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Toward a Model-Based Predictive Controller Design in Brain–Computer Interfaces

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Abstract—A first step in designing a robust and optimal model-based predictive controller (MPC) for brain–computer interface (BCI) applications is presented in this article. An MPC has the potential to achieve improved BCI performance compared to the performance achieved by current *ad hoc*, nonmodel-based filter applications. The parameters in designing the controller were extracted as model-based features from motor imagery task-related human scalp electroencephalography. Although the parameters can be generated from any model-linear or non-linear, we here adopted a simple autoregressive model that has well-established applications in BCI task discriminations. It was shown that the parameters generated for the controller design can as well be used for motor imagery task discriminations with performance (with 8–23% task discrimination errors) comparable to the discrimination performance of the commonly used features such as frequency specific band powers and the AR model parameters directly used. An optimal MPC has significant implications for high performance BCI applications.

Keywords—Brain–computer interface, Model-based feature, Movement imagery task, Motor task discrimination.

INTRODUCTION

A brain–computer interface (BCI) is an alternative communication pathway between the brain (human or animal) and an external device. One motivation is to give greater ability to severely disabled patients to interact with their surrounding environments.[51,68] In BCI development, neuronal signals are translated into commands to build a direct interface between the brain and a device. Although invasive techniques have shown recent promise in the application of BCI,[12,26,34,53,56,61,62] non-invasive scalp EEG based methods may be useful and more easily applied.[2,4,7,44,55,67] Feature extraction and pattern discrimination are essential steps in the design of cue-based BCI paradigms, where subjects perform imagery tasks in response to audio-visual cues on the computer screen.

In current BCI systems, simple proportional control or filter algorithms are applied to generate device control signals based on the classification of task-related features extracted from brain waves. The application of advanced control theory such as robust and optimal model-based predictive controller (MPC) algorithms, in our view, will improve the performance of BCI. As applied in control theory and presented here, models assimilate data and extract dynamics.

From the perspective of designing control algorithms, the step response of a model is an essential part in MPC design.[13,14,30] In MPC designs, as is briefly shown in the following section, the system dynamic matrix is expressed in terms of the step response coefficients; i.e., the time response of the process at each sampling instant in response to a unit change in the input over a short period of time. The transient part of the step response plays a very important role in system dynamics estimation, output prediction, and controller design. Fast and large deviations from the steady state value may influence the process significantly. This response also gives insight into the stability of the process and the ability to reach one stationary state starting from a different one.

For the design of an MPC, models of any kind—linear, non-linear, simple, or complex—that model the system dynamics can be used directly. A

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"dynamic matrix" that consists of the step response coefficients of such a model represents the system dynamics and is constructed in an MPC design by the transformation of the model. Alternatively, the step responses, if available, can be used directly to construct the system "dynamic matrix". We here generated the step response parameters to be used directly for the controller design. We adopted the simplest form of all models, the linear autoregressive (AR) model, for the reason that the use of AR models for EEG signals is well-established in BCI literature.[19,40,58] There are considerable improvements, which can be instituted in order to improve our model-based approach, which include more sophisticated multivariate extensions of our linear univariate AR models, and of course models with nonlinear dynamics. As always, whether an increase in computational complexity is worthwhile for more complex models is an important issue to explore. Eventually, real-time implementation will govern these constraints on BCI model complexity.

We here developed a first step, the building block of designing an optimal MPC, by developing a model and generating model-based step responses from motor imagery task-related scalp EEG signals to be applied to BCI. We investigated task-related EEG signals and extracted discriminative features in terms of frequency specific band powers, parameters from the model and the model-based step responses. We then applied pattern discrimination algorithms such as linear discriminant analysis and neural network methodologies[43] for a classification of these features. A review of EEG features used in BCI can be found in Fatourechi *et al.*[21] and a survey on the classification algorithms used to design BCI systems can be found in Lotte *et al.*[39] We here showed that the step response parameters generated for the controller design can as well be used for motor imagery task discriminations with performance comparable to the discrimination performances of commonly used features such as frequency specific band powers and the AR model parameters directly used. The next step of merging optimal control theory in controller design using the step responses will build on these findings.

