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Adaptive estimation of hand movement trajectory in an EEG based brain–computer interface system

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Abstract

Objective. The various parameters that define a hand movement such as its trajectory, speed, etc, are encoded in distinct brain activities. Decoding this information from neurophysiological recordings is a less explored area of brain–computer interface (BCI) research. Applying non-invasive recordings such as electroencephalography (EEG) for decoding makes the problem more challenging, as the encoding is assumed to be deep within the brain and not easily accessible by scalp recordings. *Approach.* EEG based BCI systems can be developed to identify the neural features underlying movement parameters that can be further utilized to provide a detailed and well defined control command set to a BCI output device. A real-time continuous control is better suited for practical BCI systems, and can be achieved by continuous adaptive reconstruction of movement trajectory than discrete brain activity classifications. In this work, we adaptively reconstruct/estimate the parameters of two-dimensional hand movement trajectory, namely movement speed and position, from multi-channel EEG recordings. The data for analysis is collected by performing an experiment that involved center-out right-hand movement tasks in four different directions at two different speeds in random order. We estimate movement trajectory using a Kalman filter that models the relation between brain activity and recorded parameters based on a set of defined predictors. We propose a method to define these predictor variables that includes spatial, spectral and temporally localized neural information and to select optimally informative variables. *Main results.* The proposed method yielded correlation of (0.60 $\pm$ 0.07) between recorded and estimated data. Further, incorporating the proposed predictor subset selection, the correlation achieved is (0.57 $\pm$ 0.07, $p < 0.004$) with significant gain in stability of the system, as well as dramatic reduction in number of predictors (76%) for the savings of computational time. *Significance.* The proposed system provides a real time movement control system using EEG-BCI with control over movement speed and position. These results are higher and statistically significant compared to existing techniques in EEG based systems and thus promise the applicability of the proposed method for efficient estimation of movement parameters and for continuous motor control.

Keywords: brain-computer interface, motor control, electroencephalography

(Some figures may appear in colour only in the online journal)

1. Introduction

The brain–computer interface (BCI) system functions by decoding the neural activity and translating the brain control states directly to output commands that communicate and control with the interfaced external devices [1, 2]. Electroencephalography (EEG) is a non-invasive technique that can acquire electrophysiological activity of the brain. EEG, owing to its simple and inexpensive setting, is widely used for neuroscience and neural signal processing research and clinical applications [1]. Several signal features, such as rhythms and evoked potentials, can be identified from the scalp-recorded EEG [3] that can effectively decipher brain activity. Recent developments also suggest that the BCI users can develop control over a specific EEG feature by feedback-training provided by an adaptive BCI system [4].

Decoding motor activity or limb movement control executed by the brain is a popular area of research in BCI. Sensory motor rhythms [3, 4], movement related potentials [5], spectral band powers [6], etc, are some of the neural features identified from EEG that are utilized in movement related studies. Various studies dealing with identifying/classifying discrete motor activity from the EEG signals have been reported in the literature [3–6]. However, a continuous reconstruction of the finer movement parameters such as speed, direction, position, acceleration, etc, from the brain activity is a less explored area in BCI research [7]. Literature reports various attempts to infer movement parameters from invasive recordings such a single/multi-unit activity (SUA/MUA) [8–10], localized filed potentials (LFPs) [11], electrocorticography (ECoG) [12, 13], etc, from primates as well as humans. Many researchers believed that the movement parameters are deeply encoded in the neuronal firing and the scalp recordings such as EEG or magnetoencephalography (MEG) [7, 15–18, 31] has low signal-to-noise ratio to decode these information. However, with the advance of signal processing and machine learning techniques, researchers are now able to identify the movement parameter information from non-invasive recordings.

In [8], researchers suggest that the movement direction may be encoded in the neural ensemble in the arm area of motor cortex and the activity of cells was studied using a population vector algorithm. A study reported in [9] investigates the spatiotemporal encoding of hand velocity and direction in primates using multi-electrode arrays. In [10] the researchers attempt to establish relationships between neural firing rates and movement parameters, and the trajectories were reconstructed using linear and Kalman filtering. The study in [12] showed that continuous two-dimensional (2D) hand position can be approximately predicted from ECoG recorded from hand/arm motor cortex. Reference [13] reports an ECoG study in primates, which uses ensemble posterior parietal cortex (PPC) neurons to reconstruct the trajectory of movement to an end target position.

There are very few studies in literature that attempt to reconstruct movement parameters from non-invasive recordings. The work in [14, 15] demonstrates a continuous decoding of 2D movement from MEG. Reference [16] reports reconstruction of three-dimensional (3D) hand velocity performed using EEG during a center-out reaching task. Our previous works [17, 18] on hand movement direction and speed analysis performs reconstruction of speed components during hand movement from the simultaneously recorded EEG and multiclass classification of movement direction. Another study in [19] also reported the effective reconstruction hand movement velocity from EEG data. In our previous study on hand movement trajectory reconstruction [20] we used multiple linear regressor models for estimation. Further, various studies in literature have reported use of motor imagery and the resultant event-related synchronization/desynchronization patterns to achieve continuous and defined movement control. Studies have reported continuous 3D control of a quadcopter [21], asynchronous control of a car in a 3D virtual environment [22] and a virtual helicopter in 3D space [23] using EEG signals.

In this study, our objective is to adaptively estimate hand movement trajectory parameters with higher accuracy and lesser number of predictors from simultaneously recorded EEG. To acquire the brain and hand movement data, an experiment was designed. The subjects performed cue-based right-hand center-out movements in four different directions and at two different speeds to reach a target. The movement task performed in a 2D horizontal plane produced a movement trajectory defined by the parameters x, y co-ordinates and absolute values of speed and position. We perform wavelet analysis on the recorded EEG data. Wavelet analysis is a widely used tool for processing non-stationary signals, such as, EEG. In BCI, wavelets are used for various purposes such as data de-noising, construction of time-frequency representations and weighted transforms [24, 25], etc. In our algorithm, we use discrete wavelet transform (DWT) to decompose EEG signal into different subbands. The subband signals along with their time delayed versions form the predictor matrix, onto which the movement parameters are fitted.

Kalman filters have been widely used for estimation problems ranging from target tracking to vehicle control [26–29]. Kalman filters have been applied for decoding hand kinematics from neural activity recorded using invasive [10, 27] data acquisition methods. In the proposed method, we use Kalman filters to adaptively estimate hand movement parameters from EEG signals. Furthermore, we propose a method to select the most informative predictor variables to model the estimator. The proposed method includes *a priori* selection of channels by a ranking algorithm and a backward elimination of predictors to create the best fit model. The system is validated and performance is evaluated in terms of correlation between recorded and estimated parameters.

The rest of this paper is organized as follows: section 2 describes the different signal processing and statistical tools involved in the proposed movement parameter estimation technique. Section 3 reports the results of the experiment and analysis performed. Section 4 provides a detailed discussion of the results followed by conclusions of our work.

