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Classification of Intended Motor Movement using Surface EEG Ensemble Empirical Mode Decomposition

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***Abstract*—Noninvasive electroencephalography (EEG) brain computer interface (BCI) systems are used to investigate intended arm reaching tasks. The main goal of the work is to create a device with a control scheme that allows those with limited motor control to have more command over potential prosthetic devices. Four healthy subjects were recruited to perform various reaching tasks directed by visual cues. Independent component analysis (ICA) was used to identify artifacts. Active post parietal cortex (PPC) activation before arm movement was validated using EEGLAB. Single-trial binary classification strategies using support vector machine (SVM) with radial basis functions (RBF) kernels and Fisher linear discrimination (FLD) were evaluated using signal features from surface electrodes near the PPC regions. No significant improvement can be found by using a nonlinear SVM over a linear FLD classifier (63.65% to 63.41% accuracy). A significant improvement in classification accuracy was found when a normalization factor based on visual cue "signature" was introduced to the raw signal (90.43%) and the intrinsic mode functions (IMF) of the data (93.55%) using Ensemble Empirical Mode Decomposition (EEMD).**

I. INTRODUCTION

BRAIN Computer Interface (BCI) is a frontier for neural engineering research that has gathered a great deal of attention from scientists and the general public. One of the most challenging and vital aspect of BCI is the feature extraction and translation of the intended brain activity [1], which may translate the brain activities into useful motor commands for the arm reaching and hand grasping movement for neuroprosthetic devices [2][3]. While most other research focused on discriminating EEG signals between left hand, right hand, toe, and tongue imagined movement [4][5], our study endeavors to decode the EEG from posterior parietal cortex (PPC), which is the area related to the processing of visumotor transmission. The EEG features near the PPC region were used in the context of upper limb neuroprosthetic applications. Our result demonstrates that by using multichannel surface EEG surrounding the PPC regions, along with a visual cue driven normalization factor, the direction of intended arm reaching movements towards the left and the right can be decoded at over 90% accuracy.

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II. METHODS

A. EEG Measurement

Four healthy, right-hand participants with normal or corrected to normal eye sight (all males, age 20-29) were recruited in this study. All of the subjects had no prior experience with BCIs. The protocol has been approved by the Louisiana Tech University IRB Committee. Fig. 1 outlines the setup where touch pad sensors were placed to record the subject responses.

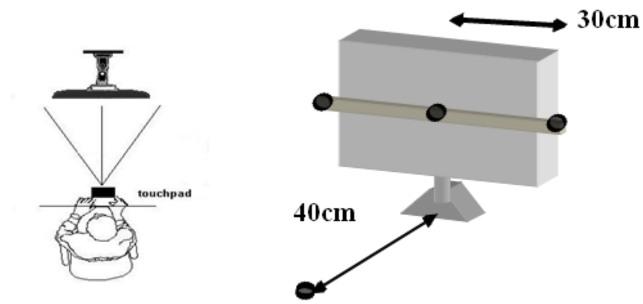

Fig. 1. Illustration of the experimental setup is shown. Touch pads (circles) are placed at the base location and the targets to track whether the subject has performed the tasks correctly.

The sequence of each trial is shown in Fig. 2 where visual cues were provided using the E-Prime 2.0 system to inform the subjects of the proper movements to perform in a dark room. Two types of visual cues were provided. First, the "Effectors cue" instructed whether the user should physically perform the reaching task (with eyes open or closed) or to imagine the movement only. The second cue, called the "Action cue" informed the user of the appropriate reaching directions: left, right and center. A total of 450 trials were performed by each subject over five session blocks, with a 5 min break in between. The contact impedance of the electrode was kept under 20kΩ, which is lower than the recommended value of 50kΩ from the user manual. EEG signals were recorded using 128 channels HydroCel Geodesic Sensor Net

(HCGSN) by Electrical Geodesics Inc. (EGI) with the Net-Station 5.3 software. All signals were amplified and anti-aliasing low-pass filtered at 100Hz. The data was then digitized at a sample rate of 256Hz.

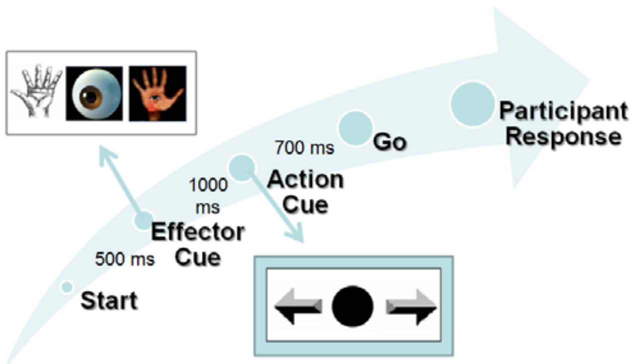

Fig. 2. The time course of one trial is illustrated.