METHODS

Background on MPC Design

The basic principle of the MPC algorithm is as follows: a simplified dynamic model of the process is used to predict future outputs of the process based on past/present inputs. These predicted outputs are then compared with the actual outputs at the present time step. The controller is then designed to optimize a user-specified performance index, for example, minimize the error between the predicted values and the desired values of the variables of interest. Consequently, the values of the manipulated variables or the control signals for the current time step are calculated. Some of the advantages of MPC[11,29,49,54] are (1) MPC concepts are very intuitive and easy to understand and implement, (2) MPC can handle large-scale multivariable systems which are often difficult to handle by individual feedback controllers, (3) MPC can deal with hard constraints on inputs/outputs which are difficult to include in other control scheme implementations, (4) because the objective function typically has a finite time horizon and the optimization problem is linear or quadratic in nature, it is not difficult to solve the optimization problem at every sampling instant, (5) when the inequality constraints on the process inputs/outputs are inactive, the final control law is linear and easy to implement with considerably higher speed of convergence compared to a constrained problem, and (6) with its flexible and open methodology, MPC can be extended and improved in many different ways. Limitations of MPC include proper selection of the prediction horizon over which to predict the future outputs. Improper selection may cause poor control performance even for a good model. This is where the step response parameters as are presented in this article can be useful. Other limitations such as the need for a complex or non-linear model for some applications and a disturbance/noise model should be carefully considered. This is especially important for BCI applications since it involves complex brain dynamics that includes task-related as well as ongoing brain activities.

In comparison to proportional feedback control, the MPC algorithm predicts the output such as the desired movement of an external device over an extended period of time (multi-step sampling time) into the future (called the prediction horizon) and minimizes the error between the predicted and desired movements using an optimization algorithm. As is depicted in MPC literature, the resulting controller is an optimal, high performance and robust and has the ability to be tuned for performance, and robustness using a number of tuning parameters, for example, prediction horizon (p_N), control horizon (M), and other weighting parameters.

In an MPC framework as is shown in Fig. 1, the controller design includes the estimation of the control (or manipulated) variable as follows:

$$\hat{\mathbf{u}}(k) = K_{\mathrm{MPC}}[\mathbf{r}(k) - \mathbf{f}(k)] \tag{1}$$

where $\hat{\mathbf{u}}$ is the control variable, $\mathbf{r}$ the desired output such as the desired movement of an external device,

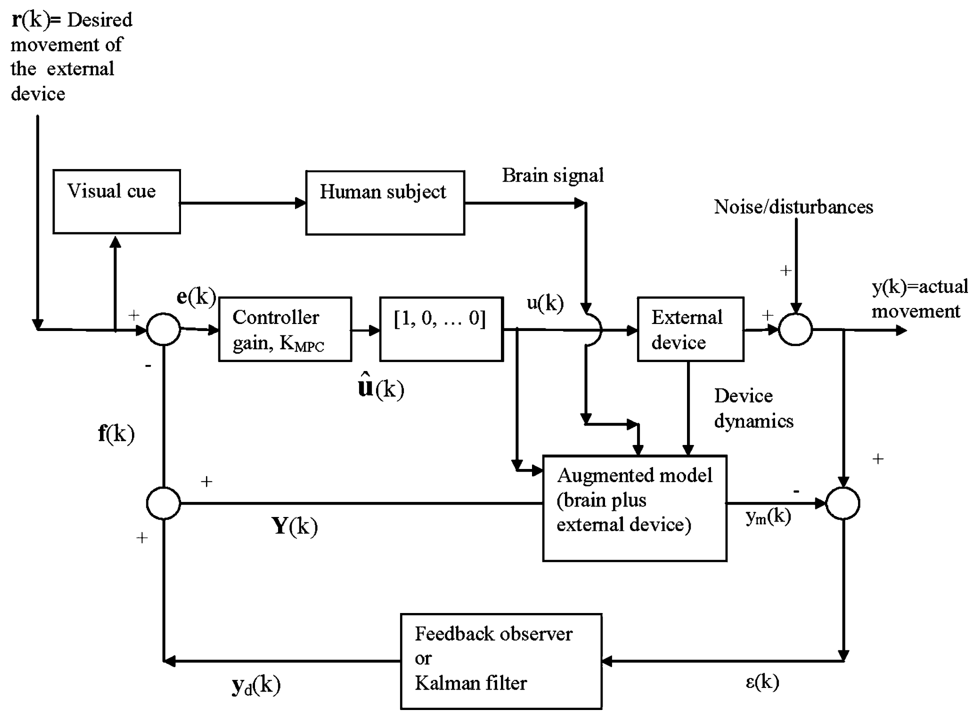

FIGURE 1. A closed-loop, model-based predictive control framework of a brain–computer interface system in application to controlling the movement of an external device, for example, a robot. Y(*k*): model prediction over p_N future time points (called 'prediction horizon'), $y_m(k)$: predicted movement at the current time, $y(k)$: actual, measured movement at the current time, $y_d(k)$: predicted noise/disturbances over the prediction horizon p_N, ε(*k*): error between the measured and predicted movements at the current time, f(*k*): model-based predicted movement of the external device plus noise, predicted over the prediction horizon, e(*k*): error between the model-based predicted movement (plus noise) of the external device over the prediction horizon and the desired movement of the device over the same period of time into the future, and u(*k*): control command or input to the device. '+' and '−' signs indicate whether the signals are added or subtracted.

