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Optimization of Electrode Channels in Brain Computer Interfaces

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Abstract— **What is the optimal number of electrodes one can use in discrimination of tasks for a Brain Computer Interface (BCI)? To address this question, the number and location of scalp electrodes in the acquisition of human electroencephalography (EEG) and discrimination of motor imagery tasks were optimized by using a systematic optimization approach. The systematic analysis results in the most reliable procedure in electrode optimization as well as a validating means for the other feature selection techniques. We acquired human scalp EEG in response to cue-based motor imagery tasks. We employed a systematic analysis by using all possible combinations of the channels and calculating task discrimination errors for each of these combinations by using linear discriminant analysis (LDA) for feature classification. Channel combination that resulted in the smallest discrimination error was selected as the optimum number of channels to be used in BCI applications. Results from the systematic analysis were compared with another feature selection algorithm: forward stepwise feature selection combined with LDA feature classification. Our results demonstrate the usefulness of the fully optimized technique for a reliable selection of scalp electrodes in BCI applications.**

I. INTRODUCTION

BRAIN Computer Interface (BCI) is an alternative communication pathway between the brain (human or animal) and an external device (e.g. computer) with the hope to give greater ability to severely disabled patients without reliable muscular ability to interact with their surrounding environments [1, 2]. 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 promises in the application of BCI [3-9], non-invasive techniques such as scalp EEG based methods may be useful and more easily applied [10, 11].

In a BCI system, a classification algorithm discriminates mental task performance by identifying the subject-specific EEG patterns corresponding to each mental task. With the availability of electrode caps and nets for EEG acquisition with increased number of electrode channels, it is possible to use as many electrode channels as possible for this kind of study. However, it is essential to know if too many electrode channels, as available, really add more information for the task discrimination under study. If all available features are used to train a classifier, the risk of data over-fitting increases. Too many electrode channels and corresponding features also increase computational complexity to the degree that makes real-time BCI application infeasible. Therefore, a dimensionality reduction technique should be employed to find a subset of electrodes that minimizes the error of task discriminations.

Typically, in BCI study, electrode locations are selected arbitrarily from scalp area corresponding to the motor cortical regions without much systematic study. Two different methodologies such as principal component analysis (PCA) [12-14] and independent component analysis (ICA) [14-16], have been widely adopted for data reduction in BCI research. These methods transform the original features into alternative dimensional spaces where the dimensionality reduction is simpler. Recently, Georgopoulos *et al* [17] employed a sub-exhaustive search of sensor pairs in order to discriminate magnetoencephalography correlations reflective of a variety of disease states. As computational power increases, it is now possible to fully optimize discrimination analysis by taking all possible combinations of electrodes for feature classification. Using this strategy, Kruglikov *et al* [18] presented an optimization study on the discrimination analysis of physiological responses to auditory stimuli and showed that an optimized discrimination performance can be obtained with a relatively small number of electrodes. We here conducted a systematic optimization on the number of electrodes in EEG acquisition required for task discrimination in motor imageries, which has not been, to the best of our knowledge, done before.

II. METHODS

In data acquisition , preprocessing, feature extraction, and feature classification, we used the same procedures as described in our earlier work [19, 20]. However, to give a complete picture of the algorithm developed in this paper, we below provide a short description of these procedures.

A. Experimental Paradigm

Five healthy human subjects, 25 to 32 years old, four males and one female, none of them under any kind of medication, participated in the motor imagery tasks. The

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experiments were conducted under Institutional Review Board (IRB) 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 left or right hand movements and the last two runs were for imagery tongue or bilateral toe movements. Of the 40 trials in the left or right hand movement task, 20 randomly permutated 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" or "down" arrows were used for tongue or toes tasks.

B. Data Acquisition and Pre-processing

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 earlobes were selected for acquiring EEG under open loop conditions while the participants performed the imagery tasks. Data were sampled at 256 Hz rate and passed through a fourth order band-pass Butterworth filter of 0.5-60 Hz.

Data Preprocessing: Data were epoched from two 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.

Data Transformation: Two different techniques were applied on the EEG signals acquired using linked earlobe reference electrodes (a referential montage) to increase the spatial resolution and decrease the dependence on the reference location. In a referential montage, each channel represents the difference between a certain "recording" electrode and a designated reference electrode, typically at a different position than the "recording" electrodes. A popular reference, which was used here, is "linked earlobes". The Laplacian derivation [21-24] is a discrete second derivative, calculated as the difference between an electrode and a weighted average of the surrounding electrodes. Laplacian derivations were developed for 9 inner loop channels (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4) using four channels surrounding each active channel for deriving the weighted average. In the common average reference (CAR) calculation, the outputs of all of the amplifiers were summed and averaged, and this averaged signal was used as the common reference for each channel. CAR was applied to the 19 channels described above.

