34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

EEG-based Motor Imagery Classification Accuracy Improves With Gradually Increased Channel Number

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***Abstract*— The question of how many channels should be used for classification remains a key issue in the study of Brain-Computer Interface. Several studies have shown that a reduced number of channels can achieve the optimal classification accuracy in the offline analysis of motor imagery paradigm, which does not have real-time feedback as in the online control. However, for the cursor movement control paradigm, it remains unclear as to how many channels should be selected in order to achieve the optimal classification. In the present study, we gradually increased the number of channels, and adopted the time-frequency-spatial synthesized method for left and right motor imagery classification. We compared the effect of increasing channel number in two datasets, an imagery-based cursor movement control dataset and a motor imagery tasks dataset. Our results indicated that for the former dataset, the more channels we used, the higher the accuracy rate was achieved, which is in contrast to the finding in the latter dataset that optimal performance was obtained at a subset number of channels. When gradually increasing the number of channels from 2 to all in the analysis of cursor movement control dataset, the average training and testing accuracies from three subjects improved from 68.7% to 90.4% and 63.7% to 87.7%, respectively.**

I. Introduction

Cursor movement control [1], including one-dimensional and two-dimensional control, is one of the most popular paradigms for motor imagery based brain-computer interface [2]. The ability to discriminate between left and right motor imageries is typically the key issue in such paradigms, and this has already attracted the attention of many researchers. One crucial factor that affects the discrimination accuracy is the selection of EEG channels. Theoretically speaking, the more channels that are used, the more information we can extract and thus the higher accuracy rate can be achieved. However, recent studies have shown that there are an optimal number of channels used for the motor imagery tasks paradigm, after which classification accuracies decrease [3], [4]. This may be true because of over fitting or irrelevant channels. Since left-and right-hand motor imagery is not a real-time control paradigm and no feedback is given, its feature patterns are simple. However, few researchers have studied the question of how many channels should be used for cursor movement control paradigm, which is more complicated, including real-time control and feedback.

In this study, we utilized a modified time-frequency-spatial synthesized approach [5] to perform an offline analysis on online-recorded cursor movement control dataset. Data of three subjects performing imagery-based cursor movement control were processed and analyzed. This study also investigated how classification accuracy is affected by algorithm parameters, such as the sliding window, training trial number, and the electrode montage. As a comparison, an offline analysis on the motor imagery tasks dataset was also conducted.

II. Methods

A. Data Description

Two sets of EEG data were used in this study. One dataset was recorded from the online one-dimensional cursor control experiments, in which three healthy subjects were instructed to move the cursor to hit the right/left target, by using right or left motor imagery [6]. The human study was approved by the Institutional Review Board of the University of Minnesota. EEG data were recorded from 64 electrodes distributed over the entire head (according to the international 10/20 system) with a 200Hz sampling rate. The system used here includes a NeuroScan amplifier and general-purpose BCI2000 [7]. The data of each subject processed in this study included 156 trials; 78 for left and 78 for right.

The other dataset is from the motor imagery tasks experiments, which were received from a data analysis competition during the Neural Information Processing Systems (NIPS2001) [8]. In this paradigm, nine subjects were asked to start and end imagination of either left hand or right hand movement indicated by timing cues, which was shown on a computer screen. During each trial, no feedback was given. The scalp EEGs of nine subjects were recorded from 59 channels (international 10/20 system) with a sampling rate of 100Hz. For each subject, the total number of trials is 180; 90 for left motor imagery and 90 for right motor imagery.

B. Data Preprocessing

Surface Laplacian Filter. For all of the raw EEG data from 64 channels, we implemented the Surface Laplacian [9] filter to each channel.

$$V_j^{Lap} = V_j - \frac{1}{4}\sum_{k \in s_j} V_k \qquad (1)$$

Where V_j is the target channel we care about, S_j is an index set of four surrounding channels. For the channels that had four

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This work was supported in part by the Multidisciplinary University Research Initiative (MURI) through ONR (N000141110690), and by NSF grant CBET-0933067. H.J.S. was supported by a China Scholarship Council Fellowship.

neighboring channels, we applied the regular filtering, as shown in equation 1. For the channels that were located at the periphery, such as T7, FT8, etc., their surface Laplacians were calculated by subtracting the mean of the 2 or 3 adjacent channels from them.

Bandpass Filtering and Feature Extraction. We focused on the frequency range from 5 to 30Hz because it spans over *mu (8-12Hz)* and *beta (13-28Hz)* rhythms, which play an important role in motor imagery [5-6,10,12-20]. We divided the entire frequency band into 13 overlapping sub-bands with a constant-Q (also called the proportional band width). For each sub-band, a third order Butterworth band-pass filter was constructed to process the EEG. The envelope of each sub-band data was then extracted by performing the Hilbert transform. Extracted envelopes were treated as the leading feature because they carry information of the power modulation in frequency bands.