2. Methods

In this study, our aim is to adaptively estimate parameters of hand movement trajectory solely from scalp recordings. The data acquisition unit of the designed BCI simultaneously records the brain activity and hand movement speed and position information, while the subject performs defined hand movements. The experiment design consisted of cue-based center-out 2D hand movements in the horizontal plane. The

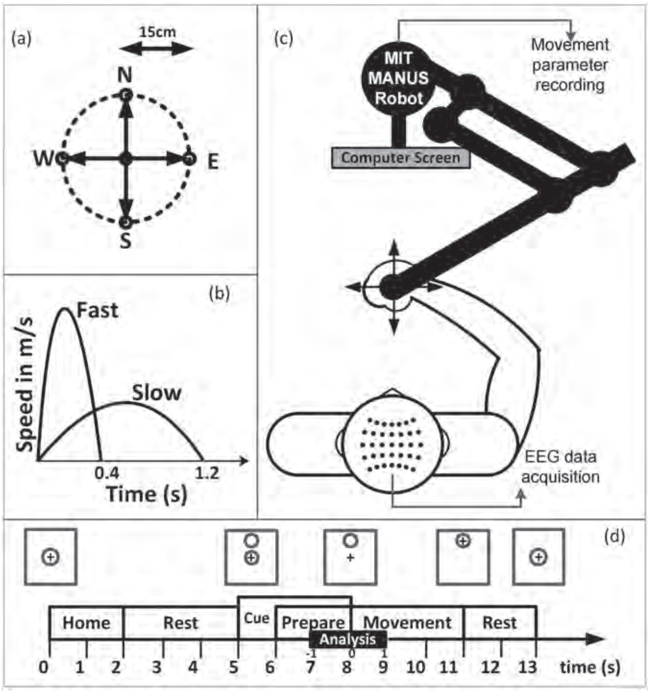

Figure 1. The experimental setup and timeline. (a) and (b) shows the details of direction and speed movement tasks that the subjects performed. (c) The experimental setup. (d) Timeline for experiment. For details see text.

movements involve aiming at targets in four different directions at two different speeds. The details of the experiment are given in sub-sections 2.1 and 2.2 followed by the data analysis methods.

2.1. Subjects and equipment

The experiment was conducted at the Brain Computer Interface Laboratory, Institute for Infocomm Research, Agency for Science, Technology and Research, Singapore. A Neuroscan SynAmps 128 channel EEG amplifier was used for recording EEG from seven healthy male subjects. Ethics approval from National University of Singapore Institutional Review Board (NUS-IRB) and written informed consent from subjects were obtained. The lower cut-off frequency of amplifier is 0.05 Hz and it works at a sampling rate of 250 Hz. While performing the experiment, the subjects were strapped to an MIT-Manus robot [29] to record the exact hand position and speed at every sample time. The setup of the experiment is shown in figure 1(c).

2.2. Experiment protocol

The movement tasks involved in this experiment are center-out right-hand movements in horizontal 2D space. Eight different types of movement consisting of four orthogonal directions and two different speeds as shown in figures 1(a) and (b) are included in the protocol. The directions are termed as North (N), South (S), East (E) and West (W) that correspond to forward, backward, rightward and leftward movements, respectively of the hand from a fixed center position. A maximum center-to-target distance of 15 cm is achieved by the subject for each task. The subject is also required to move at different speeds, fast and slow, that are movements completed within 0.4 and 1.2 s respectively. The timeline for each experiment trial is indicated in figure 1(d). The cues used in the experiment to indicate various tasks are also provided. The screen with encircled cross at the center indicates home screen. The cue 'N' is indicated by an empty circle at the target position as shown in the figure. This notifies the subject to prepare for a movement task-North. As the center circle disappears, the subject starts to execute the task. At the end of the trial, the home screen re-appears. The experiment is conducted for eight sessions for each subject. Each session consists of 50 cycles of experiment, in which each cycle includes eight trials corresponding to the eight tasks in random order.

2.3. Data preprocessing

The preliminary data analysis step in a BCI system is signal pre-processing which improves the signal-to-noise ratio of the signal by removing noise and artifacts. Similar to our previous studies, 35 channels from the primary and supplementary motor cortex are used to perform further analysis. The time segment including last 1 s of preparation and 1 s of movement task from every trial (indicated as 'analysis' in figure 1(d)) is considered for further processing. The EEG signal is low pass filtered at a cut-off of 96 Hz, and the power line frequency, 50 Hz, is notch-filtered. The muscular movement and ocular artifacts that could affect the EEG data is removed using specialized signal processing steps. Multiple-lag regression model [30] is implemented to identify the effect of eye movement (using the recorded EOG (electro-oculagraphy) signals and its time shifted components) on the EEG data. This is then subtracted from the recorded EEG to remove eye movement artefacts. The muscular artifacts that are present as diffused activity in EEG signals can be removed using spatial filtering [31]. The data undergoes spatial filtering using Laplacian filters [32] to remove movement artifacts.

The trajectory parameters that are recorded in this experiment are 2D co-ordinates of speed and position. In order to remove the sensor noise during measurements, low pass filtering at 1 Hz is performed. For the continuous estimation of movement parameters, reconstruction must be performed at every sample, equivalent to an estimation interval of 4 ms (250 Hz sampling). However, the low frequency of the parameters allows the increase of estimation interval up to 500 ms. The estimation value is set as 200 ms in our study. In order to estimate the movement parameters, we use only the corresponding time samples from EEG.

We define the trajectory parameter as,

$$Y = \{s_x, s_y, s, d_x, d_y, d\}, \quad \in \Re^{6\times(T\cdot R)} \tag{1}$$

where T is the number of samples/trial and R is the number of trials recorded. This includes x and y co-ordinates of speed (s) and position (d) and the absolute speed and position given by, $s = \sqrt{{s_x}^2 + {s_y}^2}$ and $d = \sqrt{{d_x}^2 + {d_y}^2}$.

2.4. Wavelet analysis and predictor definition

The preprocessed EEG signal is used to a define predictor set that models the estimator for the movement parameter information. The brain activity recorded as multi-channel EEG is characterized by its non-stationary behavior. The analysis of non-stationary signal poses a challenge, as this brings about a requirement for continuously estimating optimal signal features or extracting stationary features from the signal. This requires a multi-resolution analysis on the non-stationary EEG data. As our objective is to estimate low frequency movement parameters using linear fitting strategy, it is essential to utilize low frequency EEG signal. Hence, EEG signal needs to be decomposed into subbands with increasing resolution towards low frequency EEG. The DWT provides an effective solution for non-stationary signal analysis by performing multi-resolution analysis on the signal thereby addressing the time-frequency resolution trade-off [33]. DWTs make use of prototype functions, called wavelets whose dilated and contracted versions can provide fine spectral and temporal analysis, respectively. The wavelet analysis involves signal decomposition into approximate and detailed coefficients by successive low pass and high pass filtering followed by sub sampling. Orthonormal wavelet bases are used to create filter banks such that they span non-overlapping subspaces. The orthogonal filter bank performs half band filtering by splitting the signal into these subspaces.