and $\mathbf{f}(k)$ called the future predicted output that depends only on the past control moves and the process model. K_{MPC} represents the controller gain matrix. In general, MPC is defined as a class of controllers that, using a process model, determines a set of manipulated variables by minimizing/maximizing some open-loop performance objectives over a finite time horizon from current to some extended future time. The most commonly used performance objective function is defined as

$$J_{\mathrm{MPC}} = \sum_{i=1}^{p_N} (r(k+i) - \hat{y}(k+i))^T Q_i (r(k+i) - \hat{y}(k+i)) + \sum_{j=1}^{M} u(k+j-1)^T R_j u(k+j-1) + \sum_{j=1}^{M} \Delta u(k+j-1)^T \Lambda_j \Delta u(k+j-1) \qquad (2)$$

where $\hat{y}(k+i), i = 1,\ldots,p_N$ are the predicted future outputs over a finite prediction horizon p_N, $r(k+i)$ are the future reference or desired (or target) signals that are assumed to be known and $u(k+i-1)$, $\Delta u(k+i-1)$ are the present/future control and incremental control moves, respectively, that are determined by solving the quadratic optimization problem (2). In MPC literature, M is called the control horizon, Q_i is the output weighting matrix, R_j is the input weighting matrix, and Λ_j is known as the move suppression factor matrix. The controller parameters p_N, M, Q_i, R_j, and Λ_j can be used as tuning knobs for different performance and robustness of the feedback control system. Although M control variables (present plus $M-1$ steps into the future) are calculated in Eq. (1), only the first one, i.e., at the current sampling step is implemented as is shown in Fig. 1. The future predicted output vector defined by $\mathbf{f}(k)$ in Eq. (1) can be expressed as $\mathbf{f}(k) = [\hat{y}(k+1), \hat{y}(k+2), \ldots, \hat{y}(k+p_N)]^T$. The controller gain K_{MPC} is calculated as $K_{\mathrm{MPC}} = (G^TQG+R)^{-1}G^TQ$ where Q and R are weighting matrices on future inputs and outputs, respectively, consisting of the Q_i and R_j which are defined above in the objective function J_{MPC} and construct the Q and R matrices in calculating K_{MPC}. The matrix G is called the "*dynamic matrix*." Although Q and R are design parameters and can be user defined, the *dynamic matrix*, G represents the system dynamics. G consists of the first p_N step response coefficients of the model for a specified output prediction horizon p_N and is calculated as

$$G = \begin{bmatrix} S_0 & 0 & \cdots & 0 \\ S_1 & S_0 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ S_{p_{N-1}} & S_{p_{N-2}} & \cdots & S_0 \end{bmatrix} \tag{3}$$

Step response coefficients S_i, $i = 0, \ldots, p_{N-1}$ play a crucial role in designing a robust and optimal controller and determining the performance of the controller. Step response characteristic parameters that are indicative of the dynamics of the system are also useful in determining how many coefficients should be used in constructing the *dynamic matrix* and defining the MPC design parameters such as the prediction horizon p_N. This, in turn, determines the aggressiveness or conservativeness of the MPC controller. Sometimes, the $(G^TQG + R)$ matrix may be ill-conditioned, leading to an ill-posed optimization problem. Measures can be taken in numerically solving such problems, for example, by calculating the pseudoinverse of the matrix.

Detailed formulation of an MPC can be found in Clarke *et al.*, Cutler and Ramaker, and Kamrunnahar *et al.*[13,14,30]

Step Response Generation

The step response of a dynamic model is the output signal that results when the input is a step. That is, if we consider a common form of an input–output model,

$$y(t) = \sum_{i=1}^{n} a_i y(t-i) + \sum_{j=1}^{m} d_{j-1} u(t-j) + \varepsilon_t \tag{4}$$

with u as the input, then the step response is the output $y(t)$ where $u(t<0) = 0$ and $u(t>0) = 1$. n and m define the model orders in inputs and outputs, respectively, a_i and d_j are model parameters, and ε_t is white noise. In generating the step response from the model, the general idea is to make a step change in the input, not necessarily from zero initially. A sample step response is shown in Fig. 2. Characteristic parameters of the step response include: *rise time*, defined as the time required for the response to reach a certain level (e.g., 80–90%) of the steady state value; *settling time*, defined as the time required for the response to reach and remain at the final value with a certain error band; *overshoot*, defined as the amount of the response exceeding the final steady state value; *peak time*, defined as the time at which the maximum overshoot occurs; and *ringing*, defined as the oscillation around the steady state value.[36] The step response coefficients S_i described in section "Background on MPC Design" are these responses to a unit step at every sampling time. As step response coefficients are directly used in the construction of the *dynamic matrix*, G in MPC, the step response characteristic parameters that are also the characteristics of the dynamics of the system define the MPC design parameters such as the prediction horizon p_N.