B. *Data Preprocessing*

The data was digitally filtered between 0.1~30 Hz. Signals from 0 to 500 ms following the “Action cue” were segmented and extracted from the data set. Since this project focused only on directional information, the three different effectors were all included. This will eventually become the first part of a two stage process, with the second part potentially being a motor imaginary classifier which is not discussed in this paper. Bad channels containing motion artifacts were detected based on abnormal amplitude information and signal characteristics and were replaced by the averaged signals from neighboring channels. The data were re-referenced to the average signal. The time period of the first 100ms was also used as baseline correction for every trial.

C. *Spatial Filtering*

The activity between the “Action cue” and the “Go cue” was used because we were interested in distinguishing the intended direction of arm movement. Independent component analysis (ICA) was implemented for artifact removal [6][7]. Fig. 3 illustrates the projection of the components once artifacts were removed. Independent clusters associated with the activation regions provided spatial information on the region of interests.

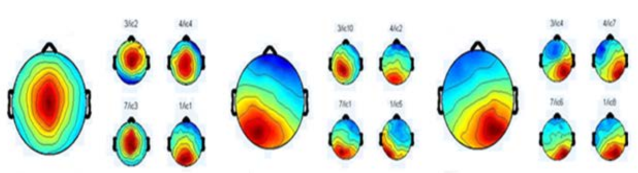

Fig. 3. The three independent component clusters demonstrate the activation of the PPC regions. The larger map shows the average across four subjects. The smaller maps are the individual subject responses.

D. *Source Localization as a Validation Tool*

To further validate the active brain regions associated with this project, DipFit 2.0 algorithm was used to estimate the dipole sources. The dipoles were projected onto the boundary element mode then plotted on the average MNI brain images [7]. Using the Talairach co-ordinate system, we were able to observe that the dipole source for each intended arm movement direction was close to the PPC areas, consistent with the literature [8]. The left component (-20, -40, 24), the center component (0, -33, 40), and the right component (28, -40, 23) were shown in Fig. 4.

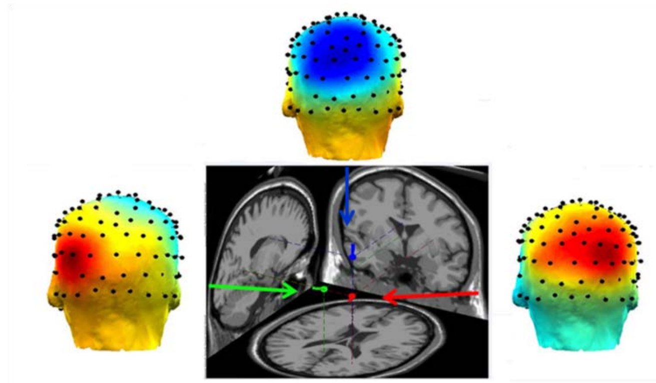

Fig. 4. Source reconstruction for the three components is shown. The residual variance for each dipole estimation was <6% for all cases, which indicated the goodness of the dipole fit [9].

E. *Ensemble Empirical Mode Decomposition*

The illustration of Ensemble empirical mode decomposition (EEMD) is shown in Fig. 5.

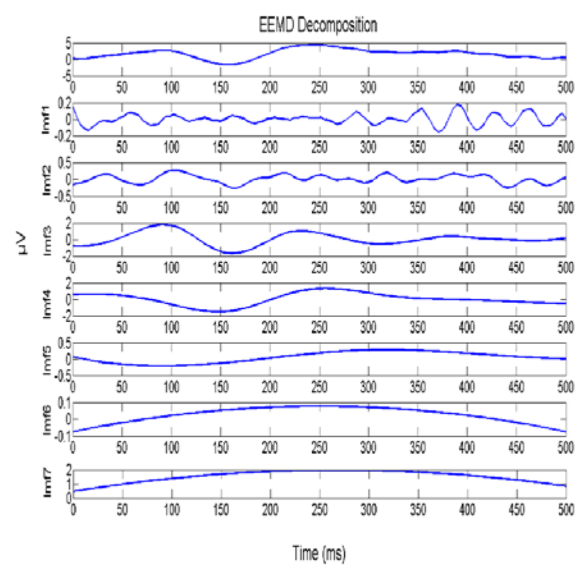

Fig. 5. An illustration of EEMD. Raw signal is shown on the top and the IMFs are plotted below.

