EEG for individual limbs, whereas the prediction of movement intention was made from the temporal development of ERD (time course) before movement. Another study (Blankertz et al., 2003) was also not comparable with this study since the condition and signal for prediction are much different in nature. The prediction in the previous study was from the signal 130–100 ms before keypress with the fact that the timing of the keypress was already known, and the signal for prediction was back retrieved according to the keypress onset that was only available during offline process for self-paced movement. In this study we did not have any *a priori* of the timing of the movement since we wanted to make prediction

BEFORE the movement occurs. Our results showed that the prediction time corresponding to movement varied among individual predictions. The prediction of movement intention in this study was established on the pre-movement ERD activity that was demonstrated in an early study (Stancak and Pfurtscheller, 1996). However, a strong averaged pre-movement ERD does not necessarily indicate good single-trial prediction since single-trial activity shows high inter-trial variance during natural movement.

4.3. Performance analysis

State-of-the-art BCIs have been optimized using various strategies, such as event-related averaging for P300, rhythm regulation after extensive training (Wolpaw and McFarland, 2004), or enhanced motor-related activity by vivid kinematic motor imagery (Neuper et al., 2005). Though peri-imagery and post-imagery ERS may provide better signal for BCI use, this study has a different purpose compared with conventional BCIs that we wanted to predict movement online in real-time before movement occurs so that only the activity before natural movement can be used for the prediction. Since motor-related activities of ERD and MRCP during the preparation of natural movement are smaller than activities during the active motor task of either physical movement or motor imagery, the prediction of movement is much more difficult than rhythm decoding. Therefore, direct performance comparison between the prediction of movement and previous BCI methods may be not appropriate since the objectives are quite different. There have been a few prior comparisons of offline prediction between movement preparation and movement execution; about 40–50% accuracy for prediction during motor preparation in contrast to more than 80% accuracy when detecting during movement (Muller-Gerking et al., 2000; Blankertz et al., 2003). We consider that the performance of movement prediction before movement that we have produced in this study is in-line with previous similar approaches performed offline. Though the false positive and false negative rates are not fantastic, it is at least a beginning for the prediction of movement in real-time.

As we want to predict movement before it occurs, we want to be sure that a movement will happen in a short time window when a positive prediction is made. Therefore, the false positive rate should be small. In the BCI context, this means that when an effect occurs, it will generally be actually intended. Moreover, the potential scientific interpretation of data to answer questions about when and how humans initiate their voluntary movement would be more reliable. Though a higher true positive rate is preferred, some missed predictions are allowable since it does not affect the feature estimation. In the BCI context, if an intention is not recognized, the intention can be repeated and performance can still be faster than current BCIs.

In this study, the limits from heavy computational loads only allowed us to make predictions every 100 ms. The length of signal for prediction was 1 s for each of the consecutive prediction time points (the prediction was made on overlapped windows). A longer window for power spectral estimation was utilized for a more smoothed estimation to minimize false positives. The maximum delay for prediction was then 100 ms. Since the motor preparation is a relatively long, we consider that 100 ms is reasonable as the prediction interval. In future studies, faster predictions might be possible with smaller prediction intervals employing faster computers and more optimized algorithms for faster calculation.

4.4. Possible applications

The significance of this study is twofold: one is to develop a system for the exploration of the physiological mechanism underlying the production of human voluntary movement. The second one is intended for a potential BCI use as an early detector of human voluntary movement intention.

Exploration of the physiological mechanisms of how humans make voluntary movement: we demonstrated that human voluntary movement can be predicted about 0.6 s before movement occurs with a small false positive rate. The early prediction of movement provides a potential faster control of devices than voluntary physical control. Though we may have some miss-predictions, it is possible, at least sometimes, that the devices may be responded earlier, which may be crucial in some applications requiring faster operation. On the other hand, the early prediction of human voluntary movement may allow a short time for computer to evaluate the risk of the forthcoming action, and the computer may block the human incoming operation to avoid potential damage. Libet and his colleague found that humans have a conscious awareness of wanting to move ('W' time) about 350 ms before actual movement. As they observed the neuronal activity or the MRCP starting about 800 ms earlier than the 'W' time, they interpreted that human voluntary movement may initiated subconsciously (Libet et al., 1983). In this study, we found that many predictions were made earlier than 350 ms before movement. Therefore, these predictions were made while human might not be consciously aware that he wanted to move. If it is the case, it might be possible, for example, when we are surfing on the web, a new web page might be on the monitor just at the time we are know that we want to visit that page. The above assumptions, however, need further study to confirm the subjective feelings.

Extending the state-of-the-art BCI capability: BCI provides a therapeutic option for paralyzed patients to restore their motor function. Current BCIs allow the users to volitionally or consciously control external assistive devices. BCI control can be achieved from artificial signals by attentionally regulating mu rhythm (Wolpaw et al., 1991; Wolpaw and McFarland, 2004) or slow cortical potentials (Hinterberger et al., 2004), which are available after extensive training. The successful prediction of human voluntary movement from human intention-related natural signals may provide another effective and faster or even subconscious control of external devices. Because the user may tire due to sustained attention (Sellers and Donchin, 2006), the accurate prediction of human voluntary movement may provide a more convenient BCI method which does not rely on attentional control of external devices. The successful prediction of human natural movement will also extend the capability of the state-of-the-art brain–computer interface as an early detector of natural movement intention, or to provide intervention to impede forthcoming movement in patients with certain clinical conditions.

This is a pilot study to explore methods to prediction human natural movement before movement occurs online in real-time. We will further explore computational methods to improve the prediction performance, i.e., improve the true positive rate to about 90% with a reasonable false positive rate of less than 10%. Better spatial filters to form a better quality signal may be a rational approach to achieve high prediction accuracy.

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