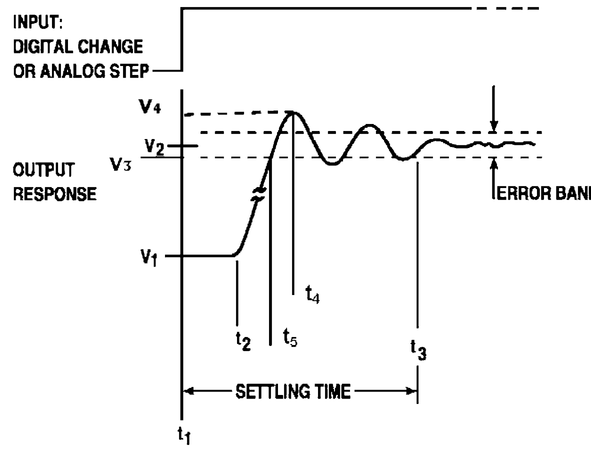

FIGURE 2. A typical step response of a second order system. V_1 = initial value, V_2 = final steady state value, V_3 = 95% of steady state value, V_4 = Peak value, $V_4 - V_2$ = overshoot, $t_3 - t_1$ = settling time, $t_4 - t_1$ = peak time, and $t_5 - t_1$ = rise time.

Time Series Model

For time series data, mathematical models such as AR, autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA) are well described in.[8] AR models and model parameters have been used as features for BCI task discriminations, as described in the literature.[3,58,59] We here adopted an AR model as the simplest of the time series models to fit the scalp EEG data with the ultimate goal of incorporating more complex including non-linear models. The AR model is written as

$$y(t) = \sum_{i=1}^{n} a_i y(t-i) + \varepsilon_t \tag{5}$$

The model parameters can be estimated using a least squares technique by fitting scalp EEG time series.

AR model parameters are usually used in BCI literature in order to calculate spectral properties which, in turn, are used for spectral feature discrimination. However, we here applied the AR model to calculate the step response with a view toward applying them in developing an MPC algorithm.

Experimental Paradigm

Five healthy human subjects, 25–32 years old, four males and one female, none of them under any kind of medication, participated in the motor imagery tasks. The experiments were conducted under Institutional Review Board approval at Penn State University. Each subject conducted one session of tasks that consisted of four runs, each with 40 trials. Each trial was designed as follows: the subject would be quiet and relaxed, a cross would appear on the computer screen, a left, right, up, or down arrow, depending on the task to be performed, would appear during which time the subject would imagine the task, and then both the cross and arrow would disappear to end the trial. Of the four total runs, the first two were designed for imagery of left or right hand movements and the last two runs were for imagery of tongue or bilateral toe movements. Of the 40 trials in each left–right hand movement run, 20 randomly permuted trials showed ''left'' arrows indicative of imagined left hand movements and the other 20 showed ''right'' arrows indicative of imagined right hand movements. Similarly, ''up'' and ''down'' arrows were used for tongue–toes tasks. Figure 3 shows the experimental setup for our study. Chance error for feature discrimination may depend on the number of trials used for a certain number of classes to discriminate, as discussed in.[46] We tested the efficacy of our algorithm with a limited number of trials and compared the classification results with more commonly used approaches such as frequency specific band power features. We tested our classification results through the measure of Muller-Putz *et al.*,[46] as discussed in ''Results and discussion'' sections.

Data Acquisition and Analysis

Nineteen monopolar electrode positions (FP1, FP2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, and O2 as per the International 10–20 standard electrode locations) referenced to linked earlobe electrodes were selected for acquiring EEG under open-loop conditions while the participants performed the imagery tasks. Data were passed through a fourth order band-pass Butterworth filter of 0.5–60 Hz and sampled at 256 Hz.

Data Preprocessing

Data were epoched from 2 s before to 4 s after the presentation of each arrow cue. Recordings were visually inspected for artifacts, and by using an amplitude threshold (55 μV) criterion, trials that contained artifacts were excluded from further analysis. For each subject, the number of per class trials remaining after artifact exclusion was 70–80 out of signals recorded in 80 trials. Artifact rejection is a standard and sometimes automated step in most online BCI applications. The amplitude threshold criterion is simple and the time needed for this step is acceptably short making it easy for online application.