C. Model-based Feature Extraction

Model-based responses and features were used for the motor imagery task discriminations. Model based techniques have the potential to use advanced control systems theory in the development of BCI to achieve improved performance compared to the performance achieved by currently applied proportional control or filter algorithms. We here adopted an autoregressive (AR) model-based technique for feature extraction from the EEG signals [19, 20]. Unit step responses were generated for each of the AR models developed using preprocessed and transformed EEG signals. Then, we used step response parameters such as *rise time*, *settling time*, *and peak time* as the discriminative features for pattern classification.

We used an AR model as the simplest of time series models to fit the scalp EEG data from each channel. The AR model is written as:

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

where $y(t)$ represents output, n defines the model order, a_1, a_2, …, a_n are model parameters, and ε_t is white noise. The model parameters can be estimated using a least squares technique by fitting scalp EEG time series.

Step Response Generation: The step response of a dynamic model is the output signal that results when the input is a unit step. 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; *and peak time*, defined as the time at which the maximum overshoot occurs [25]. Note that in an AR model structure, there is no external input and the step response would be in response to a step change in the noise signal, while the ongoing signal remains the same. For each electrode, we extracted 3 step response coefficients: rise time, peak time, and settling time for each 1s time segment after the cue (4 total time segments).

D. Feature Optimization

We here chose all possible combinations of electrodes. For n_e electrodes, there are $\sum_{k=1}^{n_e} \frac{!n_e}{!n_e!(n_e-k)} = 2^{n_e} - 1$ unique combinations. We calculated $2^9-1=511$ combinations of 9 electrodes common in the referential, Laplacian, and CAR data sets. For each electrode combination, we calculated linear discriminator functions and computed classification error rates as described in the next subsection. In order to compute classification error for a particular combination, it was necessary to calculate 240 discriminators (four classes: left hand, right hand, tongue, and toes movements in each of the 4 time segments in each of the 3 data sets (referential, Laplacian, and CAR) for 5 subjects), for a total of 240 × 511 = 122,640 discriminators. The combination of electrodes that resulted in the lowest classification error was accepted as the optimal number of electrodes for a specific subject. Note that, on occasions, multiple combinations resulted in the same classification error. In those cases, the combination with the smallest number of electrodes was selected as the optimum combination. Work is in progress for a systematic optimization of 27 features (3 features for each of the 9 channels) per task per time segment per subject. This calculation will require $2^{27}-1=134,217,727$ combinations of features for each of the four time segments for each of the four tasks and for each of the 5 subjects in each of the 3 data sets. High performance computing is in application to conduct these calculations and will be reported in the future.

We also employed another feature selection algorithm (forward stepwise) to the same data and compared the classification errors resulting from these two algorithms. We briefly describe the stepwise algorithm below.

Stepwise Method: The discriminant stepwise method [26, 27] is based on a multivariate canonical discrimination technique and uses correlation of variances to remove features with insignificant discrimination effect. The largest absolute value of the correlation between each column of the original feature matrix Y and a transformed observation vector z corresponds to the first selected variable. Iteratively, the criterion is compared with canonical functions generated from: 1) adding an extra variable from the remaining variable set, 2) replacing a previously selected variable by one from the remaining variable set, or 3) removing a previously selected variable. More details of this method are described in [27, 28].

E. *Task Discrimination*

We here used a linear discriminant analysis (LDA) algorithm as implemented by Schiff *et al* [29]. This LDA is a numerical approach based on a coordinate system change that uses singular value decomposition of the covariance (of the feature) matrix to find a set of canonical discrimination functions. A 10x10 cross validation that mixes the data randomly into 10 segments of which 9 segments are used for training, the tenth is used for validation, with the error averaged over all training/validation combinations, was used.

III. Results and Discussion

We here conducted a systematic optimization on the number of electrodes in EEG acquisition required for discrimination of four imagery tasks (left vs. right hand and tongue vs. toes movements). Model-based features such as step response parameters corresponding to the AR models developed using acquired and transformed EEG signals for each trial for each of the 5 subjects were used.