The discrete wavelet analysis proceeds as the signal is convolved by these bases and down sampled by a factor of 2. This process is repeated by successive decomposition of the approximate coefficients from the previous level. The maximum number of decomposition levels achieved is given by $L = \log_2(T)$, where T is the signal length. We obtain the wavelet coefficients of the signal as $\{A_L, D_L, D_{L-1}, \ldots, D_1\}$, where A_l and D_l denote the approximate and detailed coefficients for level l. These coefficients span various non-uniform subbands of the signals. The inverse process of reconstruction is performed to obtain the subband signals. Up sampling by 2 followed by convolution with time reversed wavelet bases reconstructs the signal from the approximate and detailed coefficients. The signal from each subband can be reconstructed by using the respective coefficients while nullifying others.

In our study, the single trial recorded brain activity is given by E, $E \in \mathfrak{R}^{C\times T}$, where C is the number of channels recorded. This is divided into $L + 1$ subband signals by wavelet decomposition followed by subband reconstruction. The proposed approach requires spatial, spectral and temporal information of EEG to be included in the variable/predictor set on which the recorded movement parameters are fitted linearly. The predictor set, $X \in \mathfrak{R}^{P\times(T\cdot R)}$, where $P = (C(L + 1)\theta)$ is thus defined as

$$\left\{x_{l\tau c} \in \mathfrak{R}^{1\times TR}\ l = 1 \text{ to } L + 1,\ \tau = 1 \text{ to } \theta,\ c = 1 \text{ to } C\right\} \quad (2)$$

where $x_{l\tau c}$ denotes the EEG recorded from channel c, reconstructed at subband l and delayed by $\tau - 1$. In the rest of this paper, the predictor at time sample k will be denoted by X_k which is equivalent to $x_{l\tau c}(k)$ and the trajectory parameter at instant k is Y_k.

2.5. Adaptive estimation: Kalman filter

The Kalman filter is an optimal linear estimator that infers parameters of interest from indirect, inaccurate and uncertain observations. It is a recursive process that updates the filter model every time a new measurement arrives. Hence Kalman filtering is a preferred method for real time processing in various applications and is proved to provide better results than in batch processing. The Kalman filter minimizes the mean square error of the estimated parameters in the presence of Gaussian noises with known mean and variances [26]. The Kalman filter models a discrete time linear dynamic system in which the state of the system at any instant of time can be defined by a linear model. It consists of generative model which assumes the measured output of the system (EEG signal) is linearly related to the state (movement trajectory). In our study, we define the generative model as,

$$X_k = H_k Y_k + q_k \quad (3)$$

Here, H_k is the matrix that linearly relates predictor with state of the system and the measurement noise is denoted by q_k, which is approximately the normal distribution, $\aleph(0, Q_k)$ where Q_k is the noise covariance matrix. The state of the system at $(k + 1)$th instant is assumed to be linearly dependent on state at instant k. This concept is used to create system model which in our system estimates the state of hand at $(k + 1)$.

$$Y_{k+1} = A_k Y_k + w_k \quad (4)$$

In the system model, A_k represents the linear coefficient matrix and process noise, $w_k \approx \aleph(0, W_k)$ where W_k is the noise covariance matrix. The Kalman filter algorithm aims to predict or estimate hand movement state Y_{k+1} from Y_k by following equation (4). The parameters in the model H_k, Q_k, A_k, W_k are estimated from the data. In this study, it is assumed that these variables are constant and hence are estimated from the training data using least square estimation [27].

The estimation of hand state using a Kalman filter algorithm consists of *a priori* step estimation, $\hat{Y}_k^-$ of the obtained state and *a posteriori* step that provides the final estimation, $\hat{Y}_k$ by an update $\hat{Y}_k^-$. The measurement update equations are further used to estimate the state,

$$\hat{Y}_k = \hat{Y}_k^- + K_k\left(X_k - H\hat{Y}_k^-\right) \quad (5)$$

where, K_k denotes the gain matrix. The estimated data, $\hat{Y}$ is obtained by accumulating $\hat{Y}_k$ at all k instants.

2.6. Multiple linear regression (MLR)

In this study, we use MLR as a baseline method for trajectory reconstruction. The objective is to fit the recorded trajectory parameters over multiple regressor variables by a linear fitting strategy. The challenge involves defining the multiple regressor variables or predictors such that the fitting is efficient for a least square regression approach. The linear regressor problem can be modeled as,

$$\hat{Y}_{\mathrm{MLR}}(k) = \sum_{l=1}^{L+1}\sum_{\tau=1}^{\theta}\sum_{c=1}^{C}\beta_{l\tau c}x_{l\tau c}(k) \tag{6}$$

Here, $\hat{Y}$ is the estimated value of Y, $\beta_{l\tau c}$ is the estimated regression weight, $x_{l\tau c}(k)$ denotes the predictor at instant k belonging to subband l and recorded from channel c and τ denotes the time lags provided. The regressor equation in (3), can be expressed in the form,

$$\hat{Y}_{\mathrm{MLR}} = \beta \cdot X \tag{7}$$

where $\beta \in \Re^{6\times(P+1)}$. An extra column of ones is included to introduce constant term introduced in the model. This is solved by using the least-squares method as,

$$\beta = (XX')^{-1}X'Y \tag{8}$$

2.7. Predictor subset selection

The estimators in this study uses a set of defined predictors that includes recorded EEG data from a set of channels, their time lags and components in various subbands. In a real time scenario, this amounts to a huge dataset to be processed instantaneously. Hence there is a requirement to select the predictors that carry optimal information regarding hand movement parameters, for their better estimation. It has other advantages of improving the prediction performance of the system by removing redundant data and, also, reduction in processing time. More importantly, the selected predictors are the ones that can provide best estimation of movement parameters and hence will point to the brain activity that is significant in movement definition.

In this study, we use a regression based predictor subset selection by a backward elimination process [34]. This mode of predictor subset selection is usually applied for MLR models to obtain the best fitting combination of variables. Further, it takes into account the joint predictive capability of the variables and hence offers better selection than the other stepwise regression based approached. However, in this study, we propose to use this approach in a generic manner that selects an optimal subset of the input predictors which can later be used for linear estimators such as MLR or Kalman filters. The explanation for this backward elimination procedure is as follows: the MLR model for any given set of variables is of the form equation (7). Initially, the entire predictor set is used to determine β using equation (8) and the p-values corresponding to each predictor. From the non-significant predictor set (p-value greater than critical α), the predictor that is least significant (highest p-value) is removed. The MLR model is re-calculated using the modified set. The process is repeated until all the predictors are statistically significant or have p-values less than critical α. The resulting predictor set provides that linear combination that best estimates output parameter.