Data Transformation

Two different techniques were applied on the EEG signals acquired using linked earlobe reference electrodes (referential montage), to increase the spatial resolution and decrease the dependence on the EEG reference. The Laplacian derivation[47,48,63,64] is a discrete second derivative, calculated as the difference between an electrode potential and a weighted average of the surrounding electrode potentials. Laplacian derivations were developed for nine inner loop channels (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4) using four channels surrounding the active channel for deriving the weighted average. In the common average reference (CAR) calculation, the outputs of all of the

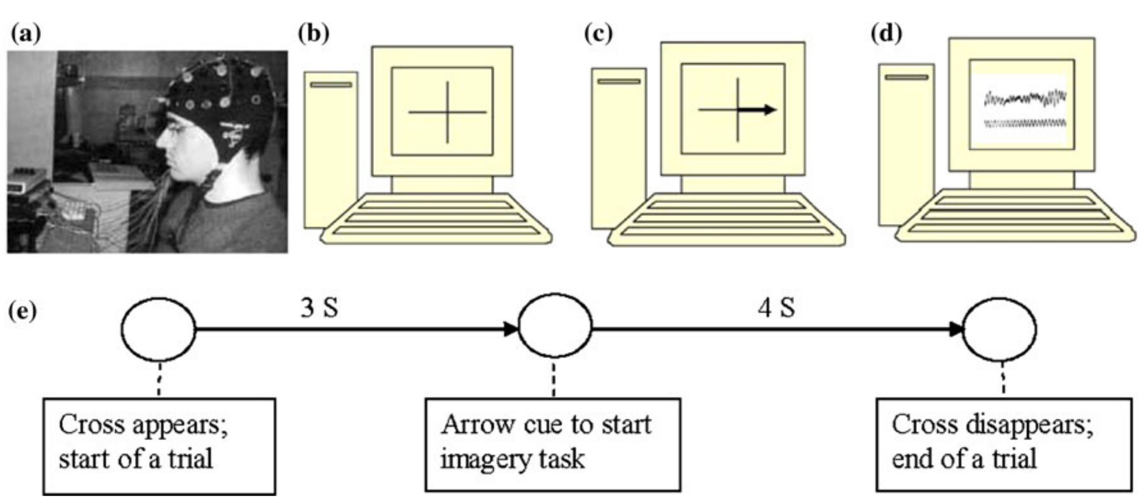

FIGURE 3. Experimental paradigm: (a) Subject sitting relaxed in front of a computer, (b) cross appears on the screen, (c) arrow cue appears, (d) EEG data being acquired, (e) time segments of a trial.

amplifiers are summed and averaged (19 channels), and this averaged signal is used as the common reference for each channel. It is well-established in the literature on spatial filtering that Laplacian outperforms CAR or any other reference for BCIs applications.[41] Our study was consistent with such findings, as we reported earlier[31] and we present here the results using the Laplacian filtered signals only.

Feature Extraction

Model-Based Features

For each 1 s time window (without overlap), a third to fifth order AR model (with 3–5 "a" parameters as in Eq. 4) was developed for each of the 9 (as in the Laplacian derived) EEG channels without the consideration or separation of training or test data. The AR model was different for different EEG channels and each model order was selected such that the model fitted more than 90% of the data signal (i.e., there was less than 10% error in fitting the model to the data). The error bound was chosen arbitrarily without any formal statistical implications. However, this error bound can be used in MPC formulation as tuning knobs for performance–robustness trade offs. Once we estimated the parameters of the AR model, we then generated the step response of the model corresponding to each EEG channel. Characteristic step response parameters were calculated as features corresponding to each imagery task performed by the subjects. These parameters can be extracted from the step response either by plotting the response and calculating the parameters from it, or by using standard numerical algorithm (e.g., Matlab) to generate step response parameters. We used three parameters: rise time, settling time, and peak time from each step response corresponding to each channel, since these parameters are critical for the dynamics of the AR model and are expected to be task discriminative. These three parameters represent the fast dynamics as well as slow dynamics of the system. Other step response parameters, e.g., overshoot, may or may not provide additional discriminative information, but will certainly increase feature dimension. 27 features (3×9) for 9 (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4) channels were available for feature selection and classification.

We also used the AR model parameters directly as features. In doing that, we used 3×9 to 5×9 AR parameters for models of orders 3–4 for the 9 electrode channels we chose from the Laplacian-transformed signals. Note that the higher the model order, the higher is the feature dimensionality. In contrast to that, the dimensionality of the step response-based parameters remains the same, i.e., 3×9. In the current presentation, feature dimension is smaller for the step response parameters than if the AR parameters were directly used.

