 

# An EEG Inverse Solution based Brain-Computer Interface

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*Abstract*— **We have developed a novel approach using EEG inverse solutions for classifying motor imagery tasks. Two-equivalent-dipole analysis was proposed to aid classification of motor imagery tasks for brain-computer interface (BCI) applications. By solving the EEG inverse problem of single trial data, it is found that the source analysis approach can aid classification of motor imagination of left or right hand movement without training. In four human subjects, an averaged classification accuracy of 80% was achieved. The present study suggests the merits and feasibility of applying EEG inverse solutions to BCI applications from noninvasive EEG recordings.**

*Keywords*— **Brain Computer Interface, Motor Imagery, Source Analysis, EEG.**

## I. Introduction

Over the last three decades, the development of a technology called brain–computer interface (BCI) (for review see [20] and [23]), has provided a novel and promising alternative method for interacting with the environment. The ultimate goal of BCI research is to create a new communication channel (by means of directly reading the patients intent and translating it into physical commands) for people suffering from severe motor disabilities but being cognitively intact.

Present-day BCIs use various signals to detect subjects' intention. In the present study, we use electroencephalogram (EEG) and focus on $\mu$ rhythm associated with left and right hand movement imagination.

Recently a new means of extracting subjects' intent by means of source analysis has been suggested by applying the equivalent current dipole model and cortical imaging technique to a human subject undergoing left or right hand movement imagination [17]. Such inverse solutions from the scalp EEG provide reconstructed source distributions over the source domain, which may be regarded as an alternative representation of intracranial recordings, that compensates the distortion and smearing effect caused by skull low conductivity and volume conduction effect [5], [9].

In the present study, we propose the two-equivalent-dipole model for source analysis of BCI applications, and test the hypothesis, in a group of four human subjects, that the source analysis methods can aid the classification of motor imagery by revealing the activity of the brain, thus facilitating BCI from single trial scalp EEG data.

## II. Methods

### A. Data Description

The EEG dataset used in this study was made available by Dr Allen Osman of University of Pennsylvania [13]. EEG data were recorded from 59 channels placed according to the international 10/20 system with a sampling rate of 100 Hz. Subjects were asked to imagine either left or right hand movement (each subject 180 trials, 90 left, 90 right). Each trial epoch lasted 6 seconds as shown in *Fig. 1*.

For each trial, EEG data were recorded from all 59 electrodes but since we were only interested in the activity of sensorimotor cortex, the signals from 15 channels over the sensorimotor area were used in the present study.

### B. Data pre-processing

*1) Surface Laplacian filtering:* The surface Laplacian method [1], [8], [11], which derives the second spatial derivative of the instantaneous spatial potential distribution, serves as a high-pass spatial filter and attempts to accentuate localized activity and reduce diffusion in multi-channel EEG.

*2) Time–frequency analysis:* Each trial lasts 6 seconds but not all time points of this 6-second period carry information about the difference between left and right hand movement imagination. In addition, the desynchronization phenomenon during motor imagery tasks is highly frequency related.

With the aid of TF representation, we can obtain the time-varying energy of the signal in each frequency band [18] and choose the time window and frequency band in which the largest difference between right and left hand movement imagination appears.

In this work, we chose the time window from 4 s to 5.5 s and frequency band from 8-12 Hz and used a fifth-order Butterworth filter for temporal bandpass filtering.

*3) Noise normalization:* The EEG recordings from all sensors were normalized by their corresponding noise level which was estimated from certain time points taken from histographic analysis of the data (for details refer to [4]) and

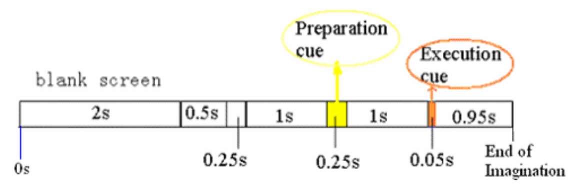


Fig. 1. Time sequence of one trial epoch of the experiment.

the original data were then transformed to signal-to-noise-ratio (SNR) values by normalization of the measured signals to their corresponding noise level, yielding unit free measurements.

*4) Independent component analysis:* Independent component analysis (ICA) is a statistical method for finding underlying components from multidimensional data that are statistically as independent from each other as possible [3].