The backward elimination method offers search for the linear combination of the predictors that provides the 'best' fit using a statistical approach. However, the method fails to utilize the class labels or movement parameter characteristics for selection of predictors. To achieve this, we can utilize variable ranking and selection algorithms based on ranking parameters such as mutual information (MI), I or correlation (XC), Π. MI is calculated using a supervised approach that consider the class labels, ω of the movement trials [35]. We have a multiclass problem and hence the calculation is as follows,

$$\begin{aligned} I(f;\omega) &= \Phi(\omega) - \Phi(\omega|f),\ \omega \in \{\omega_1, \omega_2, \ldots.\ \omega_8\} \\ \Phi(\omega|f) &= -\sum_{i=1to8}\rho\left(\omega_i\middle|f\right)\log_2\rho\left(\omega_i\middle|f\right) \end{aligned} \tag{9}$$

In the equation, we calculate the mutual information of variable, f with class labels. For ranking the predictors we define f as the predictor set from equation (2). Here $\Phi(\cdot)$ indicates the various entropy measures. In this study, we have eight different classes, denoted by ω_i corresponding to four different directions and two different speeds.

We also used a simpler metric, Pearson correlation coefficient, Π to measure the relation between predictor variables and recorded movement parameter. The summation of the coefficients obtained is used to rank the predictors.

$$\Pi(f) = \sum_{i=1:6}\frac{\mathrm{cov}\left(f, Y_i\right)}{\sqrt{\mathrm{var}(f)\,\mathrm{var}\left(Y_i\right)}} \tag{10}$$

In both these methods, the number of predictors to be selected is set such that there is no significant fall in the estimation performance.

2.8. Priori selection of channels

In the methods discussed above, the approach of backward elimination is more suited for choosing the best fit model. The variable ranking algorithms fail to identify the significance of combination of predictors and also ranking is made irrespective of spatial, spectral and temporal identities. Hence, in the proposed approach we perform a priori selection of channels by variable ranking so that the most informative channels from various subbands are identified. The selection is performed using equations (9) and (10). For calculating mutual information, the variables, f is defined as the band power from each of the subbands signals. For calculating the set of channels highly correlated with the movement parameters, we define variable f as the subband signal to calculate Pearson correlation coefficient, according to equation (10). Further, this subset of channels are used to derive the predictor as per equation (2). In the proposed approach, the predictors thus obtained undergo a backward elimination step to get best regressor model. Thus the combined selection approach provides a considerable reduction in the number of predictors that builds a faster and more efficient estimator.

2.9. System block diagram

The previous sections explained the major signal processing and statistical processing steps in the proposed system. The

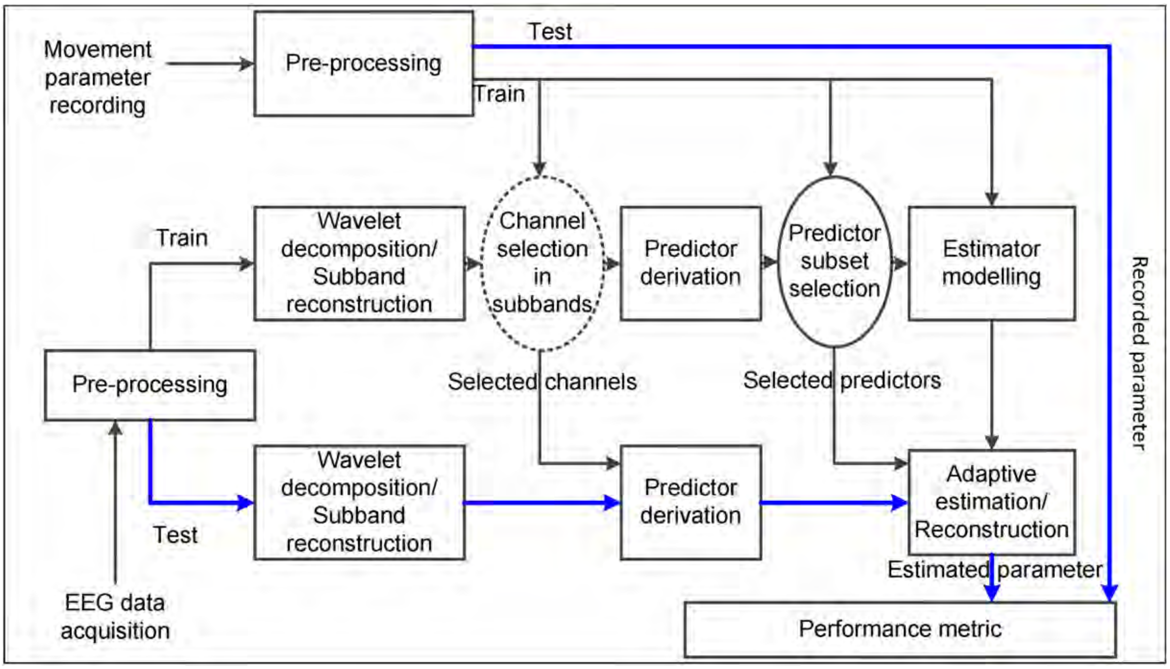

Figure 2. Schematic of the proposed BCI system. The various functional blocks of the system and data flow for training and test data are shown.

schematic of the BCI system is shown in figure 2 along with the experiment set-up. The data inputs to the system are EEG and movement parameter data recorded from the subjects. The data is then pre-processed. It should be noted that the pre-processing steps are applied to each trials separately to avoid the overlap of training and test data. The signal then undergoes a 10-fold cross-validation analysis for performance evaluation. In each fold the data is divided into train and test samples that are decomposed and reconstructed in non-overlapping subbands by wavelets. The orthogonal wavelet 'sym5' from the symlet family is used in this study. If channel selection is included in the system, then the training data is used to choose the informative channels and applied to the test data. The predictors are then defined using the proposed approach. The training data is used to perform a predictor subset and later to calculate a regressor model. The selected predictor indices and estimator model are used to estimate the movement trajectory parameters of the test trials. In our analysis, the constants in the equation (3) are set to $C = 35$, and $\theta = 10$ which is the total number of channels used for analysis and the time lags respectively. The performance of the algorithm is reported in terms of correlation between estimated and recorded movement parameters. We use Pearson's correlation coefficient for this calculation.

3. Results

The results obtained using the proposed estimation approach and the related analyses are summarized in this section.

3.1. Wavelet subband-power spectra

The proposed method uses DWT for decomposing EEG data. The objective is to break down the signal into spatially localized time-frequency components that can estimate movement trajectory parameters. The power spectra of the subband signals is computed and demonstrated in figure 3(b). The decomposition into nine subbands of a single trial EEG signal recorded from channel C3 of subject-1. The data clearly indicates the orthogonal division by wavelets and shows the higher concentration of power in low frequency region. Figure 3(c) shows the EEG signal used for estimating the movement parameters at an estimation interval = 200 ms. The spectrum clearly shows division of low frequency signal components which can help in linear estimation of low frequency movement parameters. Further, the increase in estimation interval reduces the overall estimator training time, as it effectively reduces the sample size by a factor of 50. A similar pattern of decomposition is shown by all the EEG trials in the dataset.