C. Trial Means

Intra-Trial Means. For the one-dimensional cursor control paradigm, the length of trials varies from trial to trial, so it is difficult to calculate the mean value over multiple trials. However, one-dimensional cursor control is a real-time experiment with feedback, as subjects may imagine one certain hand movement to continually move the cursor to the goal. Thus, as motor imagery repeats, the envelope patterns at each channel and each frequency band will repeat over the entire single trial. Considering this, we believe we can extract a majority of the pattern information through a short time segment. In this study, a short time segment of 120 sampling points (i.e., 600 ms), which we call a sliding window, was used. Thus, the intra-trial mean will be

$$T_{i,j,m} = \frac{1}{n}\sum_{k=1}^{n} t_{i,j,m,k} \qquad (2)$$

where $t_{i,j,m,k}$ is the *k*-th time segment in a trial, with 50% overlapping, and *m*, *j*, and *i* indicate the *m*-th trial's *j*-th sub-band of *i*-th channel.

Trial-to-trial Means. To eliminate the variance from session to session, and to get generalized characteristic patterns, trial-to-trial means over the left/right training set were separately calculated after the calculation of intra-trial means.

$$AvgLeft = \frac{1}{N}\sum_{i=1}^{n} TL_i$$
$$AvgRight = \frac{1}{N}\sum_{i=1}^{n} TR_i \qquad (3)$$

Finally, we obtained the generalized characteristic patterns, *AvgLeft* and *AvgRight*, which will be used in following classification section.

D. Classification by weighted frequency patterns

We denote the characteristic patterns *AvgLeft* and *AvgRight* as $P = \{P_L, P_R\}$. Given an input feature pattern *p*, the correlation between *p* and *P* is calculated as

$$C(p,P) = \frac{(p-\bar{p})^T (P-\bar{P})}{\| p-\bar{p}\| \cdot \| P-\bar{P}\|} \qquad (4)$$

where $\bar{p}$ and $\bar{P}$ are the mean values of p and P , respectively. Thus we were able to get the classification result from the assignment function below

$$h_{i,j}(p) = \mathrm{sgn}[C(p,P_L) - C(p,P_R)] \qquad (5)$$

$h_{i,j}(p)$ denotes the classification result from the *i*-th channel's *j*-th frequency band. $h_{i,j}$ =1 indicates that p belongs to the left-hand imagery, and -1 indicates that p belongs to the right-hand imagery.

However, the envelopes at different frequency bands do not equally contribute to accurate classification. Some frequency bands may play a determinant role, while others may cause the wrong classification. Based on this, we introduced the weight for each frequency band. The weight is determined by its classification accuracy from training sets, as the following

$$w_f = \begin{cases} [(a_f - E)/(1-E)]^m, a_f > E \\ 0, a_f \le E \end{cases} \qquad (6)$$

Where a_f denotes classification accuracy of each sub-band, *E* is a threshold and *m* is the control parameter. In this study, we set *E*=0.6 and *m*=2.

III. RESULTS

In this study, we processed and analyzed two different sets of data to investigate how classification accuracies change with the number of channels increasing. The first dataset was recorded from one-dimensional cursor control experiments, and the other dataset from motor imagery tasks experiments. For both datasets, we adopted the time-frequency-spatial synthesized approach [5] for analysis, with a minor change being made to the classification approach as to cursor-control dataset. Because the length of trials is not consistent, the correlation between pattern and test trials can not be directly calculated. Thus we introduced intra-trial mean concept as the time-domain information, which is slightly different with original time-frequency - spatial synthesized approach. For both sets of data, ten fold cross-validation was used to get the overall classification accuracies, without rejecting any trials from the datasets.

A. One-dimensional cursor control paradigm results

As described in section Ⅱ, we used 62 out of 64 channels, excluding channels M1 and M2. Each channel data was decomposed into 13 sub-bands, and the sliding window = 120 sampling points (i.e., 600ms). Thus, the feature pattern of a single trial is a matrix of 62×13×120 dimension. We performed the classification algorithm under the same parameters setting (i.e. the same sliding window and electrode montage).

Fig. 1 shows the training and testing results from the one-dimensional cursor control experimental data. The results demonstrate that both mean training and testing accuracies from three subjects improved when the number of used channels gradually increased. With a small number of channels (less than 16), accuracies were sensitive to the number of channels, and improved quickly. With 32 or more channels, accuracies improved slowly.

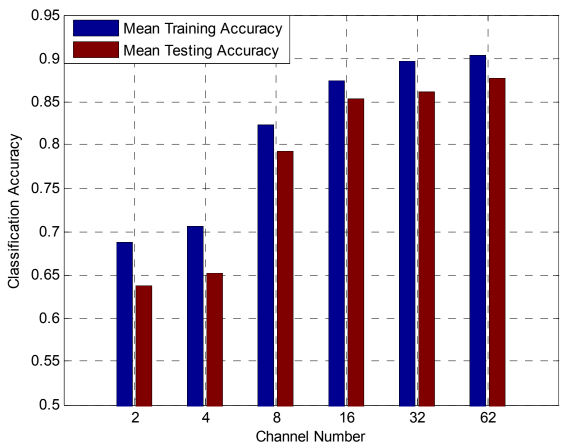

Figure 1. One-dimensional cursor control paradigm. Blue bars denote mean training accuracies over three subjects; red bars denote mean testing accuracies over three subjects.