In the present study, fixed-point algorithm was used for ICA [12]. Before implementing ICA, singular value decomposition (SVD) was used for decorrelation. This procedure can speed up the iteration process of ICA by setting all singular values which are below a certain threshold to zero.

At this work, the first three components of ICA were used for source reconstruction.

### *C. Source reconstruction*

The purpose of source reconstruction is to provide information about the electrical sources generating the scalp EEG by solving a so-called inverse problem [6]. In the present study, the two-equivalent-dipole source model was used to approximate brain electrical sources induced by motor imagery. Each dipole is movable within the brain and is characterized by 6 parameters per time point, namely its location and moment. The goal is to estimate these dipole parameters that can best explain the observed potentials in the least square sense, in other words, to minimize the residual error [10],

$$\Delta^2 = \left\| H(L)j - \tilde{M} \right\|^2 \tag{1}$$

where $H(L)$ is the lead field matrix as a nonlinear function of dipole location, $j$ is the dipole moment and $\tilde{M}$ represents the ICA processed data.

### *D. Classification Criteria*

As mentioned before, during motor imagery, due to a decrease in synchrony of the underlying neuronal populations, a decrease of power appears in the μ rhythm of the contralateral side of the brain. Such a decrease of power turns to the phenomenon of showing stronger activity on the ipsilateral side. Therefore, the equivalent dipoles corresponding to the noise-normalized data shall appear or be stronger on the ipsilateral side of the brain. Based on this hypothesis, the following classification rules were adopted in the present study:

First we obtain the two-equivalent-dipole solution at the time point with the largest SNR. If both dipoles are located on the same hemisphere (which happened in most cases), we conclude that movement imagination is correspondent to that side. If the dipoles don't appear on the same hemisphere (e.g. one appears on the left and one on the right), we look for the hemisphere with stronger source activity. We used the single dipole model for these cases.

## III. Results

We have tested the present source analysis based BCI algorithm on the data recorded from four human subjects. Fig. 2 shows examples of the two-equivalent-dipole solutions of the left hand movement imagination (MI) and right hand MI, displayed on a typical brain model. Since the source analysis was based on the spherical head model, no anatomic data were attempted to be incorporated into the source analysis.

To statistically test the present method, all 180 trials in each subject were analyzed, and results obtained directly from the source analysis without training. The maximum accuracy, obtained for subject #2, is 84.44% and the average accuracy across the four subjects is 80.00%.

## IV. Discussion

In the present study, we have tested in a group of four human subjects the hypothesis that source analysis methods such as dipole localization can be employed for classification of motor imagery tasks in BCI applications. If these methods could be used for this purpose, we can exploit their unique characteristics of detecting the source activity within the brain thus substantially reducing the distortion problem caused by the low conductivity of the skull and making the classification easier.

The present results are promising and show that reasonable classification accuracy can be achieved by this simple classification rule. In the present study the average classification rate of 80% and maximum of 84.44% were achieved in four human subjects. This result is reasonably positive because subjects didn't have any training involved and all the 180 trials provided by the UPenn database, have been used without rejecting any "bad" trial. The source analysis approach, in which EEG inverse solutions are used,

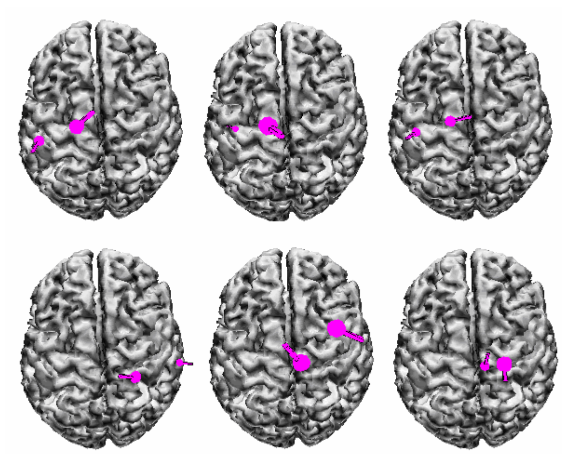

Fig. 2 Examples of estimated two-equivalent-dipole solutions corresponding to trials of left hand movement imagination (first row) and right hand movement imagination (second row). Note that the locations and moments of the equivalent dipoles varied from trial to trial, due to the low SNR of single trials.

promises to provide a useful alternative to machine learning for BCI applications.

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