3.2. Channel ranking

We studied the contributions of each spatial locations on the scalp in executing a defined movement. As mentioned in section 2.7, we adopt widely used methods of mutual information and cross correlation for evaluating this. Figure 4 shows the spatial distribution of mutual information in the three different subbands used in the study. High values can be clearly observed in the contralateral motor and midline parietal regions. It should be noted that these values shows the channels that contain most information about class labels rather than the trajectory itself. Further we look into the Pearson correlation coefficient value obtained in each

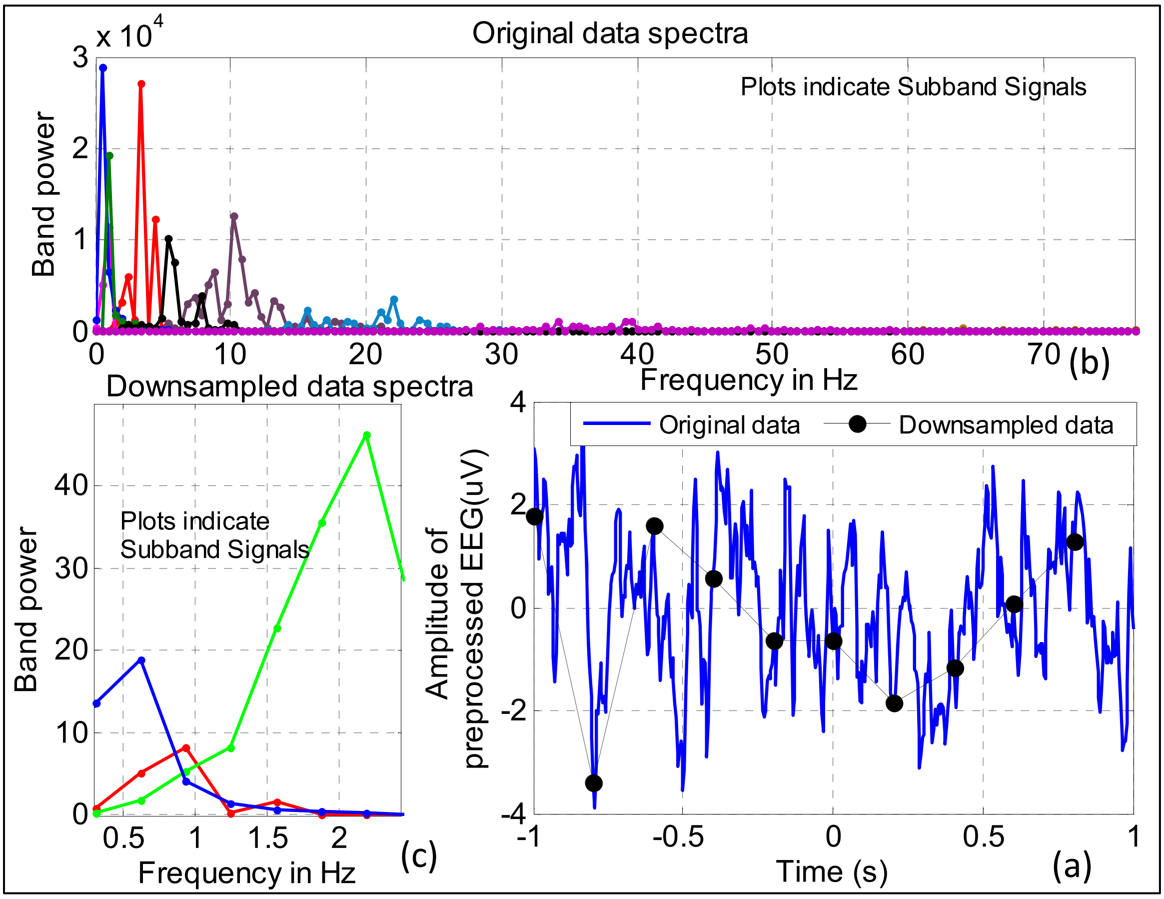

Figure 3. The decomposition of single-trial EEG signal into various subbands is displayed. (a) The original and down sampled data. (b) The spectra of original data and (c) Down sampled data. The colors indicate data from different subbands. The higher band power of low frequency subbands can be clearly observed.

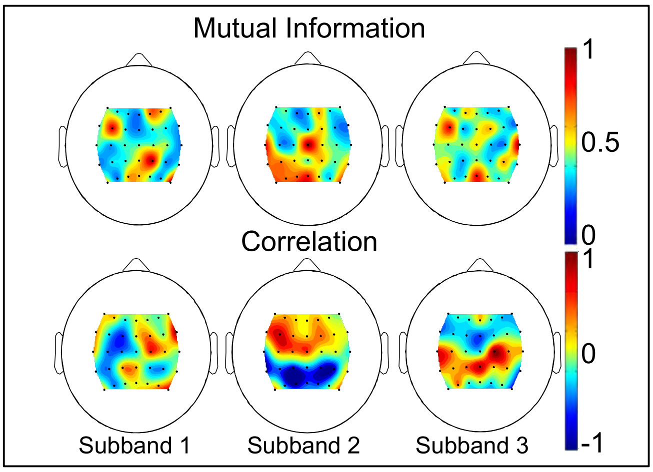

Figure 4. The distribution of metrics: mutual information and correlation spatially for each of the subbands are indicated in the figure. The scales are given aside. The data is for subject-1.

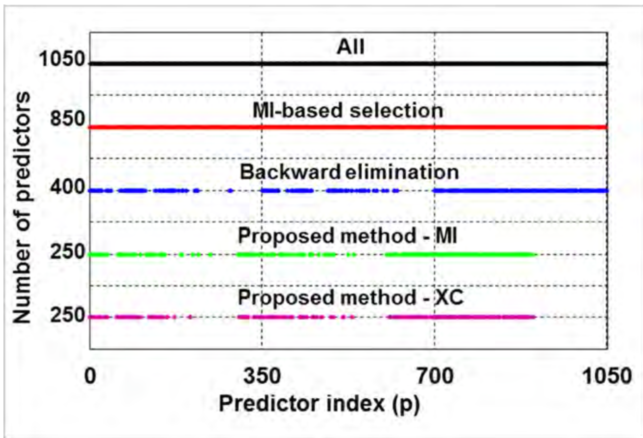

Figure 5. Selected predictor indices for the proposed and baseline methods are shown here. Refer to text for details.

subband as shown in figure 4. This gives a measure of correlation between the spatially recorded EEG and recorded movement parameters. We can observe a lack of distinct localization. A possible reason for this is the non-stationarity between trials which are not considered while calculating correlation. Hence, unlike the trial-by-trial supervised mutual information, the bad trials will have a major impact on correlation values. The results indicated are for subject 1.