EEMD is a data-driven analysis method that separates the EEG signal into a collection of intrinsic mode functions (IMFs). It is a powerful method for the analysis of nonlinear and non-stationary data such as EEG since the decomposition method is based on local characteristic time scale of the data. Gaussian white noise with standard deviation equals to 10% of the standard deviation of the EEG data was added to the signal and 50 ensembles were created [10][11]. The EEMD method broke down the signals in a subject dependent manner strictly based on the signal characteristics without specifying any frequency bands. Each IMF was then considered as a filtered signal itself [12] with IMF1 having the highest and IMF7 having the lowest frequency components.

After collecting the IMFs, the characteristics representing 0.1-30 Hz frequency components were identified using the power spectral density (PSD) of each mode [13], as shown in Fig. 6.

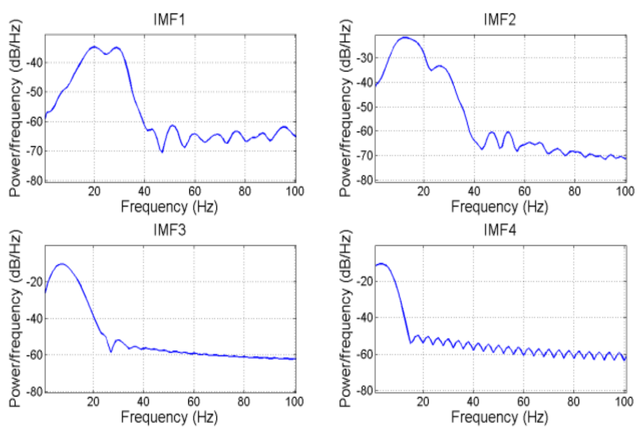

Fig. 6. The PSD estimations for IMF1 to IMF4.

F. Feature Extraction and Classification

The Statistical Pattern Recognition Toolbox for Matlab [14] was used in this analysis. The performance of support vector machine (SVM) classifiers with radial basis function (RBF) kernels and Fisher linear discrimination (FLD) were compared. The first feature set was the mean signal amplitude (280-320ms) after the "Action cue" from the region of interests (ROI) near the left and right PPC and Pz electrode. The second feature set was obtained by the summation of IMF3 to IMF7. The associated high frequency noise in the signal can be reduced through this process.

The data associated with each direction was partitioned into five parts in order to perform a 5x5 cross-validation analysis. Binary classifiers were trained using 80% of the data and evaluated on the remaining 20%. The classification algorithm procedure was repeated 25 times for each binary classifier.

Two types of normalization factors were also used to preprocess the data. The first normalization method involved scaling the amplitude of the EEG signal to span -1 to 1 cross each of the whole trial before calculating the mean signal amplitudes. We propose another cue-based "signature" normalization method (Fig. 7). The first 235ms of the signal after the "Action cue" was stored from the training data in each 5x5 cross-validation. The rationale for choosing this time window was that this part of the signal consistently showed a distinctive "signature" across different recording electrodes in the PPC regions. We normalized each trial with respect to the range of the "signature" signal defined to be the average of training data set within this time frame, so that the amplitude information was invariant to the direction of intended direction. Once that had been established, the amplitude feature after this time period was used as the feature set. We tested whether there was a need for a nonlinear classifier such as SVM by comparing the accuracy with FLD.

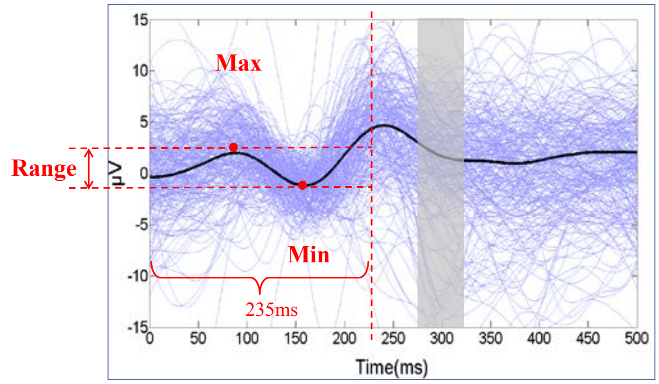

Fig. 7. The normalization factor was computed before signal classification. The light color lines indicated individual data in the training set; the dark bolded line indicated the mean across the trials. The normalized factor was found from maxima and minima of the first 235 ms of the averaged signal. The solid gray color indicated the time interval of the amplitude feature.

