# Single Trial Classification of Imagined Hand Postures

**S. Purwar[1], J. Archbold[1], C. Buzby[1], D. Erdogmus[1]**
[1]*CSL, Northeastern University, Boston, MA, USA*

Correspondence: Shalini Purwar, Northeastern University, Boston, MA, USA. E-mail: purwar@ece.neu.edu

***Abstract***. Motor imagery (MI) based brain computer interface (BCI) systems are mostly used in the design of robotic/prosthetic arm control. MI signals are asynchronous and hence have the potential of being used in systems that require dynamic manipulation. In MI there is a significant amount of user adaptation involved; to address this issue there is a need to design BCI that is intuitive for the user to adapt to. Towards this goal, in this study we present that with significant accuracy, it is possible to decode imagined hand postures sensed using EEG.

*Keywords:* EEG, Motor Imagery

## 1. Introduction

Motor imagery (MI) has been utilized in numerous BCI systems for the design of systems that control cursors in multiple dimensions, manipulating virtual objects in 3D, controlling robotic arms for performing simple daily life tasks [Ramoser et al., 2000; Blankertz, 2010; McFarland et al., 2010; Doud et al., 2011]. Studies based on human cortical activity associate μ-band (8-12 Hz), β-band (18-26 Hz) and γ-band (>30 Hz) with motor output [Miller et al., 2007]. The lower bands exhibit supression of amplitude in response to MI, event-related desynchronization (ERD) is spatially localized, higher bands exhibit increases in amplitude known as event-related synchronization (ERS).

With the use of micro-electrode implants, it has been show that non-human primates could control a robot arm [Carmena et al., 2003] for reaching out and grasping objects without moving their own. In this study, we investigate the possibility of single trial classification of EEG signals sensed during the imagery of specific hand-posture types: extension and closed.

## 2. Material and Methods

### 2.1. Experiment description

EEG data was collected from two subjects, one male and one female. During the experiment the subject was seated in front of a computer monitor and was asked to relax and avoid body movements and eye-blinks during the trial periods. Each experiment consisted of imagining two hand postures – extension and closed, for each hand, resulting in four trial types (classes). A total of 200 trials were presented with equal number of trials from each class selected in random order. Each trial started with the fixation sign presented at the center of right/left half of the screen, indicating which hand this imagery trial belongs to. An image of the posture type was shown for 5 seconds after fixation; Fig. 1 shows the images used for right hand.

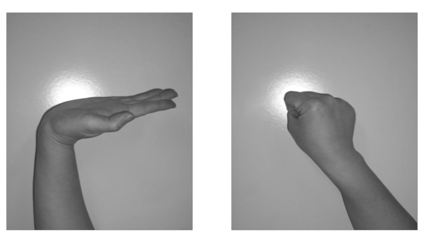

***Figure 1.*** *Hand postures used in the experiment, left image shows extension while right image shows closed.*

### 2.2. EEG recording

EEG was acquired using two 16 channel g.USBamps (g.tec, Graz, Austria) connected in daisy-chain configuration. A total of 32 channels sampled at a rate of 256 samples/second were used.

### 2.3. Common Spatial Pattern Filtering and Fisher's Linear Discriminant Analysis

We used the Common Spatial Pattern Filter method to project data from two classes such that the ratio of projected energy of one class to that of the other class was maximized [Ramoser et al., 2000]. Let $\mathbf{X} \in \mathbb{R}^{\boldsymbol{Nc}\times\boldsymbol{T}}$ be the EEG data samples in matrix form corresponding to one trial (where $Nc$ denotes the number of EEG is channels and $T$ is the number of temporal samples in each trial). The CSP transformation is given by

$$\mathbf{Z} = (\mathbf{B}'\mathbf{P})'\mathbf{X} \tag{1}$$

where $\mathbf{P}$ is the matrix that whitens the composite covariance ($\mathbf{C}_c = \mathbf{C}_1 + \mathbf{C}_2$), sum of individual normalized class covariance where $\mathbf{C}_i = \mathbf{XX}'/trace(\mathbf{XX}')$, where $i \in \{1, 2\}$ and $\boldsymbol{B}$ is the matrix containing the eigenvectors of whitened $\boldsymbol{C}_i$. Features are extracted from CSP projected data by picking subsets of most discriminative signals as indicated by eigenvalues. Further, to reduce dimensionality of Z rows corresponding to largest m and smallest $m$ eigenvalues were selected given as $\boldsymbol{Z}_p$. Fisher's linear discriminant was used to classify feature vectors derived from

$$f_p = log\left(\frac{var(\mathbf{Z}_p)}{\sum_{i=1}^{2m} var(\mathbf{Z}_i)}\right) \tag{2}$$

## 3. Results

Area under the curve (AUC) estimated using 10-fold cross-validation for two subjects is presented. Binary classification has been done on extension and closed imagined hand postures data for each hand (right and left). Fig. 2 shows the variation in AUC with increasing number of CSP filters. Blue curve in the plots corresponds to the right hand classification results and green curve shows the classification accuracy for the left hand.

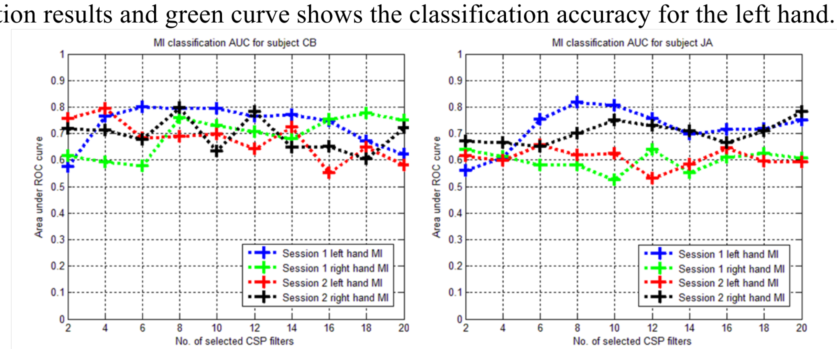


***Figure 2.*** *AUC for binary CSP-based classification between extension and closed hand postures.*

## 4. Discussion

Using the CSP method we have shown that AUC up to 80% is achievable in the classification of posture imagery for naïve subjects. This accuracy is comparable to right/left hand classification for the same subjects. Therefore it is conceivable that complicated hand posture imagery classification with EEG is feasible with high accuracy with subject training and improved pattern recognition.

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