B. Motor imagery tasks paradigm results

For the motor imagery tasks paradigm, only a few studies pertaining to channel selection have been conducted, and such studies found that a reduced number of channels can achieve optimal classification using the selection methods REF [3] and PSO [11], etc. However, few of these studies have analyzed how the number of channels affects classification, especially as it increases. In this study, we applied the time-frequency-spatial synthesized approach [5] on the motor imagery tasks dataset to classify left and right motor imagery. The results of this dataset also served as a comparison with the results of cursor control dataset. Results are shown in Fig. 2.

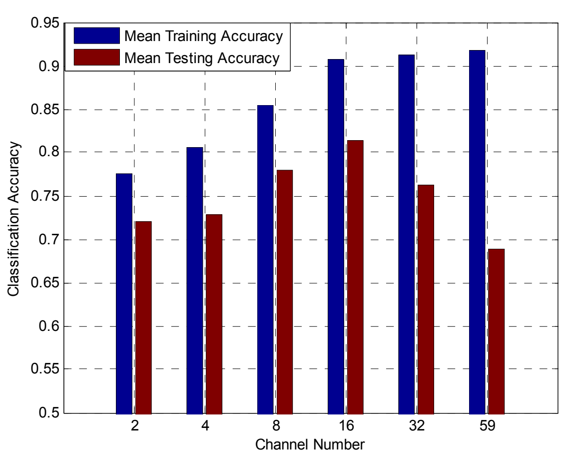

Figure 2. Motor imagery tasks paradigm. Blue bars denote mean training accuracies over nine subjects; red bars denote mean testing accuracies over nine subjects.

The results shown in Fig. 2 are very different from the one-dimensional cursor control paradigm. At the beginning, both training and testing accuracies improved with an increased number of used channels. However, after 16 channels, the testing accuracy significantly decreased, from 81.3% to 68.9%. Meanwhile, the training accuracy remained stable.

Separately analyzing the results of each subject, we found that: 1) Both training and testing classification accuracies decreased after a certain number of channels for three out of nine subjects. 2) For the remaining 6 subjects, training and testing accuracies increased at the beginning. However, after a certain number of used channels were added, testing accuracy decreased while training accuracy remained stable.

Comparing the results from both datasets, they show distinct trends when increasing the number of channels. While for one-dimensional cursor control dataset, the performance steadily increased with more channels, the performance of motor imagery tasks dataset reached the best at a subset of all channels. This was observed in both individual subjects as well as at the group level.

IV. Discussion

The present results suggest: 1) For the motor imagery tasks paradigm, there exists an optimal number of channels for selection. A reduced number of channels can achieve the best training and testing classification accuracies. Thus, much preparation work can be saved during the motor imagery experiment. 2) Increasing the number of used channels improves the classification accuracy of the one-dimensional cursor control paradigm. Thus, for conditions pertaining to accuracy, we should use as many channels as possible.

A. Number of Channels

During this study, for each dataset, the electrode montages were selected for best classification performance. The channel numbers changed from 2 to 4, 8, 16, 32 and 59/62. At each given number, all of the subjects shared the same montage. When the number of channels increased, some new channels were added into the electrode set, keeping the previous channels still in the new electrode set. Thus we can conclude that it is the increased number of channels that improves the performance, and not the montage change.

B. Length of Sliding Window

Another test was made to study how the length of the sliding window affects the classification performance. Lengths of 40, 80, 120, and 160 sampling points were separately chosen as the algorithm parameters. Our results indicate that the performance remained nearly consistent from 40 to 160 sampling points. Overall, there was no significant difference. This implies that a length of 40 sampling points (i.e. 0.2s) is long enough to include a complete motor-imagery task in an online cursor control data trial. However, in this study, the average length of the cursor control trial is around 3s and a sliding window of 120, sample points (600 ms) has proved to yield good results. Under the fast calculation condition, a sliding window of 40 or 80 points can be chosen.

C. Performance Stability

Data varies between trials as well as between sessions. If different trials are selected as training sets, the classification performance may change, especially when trials of low signal-to-noise ratio are included in the dataset. Our study shows that classification performance will be less consistent when a smaller number of channels are selected. In contrast, using a larger number of channels, such as 30, 50 or 60 channels, will keep the performance consistent through such changes. This finding represents an additional benefit of using a large number of channels.

V. Conclusion

The results of this study indicate that using a large number of channels leads to improved classification results for the online cursor control paradigm. This is in contrast to the previous understanding that in offline motor imagery tasks paradigm, a subset of scalp electrode channels yields the optimal performance. However, compared with multi-dimensional cursor control, one-dimensional cursor control is a relatively simple paradigm, which makes use of fewer brain functions and regions. It remains to be shown if higher number of electrodes would improve the performance when more complicated paradigms are involved. The present results suggest that increased number of scalp electrodes will improve online BCI performance.

Acknowledgment

The authors would like to thank Dr. T. Wang for the helpful instruction on the classification approach and Jiaen Liu for the useful discussion in the data analysis. And we also thank Dr. Allen Osman of University of Pennsylvania for making the motor imagery tasks dataset available.

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