Frequency Band Power Features

It has been shown that sensorimotor rhythms for task discrimination can be subject specific.[42,50,52,65,70] We used narrow frequency bands and optimized subject specific band powers in previous work.[17,18] We here compared our proposed approach with some more common approaches using sensorimotor rhythm based features. As such, we used mu (8–12 Hz) and beta (14–26 Hz) band power features commonly used in BCI applications. We further optimized these features for individual subjects, as described in the next step. For each 1 s time window, log-transformed mu and beta power spectra-based features were generated for each of the EEG channels. The time window was the same as in the model-based feature generation.

Feature Selection

Two different methodologies have been typically adopted in BCI research. Some studies have employed techniques that make use of common-spatial patterns (CSP),[5] principal component analysis (PCA),[27,37,38] and independent component analysis (ICA),[37] among others, that transform the original feature space into a lower dimensional space. An alternative methodology is feature down-selection, which produces a subset of the original feature set relevant to discriminate subject performance on different mental tasks. Among the methods proposed in previous studies to down-select feature sets are *wrapper* or *filter* methods based on their dependence on a learning technique.[69] The *wrapper* methods use the predictive accuracy of a preselected classifier to evaluate a feature subset. Some exemplars are recursive feature elimination[60] and sequential forward selection.[20,33,35] The *filter* methods separate feature selection from classifier training and produce feature subsets independent of the selected classifier.[69] The relief algorithm[45] and PCA[3] are often used as *filter* methods. Genetic algorithms have also been used[22] in BCI applications. Bashashati *et al.*[3] reviewed additional feature selection algorithms.

We here used an existing feature selection algorithm called forward stepwise method, for the down-selection of the feature types we investigated. In this paper, we do not intend to draw any conclusion on the comparative efficacy of the feature selection algorithm, which we treated elsewhere.[15,18]

Stepwise Method

A discriminant stepwise method,[15,16] uses correlation of variances to remove features with insignificant discrimination effect and to reduce data dimensionality. This method is based on a multivariate canonical discrimination technique that was first developed by Fisher.[23] The first step of this procedure is to select the first variable (or feature). The canonical discriminant function that best discriminates the multivariate data observations is determined. The likelihood between the discriminant function and each variable (or feature) is given by the correlation between each column of the original feature matrix Y and a transformed observation vector z. The largest absolute value of the correlation corresponds to the first selected variable. Iteratively, the criterion is compared with canonical functions generated from: (1) adding an extra variable from the remaining variables set, (2) replacing a previously selected variable by one from the remaining variables set, or (3) removing a previous selected variable. This procedure runs iteratively until no additional criterion improvements are possible. Once this procedure is finished, there is an optimized variable set and a new canonical discriminant function available to predict group membership on test data. More details method are described in.[16,17]

Feature Classification

Among available classification algorithms, linear classifiers such as LDA and support vector machine (SVM) are probably the two most popular and widely applied algorithms for BCI applications.[39] Both LDA and SVM use discriminant hyper-planes to separate data. In LDA, the separating hyper-plane is designed to maximize the distances between class means and minimize interclass variances.[23] On the other hand, SVM classifiers are designed to maximize the distance to the nearest training point.[9] SVM can also be applied as a non-linear classifier by choosing a suitable kernel function.[25,32] A regularized LDA classifier introduces a regularization parameter that allows or penalizes classification errors on the training set. The resulting classifier can accommodate outliers and may improve results for BCI.[6]

LDA using multivariate canonical discrimination, as implemented in,[57] is a numerical approach based on a coordinate system change that uses singular value decomposition of the covariance of the data matrix to find a set of canonical discrimination functions. This approach was shown to provide numerical stability for spatiotemporal EEG pattern discrimination. Instability may occur when common measures of signal frequency or correlation have very small absolute numerical values further confounded by noise and measurement error.

Cross-validation is a standard procedure in pattern recognition and task discriminations in BCI that segments data into training and testing sets and does it a specified number of times to obtain classification accuracy results by averaging over all the combinations. A 10×10 cross-validation that mixes the data randomly into 10 segments of which 9 segments are used for training, the tenth is used for testing, with the error averaged over all training/testing combinations, was used for the LDA classification. For each class pair (for example, left vs. right), there were 70–80 samples out of 80, after exclusion of artifact containing trials. The numbers of samples were both balanced and unbalanced for the classes considered for discrimination. The LDA classification applied here was able to handle unbalanced number of samples for the class pairs.

Discrimination quality was assessed by Wilks' statistic, W,[24] and further strengthened by applying a bootstrap method, where data points were randomly re-labeled and goodness-of-fit re-tested 1000 times. This strategy was formulated to handle noisy data such as EEG effectively.