3.3. Predictor subset selection

We performed the backward elimination method for subset selection to create a best fit regressor model. As a baseline test,

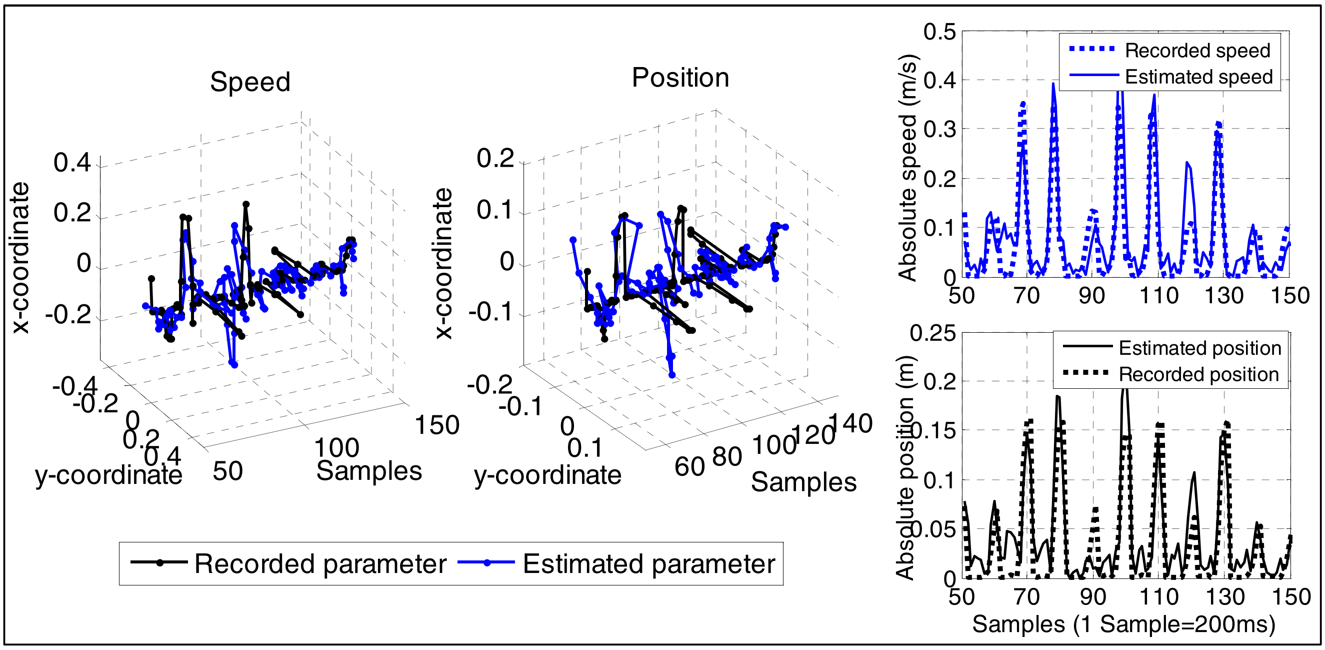

Figure 6. The trajectory parameters reconstructed using proposed adaptive estimator with selected predictors.

we also performed regressor selection based on mutual information and correlation. The predictors selected in these processes are indicated in figure 5. In the figure, the *x*-axis represents predictor indices, p. For our data, $x_{l\tau c}$ represents the predictor, where, $l = 1\ to\ L + 1$; $\tau = 1\ to\ \theta$; $c = 1\ to\ C$, with the constants set to $L = 2$, $\theta = 10$, $C = 35$. The predictors are indexed as per their order in the predictor set, X, which is mathematically given by, $p = C\theta(l - 1) + C(\tau - 1) + c$. The method in which predictor is selected using mutual information or correlation, it has been noted that the estimation error increases as the number of predictors decreases. Hence the number of predictors used is set at 850 to maintain estimation performance. The backward elimination process, reduces the predictor number from 1050 to 400 on an average across various subjects and parameters. The proposed algorithm combining channel and predictor selections using MI and XC are indicated in the last two scatter plots. The number of predictors chosen is 250 on an average in both cases and it is seen that, the selected predictors significantly overlap.

3.4. Trajectory reconstruction and correlation

The main objective of the study is to adaptively estimate the recorded movement parameters from brain activity. The figure 6, indicates the reconstructed trajectory using Kalman filters with a selected subset of predictors. The time segment selected for the plots are 50 to 150 samples of the test data for subject 1. The x and y coordinates of speed and position are indicated in the figure. The estimated absolute movement speed and position are shown in figure 6. It can be observed that there is a significant overlap between the estimated and original parameters.

The performance metric, the Pearson correlation coefficient obtained as a function of number of predictors is given in figure 7. The average performance over seven subjects in the dataset is indicated in the primary axis. We also checked the statistical significance of the proposed methods as compared to using all predictors for estimation. For better visualization, the plot displays p-values obtained from student's t-test as $-\log(p)$. The blue line indicates $-\log(\alpha)$, where $\alpha = 0.05$. The results that has statistically significant difference in performance are indicated by black squares and the others by black dash markers. For reconstruction using MLR, the change in performance is negligible, however, the p-value ($p < 0.143$) indicates that the variation in performance is statistically insignificant. In the case of Kalman filters, it can be observed that the performance falls from 0.60 to 0.58, as the number of predictors change from 1050 to 250. The p-value ($p < 0.01$) shows that the predictor selection cause a statistically significant change in Kalman filter performance and hence the estimation results.

3.5. MLR: predictors

The values of MLR coefficients estimated by equation (8) indicate the contribution of each of the predictors in the regressor model. Figure 8 indicates the coefficient values obtained for each of the predictor indices, p. It is interesting to note that the predictor contribution is significant in the last subband (predictor indices 700–1050) and is almost negligible in the others. The red plot indicates the MLR value for selected predictors.