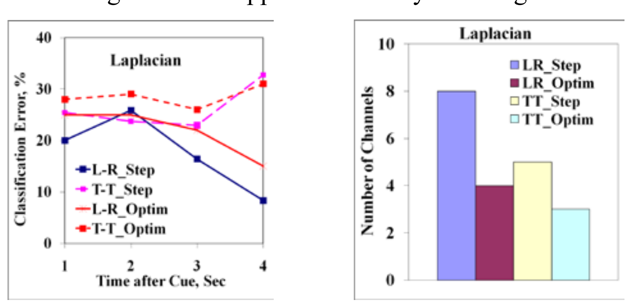
Classification errors resulting from the systematic optimization along with the errors calculated from the stepwise feature selection algorithm are plotted in Fig. 1(a) for the Laplacian transformed signals for Subject 1. The number of selected electrodes by the systematic approach should be, theoretically, equal to the number of electrodes selected by any other optimization methods, if that method is truly optimized. A comparison between the systematic approach and any optimization algorithm using statistical analysis would indicate the reliability of that algorithm. This means that those algorithms showing any difference or inconsistency in electrode or feature selection for a specific application should be more carefully used.

Feature combinations corresponding to the lowest error by the stepwise selection method were mapped back to the electrode channels and are presented on Figs. 1(b) and 2 for the Laplacian transformed signals for all 5 Subjects. A two-way multivariate analysis of variance (MANOVA2) was conducted to see any significant difference in channel selection between the systematic and the stepwise algorithms. The results are presented in Table I. It appears that the two selection algorithms are statistically different ($P>\chi^2(10.8)=0.0045$) with a given 95% confidence limit when all the data transformation (referential, Laplacian, and CAR) and both task pairs (left vs. right and tongue vs. toes movements) were considered simultaneously for all five subjects. The electrode selection is not significantly different ($P>\chi^2(3.9)=0.42$) with a given 95% confidence limit for the three data transformation techniques. There was no significant interaction between the optimization techniques and data transformation methods ($P>\chi^2(1.1)=0.9$). It is evident, in the limited context presented here, that the stepwise algorithm should be carefully applied for a reliable feature selection. As noted earlier, ongoing work on a systematic optimization of all the 27 features will provide more information to make a definitive conclusion.

The proposed algorithm can be applied to the systematic optimization of electrode channels or features in any neurological data. This technique can be applied as a one-time selection of electrodes or features for a specific subject. Further analysis or online applications using the off-line selection will reduce computational complexity.

IV. Summary

A first step in developing an algorithm for the systematic optimization of the number of EEG electrodes or features required for task discrimination in motor imageries for BCI applications is presented. Usefulness of the fully optimized technique for reliable selection of scalp electrodes is demonstrated. Future direction is provided to develop a reliable algorithm for application to any neurological data.



(a) (b)

Fig. 1. Discrimination results for Subject 1 using stepwise and fully optimized techniques for left vs. right hand (LR) and tongue vs. toes (TT) movement imagery tasks and Laplacian electrode channels. (a) Classification errors and (b) Number of electrodes selected. "Step" = stepwise, and "Optim" = systematic optimization.

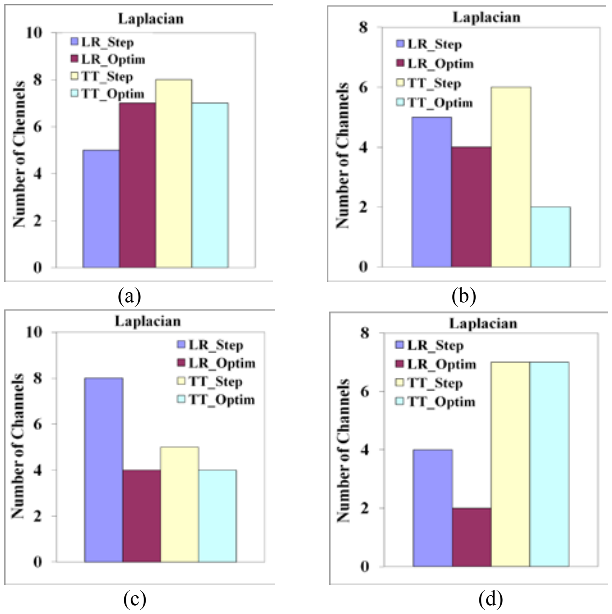


Fig. 2. Number of electrodes selected out of 9 Laplacian electrodes using stepwise and systematic optimization techniques for left vs. right hand and tongue vs. toes movements. (a) Subject 2, (b) Subject 3, (c) for Subject 4, and (d) Subject 5. "Step"= stepwise and "Optim"= systematic optimization.

TABLE I
Two-way multivariate analysis of variance (MANOVA) with 95% confidence limit. df = degrees of freedom, P = probability.

Factor	Levels	Variables	Λ (Wilks' lambda)	χ^2	df	$P>\chi^2$
Electrode selection	2	2	0.6256	10.8	2	0.0045
Data transform	3	2	0.8478	3.88	4	0.4225
Electrode selection * Data transform	6	2	0.9557	1.07	4	0.9

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