RESULTS AND DISCUSSION

As a first step in designing a robust and optimal MPC for BCI applications, we here generated step responses for the AR models developed using preprocessed and transformed EEG signals for each trial for each subject. To test the feasibility of the step responses in BCI application, we extracted step response parameters as model-based motor imagery task-related features for motor task classifications. The characteristic step response parameters such as rise time, settling time, and peak time were then used as the discriminative features for imagery task classifications. We also used the AR model parameters directly as features, as commonly used in the literature. We used 3×9 to 5×9 AR parameters for models of orders 3–5 for the 9 electrode channels from the Laplacian-transformed signals. In the power spectra-based approach, we extracted mu (8–12 Hz) and beta (14–26 Hz) band powers for different imagery tasks for each EEG channel. For each 1 s time window, same as in the model-based feature generation, log-transformed mu and beta power spectra-based features were generated for each EEG channel per subject per trial. Figure 4 shows an example application of the proposed model-based feature extraction and classification for Subject 1. Figure 4a shows the step responses of the model for four different imagery tasks using 1 s (seconds 3–4 after cue) of data averaged over all trials for Subject 1. These responses give a visual inspection indicating which tasks may have discriminatory features or not. Figures 4b and 4c show the step response

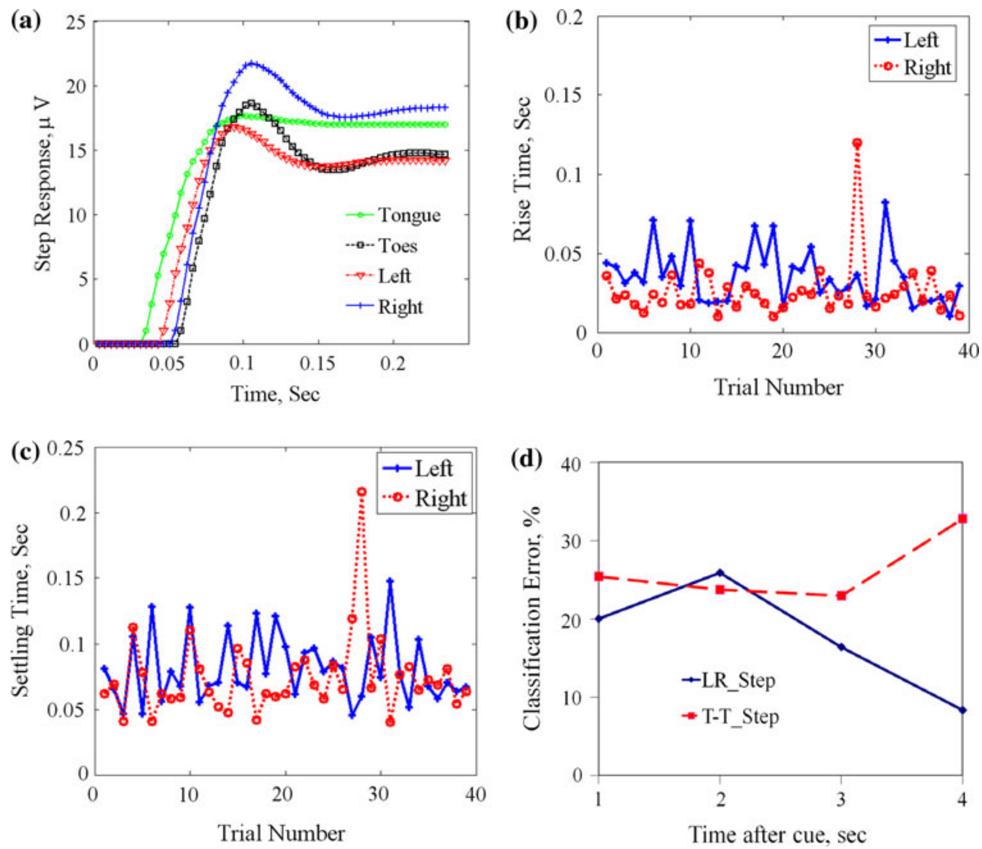

FIGURE 4. (a) Step response of a fourth order AR model using 1 s (3–4 s) data averaged over all trials, (b) and (c) rise times and settling times, respectively, of the step responses for left and right hand movement imageries, and (d) classification errors using stepwise feature selection technique. L–R_Step and T–T_Step: left vs. right hand and tongue vs. toes movement imageries, respectively, using stepwise feature selection.

rise times and settling times, respectively, for different trials for the same segment of data. Figure 4d shows the classification errors applying stepwise feature selection technique on the step parameter features for left vs. right hand (8%) and tongue vs. toes (23%) imagery movement tasks and 10 × 10 cross-validation.