3.6. Kalman: gain, time

A major contribution of this work is that our method allows estimation of movement parameters from a selected number of predictors without degrading performance. Hence, we analyze the characteristics of Kalman filters in order to justify the need of predictor subset selection. The stability of the

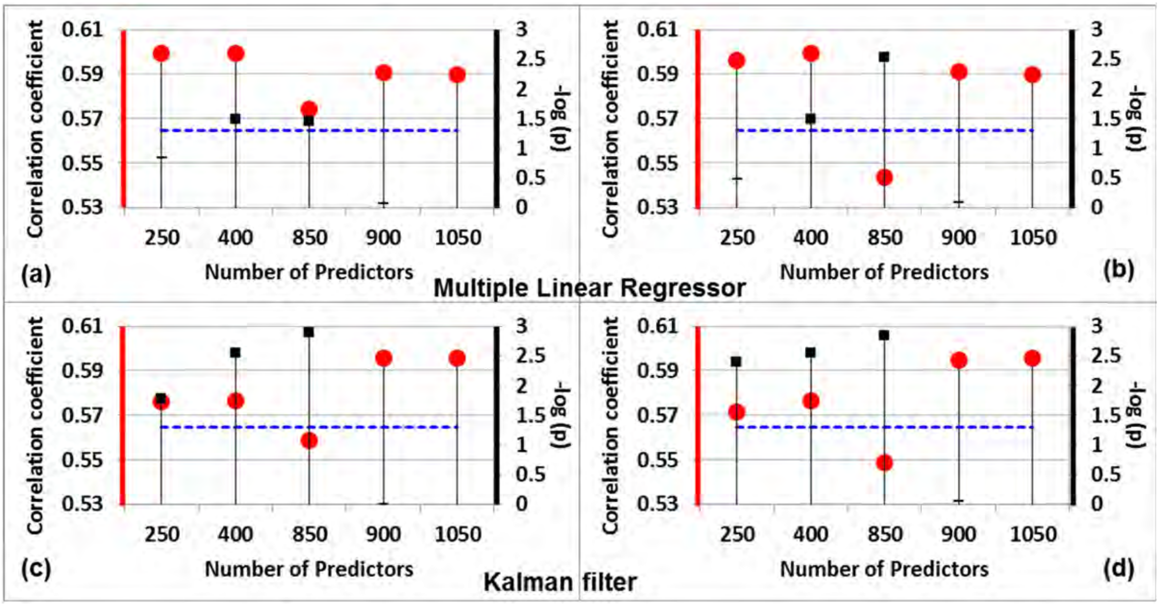

Figure 7. The results of the proposed methods and comparisons with the baseline methods are provided. Figures (a) and (c) displays results using channel and prediction algorithms based on MI. Figures (b) and (d) are based on XC.

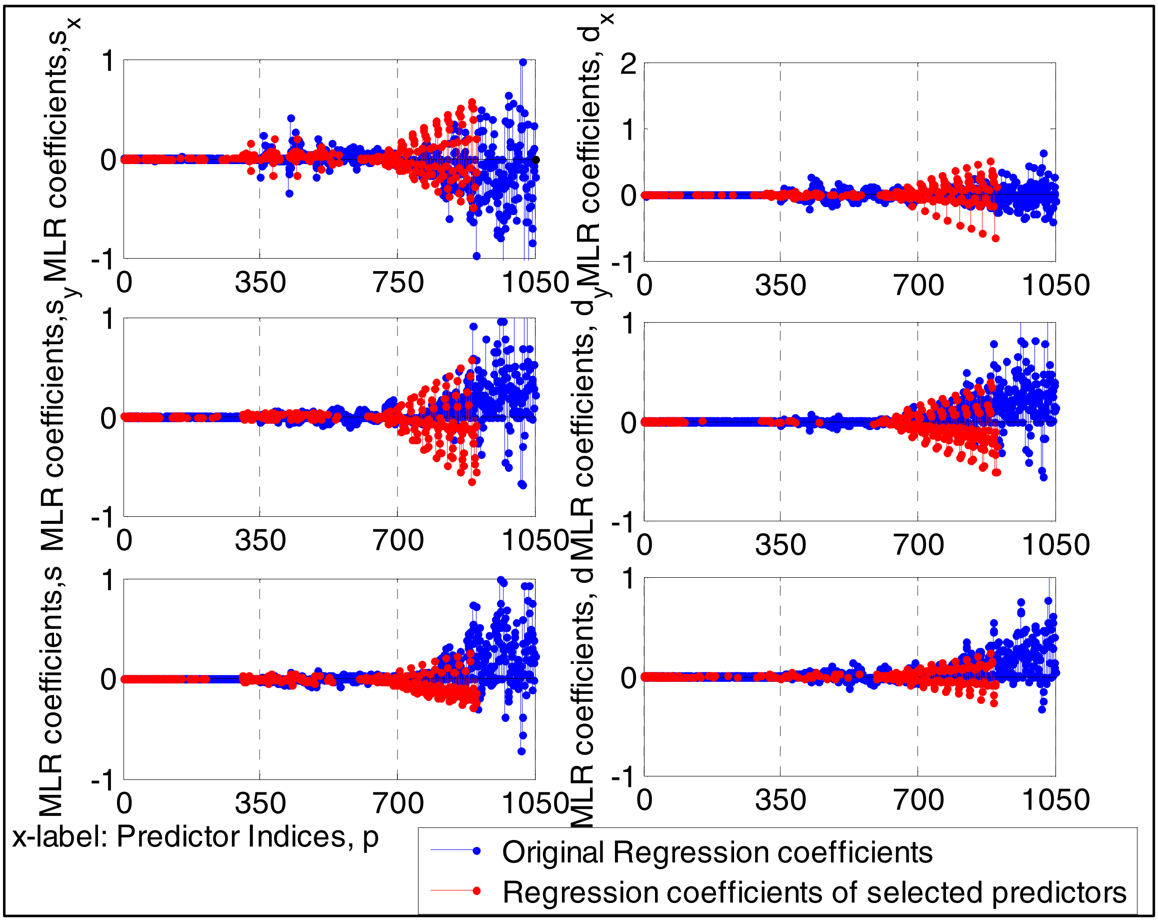

Figure 8. The linear coefficients corresponding to each of the predictors calculated using the multiple linear regressor is provided. The coefficients re-calculated using the selected predictors using the proposed approach is also provided.

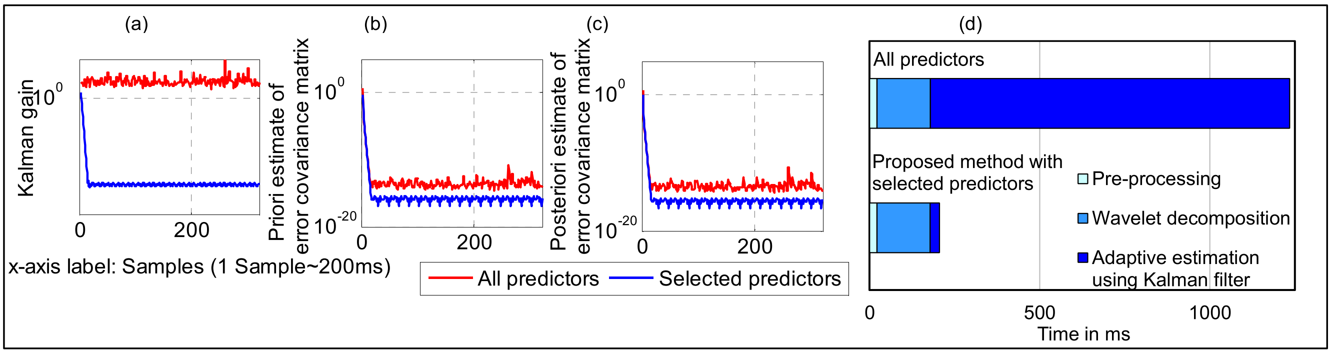

Figure 9. The various performance indicators of the Kalman filter used is shown in the figure. The L^2 norm differences between consecutive samples for (a) Kalman gain, (b) priori error covariance matrix, (c) posteriori error covariance matrix, and (d) the time consumption.