III. RESULTS

The binary classification accuracy for the FLD and SVM algorithm is shown in Table I. This preliminary result suggested that the linear classifier would be sufficient for the decoding of intended arm movement in the left and right directions since there is no statistically significant difference between the two methods. Table II illustrates the FLD classifier accuracy when the normalization was performed with respect to the "signature" signal only. It shows the overall classification accuracies have been improved significantly ($p < 0.01$) over Table I. The performance of the classifier is slightly improved using EEMD filtered signals (IMF3 to IMF7) compared to the raw data. The embedded features space for EEMD filtered signals at the three ROI, along with the FLD decision boundary is shown in Fig. 8. It suggests that a relatively simple comparison of the mean signal amplitude from ROI electrodes near the PPC can successfully discriminate the left and right intended movement.

TABLE I
SINGLE TRIAL BINARY CLASSIFICATION ACCURACY (MEAN AMPLITUDE AFTER NORMALIZATION ACROSS WHOLE TRIAL)

Subject	FLD	SVM
A	66.40 ± 8.11%	64.73 ± 7.81%
B	59.20 ± 4.05%	59.93 ± 5.43%
C	72.80 ± 5.68%	72.87 ± 6.96%
D	55.23 ± 5.48%	57.07 ± 6.54%
Mean	63.41 ± 9.02%	63.65 ± 8.96%

TABLE II
SINGLE TRIAL BINARY FLD ACCURACY (NORMALIZATION WITH RESPECT TO THE "SIGNATURE")

Subject	Raw Signal	Sum of IMF3-IMF7
A	98.23 ± 1.07%	97.67 ± 1.73%
B	97.00 ± 2.40%	98.93 ± 1.16%
C	93.27 ± 2.90%	87.67 ± 7.80%
D	73.20 ± 5.48%	89.93 ± 3.95%
Mean	90.43 ± 10.70%	93.55 ± 6.57%

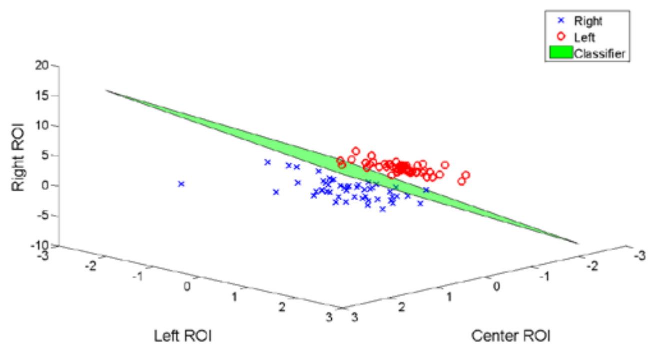

Fig. 8. Scatter plot of EEMD-based features for left and right intended movement separated by FLD classifier.

IV. DISCUSSION

The aim of this paper was to develop and validate the use of scalp EEG data to distinguish brain activity associated with the intended arm movement. In the framework of upper limb neuroprosthetic control, this paradigm could be directly implemented as a noninvasive BCI system where the user's intent can be determined to properly activate the robotic prosthetic arm for activity of daily living (ADL). Using EEMD with FLD classification technique, the overall accuracy of 93.55±6.57% can be achieved for two motor directions cross four subjects prior to actual motion, which is significantly better than any previously reported results to the best of our knowledge, making it suitable for real-time application. There is still debate over the best classification method for BCI. Our result suggested that the linear classifier would be sufficient in this application. The classification accuracy is promising and comparable to most current BCI systems [8][9]. EEMD method is adequate in removing high frequency artifacts. Further study related with different subjects, such as a left hand user, is necessary for having a better understanding of BCI control strategy. More subjects have been recruited to provide more conclusive results on the advantage of the proposed "signature" normalization and EEMD algorithm. Multi-class classification using one-against-one decomposition and majority voting classifier for intended arm reaching movement direction has now been underway. Our group is also currently investigating other feature selection methods and artifact removal techniques to improve the classification algorithm. So far, we have studied the spatial information (near the PPC) on the signal classification. Other potential features that may be relevant to this application included frequency features as well as temporal features after visual cues. The potential applications of this BCIs include a possible way for physical disable people who having intact cognitive functions to communicate with other external devices.

V. CONCLUSION

The left and right directions of intended arm movement can be distinguished at 93.55% accuracy using linear classifiers. Features extracted from EEG using EEMD method and visual cue-based signature normalization factor appeared to be relevant for this BCI application.

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