Classification errors for the four imagery tasks (left vs. right hand and tongue vs. toes movements) were compared for all five subjects among the three feature types: the step parameters from the AR model, the AR model parameters directly used, and band powers in mu (8–12 Hz) and beta (14–20 Hz) frequency bands. The lowest classification errors (among the four time segments) by each method for all five subjects are shown in Table 1. For individual subjects, when the same feature selection and discrimination algorithms (e.g., stepwise + LDA) were applied, the best classification among the four time segments (1, 2, 3, and 4 s) obtained using the step parameter features performed equally or better than the best classification errors among the same four time segments obtained using the power spectra-based features and the AR parameters directly (Table 1). In the current presentation, feature

TABLE 1. Classification error percentage for Laplacian-transformed data using stepwise selection algorithm for Subjects 1–5.

		Classification error (%)		
	Task\feature	AR-step	AR-param	Mu + beta power spectrum
Subj. 1	L–R	8	12	13
	T–T	23	19	24
Subj. 2	L–R	14	18	25
	T–T	19	23	23
Subj. 3	L–R	8	28	19
	T–T	20	30	20
Subj. 4	L–R	12	23	23
	T–T	14	22	24
Subj. 5	L–R	21	21	32
	T–T	22	25	28

dimension was smaller for the three step response parameters than when the AR parameters with model orders were directly used. Akaike information criterion (AIC)[1] is a goodness-of-fit of an estimated model and is used to compare competing models. The general formulation of AIC is: $\text{AIC} = 2k - 2\ln(L)$ where k and

L represent model order and maximum likelihood estimate of a specific model, respectively. The smaller the AIC value, the better is that particular model. We have calculated AIC with small sample correction as described in Burnham and Anderson.[10] We have calculated discrimination accuracies with AR model orders 3, 4, and 5 and compared discrimination accuracies as well as AIC values for the three step parameters extracted from each AR model and for the AR model parameters with orders 3, 4, and 5. The smallest AIC value we got is 67 for the step response parameters (with three parameters chosen) with an AR model order 4, in comparison to the AIC value of 78 for the direct AR parameters (with a model order 4).

We conducted a statistical analysis to check the significance of the difference among the different feature extraction/selection techniques and the difference among the data transformation methods. A two-way multivariate analysis of variables (Two-way MANOVA), as described in Johnson and Wichern,[28] was applied.[66] Left vs. right hand movement class errors and tongue vs. toes movement class errors were considered as two response variables each with two factors. Feature extraction/selection technique was designated as Factor 1 with three levels: AR-step parameters, AR parameters, and mu–beta band powers. Data transformation technique was designated as Factor 2 with three levels: referential, Laplacian, and CAR montages. Results show that the interaction between Factor 1 and Factor 2 effects were not significant with a given 95% confidence limit.

MANOVA results for different feature types with three-step parameters using AR model orders 3, 4, and 5; AR parameters with model orders 3, 4, and 5; and mu–beta band powers were compared and contrasted. Results showed that imagery task discriminations are *significantly better* (at the 95% confidence limit) with three-step parameters using an AR model order 4 compared with either model parameters or derived three-step parameters at AR orders 3 and 5. The differences in discriminations using three step parameters from AR models with orders 3 and 5 as well as the AR model parameters using model orders 3, 4, and 5 and mu–beta band powers are statistically not significant (p value > 0.05). Although imagery task discrimination using three step parameters from a fourth AR model is statistically as good as the discrimination results using the fourth order AR model parameters or mu–beta band powers, the three-step parameters from a fourth order AR is more parsimonious with a lower AIC value.

The statistical tests presented here provide a first step to justify the use of an open-loop model and/or discriminative features to be applied in closed-loop BCI control applications.

SUMMARY

We here developed a first step in designing a robust and optimal MPC for BCI applications. The parameters in designing the controller were extracted as model-based features for motor task discriminations. EEG signals were acquired from five healthy human subjects for motor imagery tasks of left vs. right hand movements and tongue vs. toes movements. Discrimination results showed that the best discrimination of tasks was achieved with classification errors in the range of 8–23% for the three step parameters with a fourth order AR model. This result is comparable with the performance for similar BCI available in the literature.

In this study, feature dimension was smaller and discrimination more parsimonious, for the step response parameters than when the AR parameters were directly used. However, we emphasize that our focus is to derive model-based predictive control algorithms for which the step response is the directly applied format as shown in Eqs. (1)–(3). Our results show the feasibility of incorporating an optimal MPC strategy for BCI through rigorous design of a self-paced (closed-loop) feedback system.

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