Kalman filter model is determined by the convergence of that gain and error matrices. In figure 9 we show the evolution of these matrices versus the iteration. From the figure, it is evident that the selected informative features give a stable Kalman model, which converges quickly to give stable model parameters. The performance of the Kalman filter can deteriorate due to the high number of predictors which may give redundant, non-stationary information. As we propose this method as an adaptive estimator, it is important to consider the performance in terms of time for estimation. Figure 9(d) indicates the average time taken by MATLAB R2012a and an Intel® Core™2 Duo 3.16 GHz processor. This indicates on an average, the proposed system estimates 2 s long single trial data, 205 ms after its arrival as compared to the original approach that takes 1.23 s. Thus an 83.3% speed-up is obtained in estimation of movement parameters using the proposed BCI system.

4. Discussion and conclusions

4.1. Low frequency nature of parameters

The estimation of movement parameters from brain activity have been attempted by various researchers using invasive and non-invasive methods [11–23]. A highlight in all the experiment paradigms is the nature of movement considered, which a multi-directional hand movement is at a normal pace. On analyzing the speed and displacement caused by this movement, it can be noted that, it is a low frequency, smooth curve contaminated by motion and sensor artifacts. The analysis methods in the literature discards the high frequency information in recorded brain activity, by using mathematical tools, such as linear estimators to predict the low frequency movement parameter. In this regard, our attempt is to define predictors from the recorded brain activity, in this case, EEG, such that they can best estimate a low frequency movement speed or position information.

In our proposed analysis, we chose DWT for subband decomposition of the signal over traditional filters. Wavelets can decompose the highly non-stationary EEG signal into time-frequency localized data. Also, the orthogonal filter bank structure provided by DWT, allows better localization of the low frequency signal, as clearly observed in figure 3. The use of DWT reduces the filter design costs in the traditional filter bank approaches for a real time application.

4.2. Kalman and adaptive estimation

The Kalman filter was used to adaptively estimate the movement task performed in this study. Being a widely used tool for estimation of data, the performance of the Kalman filter is undisputed. However, the predictors that we provide as input to the Kalman filter can have a major influence on the Kalman model and its stability. The predictor design which we propose thus provides a complete description of brain activity recorded at each sample time. The performance of the Kalman filter using all the predictors gives the best result of (0.60 ± 0.07) mean correlation between recorded and estimated trajectory. The proposed approach of channel and predictor selection gives a performance of (0.57 ± 0.08, $p < 0.004$) which is slightly lesser compared to the baseline method, but offers a 76% reduction in number of predictors. The Kalman filter properties were explained in section 3.6. The time overhead caused by the Kalman filter is only around 27 ms after every trial using the selected set of predictors from the proposed approach, as shown in figure 9.

4.3. Advantages of proposed predictor selection strategy

The advantages of the proposed Kalman modelling from a selected subset of predictors are evident from the performance achieved. The method clearly proves that to obtain a best fit the regressor statistics should be considered and hence backward elimination is apt for predictor selection. Incorporating a prior channel selection using MI or XC approaches to this, we are able to considerably reduce the number of predictors while maintaining the performance. This is clearly seen in figure 7, when using the Kalman filter, a prior selection of channels using both MI and XC correlation drops from 0.60 to 0.57. For the slight drop in performance both methods eliminates around 800 insignificant predictors. The further advantages of subset selection are observed in figure 9. The Kalman estimator characteristics clearly indicates a stable model with fewer, more optimal, number of predictors. The saving in time is shown in figure 9(d), that shows with a fewer number of optimal predictors the time taken for estimation is reduced from 1.05 s to 27 ms. This is a major highlight in the proposed algorithm, as delay needs to be kept at a minimum for real time BCI applications. The results obtained clearly prove that the proposed algorithm is most suited for adaptive estimation of movement trajectory using EEG signals only.

4.4. Linear decoding performance

The literature [36] reports possible misinterpretation of results when using linear decoders for reconstruction of movement kinematics. In this regard, we have included certain tests to justify the significance of our study. First the reconstruction using the linear decoders is tested against chance-level models to ensure statistical significance of the results. The original estimator model using the entire set of predictors was applied to reconstruct shuffled test data. The shuffling and decoding was repeated for 32 times and the average correlation was reported. The chance level results obtained is an average accuracy of (0.20 ± 0.03) whereas the original model provided (0.57 ± 0.07) which is higher and statistically significantly ($p < 1.6\text{e-}5$). This indicates that the proposed reconstruction strategy effectively makes use of neural correlates of movement kinematics and the results are not by chance. Further we tested the reconstruction performance in various subbands and have identified that the lower spectral region (<3 Hz) provides statistically significant and better performance. Our previous studies [17, 18] using wavelet based features for classification of movement parameters also indicated the neural correlates of movement to be in the low frequency region, even without linear decoders. Hence, the results reported in this paper are valid and future studies will aim to use the proposed wavelet-based predictors on nonlinear decoder models to confirm these findings.

4.5. Limitations and future work

The linear mathematical model used in the proposed method limits the usage of brain activity information from the higher frequency ranges in the estimator. However, there are no studies in the literature that confirm the involvement of high frequency EEG for movement reconstruction. This will be an interesting area to explore, by using nonlinear estimators to reconstruct movement parameters from wideband EEG.

Regarding the selection procedures used, even though the performances of the algorithms at two different stages can be justified, the proposed method lacks a selection algorithm that can simultaneously choose the optimal spatial, spectral and temporal predictors from the brain activity and also that can create the best-fit estimator model. Another disadvantage is regarding the use of the backward elimination method, which is not optimal as the significance of a predictor can vary depending on its varying combination with other predictors in the model. Novel algorithms that can address these issues simultaneously are desired as an extension of this work in future.

4.6. Conclusions

In this study, we used adaptive linear estimators to reconstruct the trajectory parameters. Wavelet decomposed spatially and temporally localized EEG signals were used as predictors for the estimator. Our method is advantageous as we utilize the low frequency EEG signals as predictors to estimate low frequency movement parameter signal. The proposed method uses a two-stage selection approach in which the spatial selection is performed initially and a predictor selection at the later stage. The selected predictors are used to estimate the movement trajectory by using the Kalman filter. The higher performance in terms of correlation, estimator properties and time consumption are explained in detail in the study.

The performance and analysis results of our proposed approach indicate its applicability in adaptively reconstructing movement parameters from scalp recorded EEG. This can be extended to real-time experiments considering the advantages in stability of model and delay. Furthermore, the study can be also be extended and applied in real time experiments to estimate imagined movement trajectory from brain signals.

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