Classification of Motor Imagery Tasks for Brain-Computer Interface Applications by Means of Two Equivalent Dipoles Analysis

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***Abstract*—We have developed a novel approach using source analysis for classifying motor imagery tasks. Two-equivalent-dipoles analysis was proposed to aid classification of motor imagery tasks for brain–computer interface (BCI) applications. By solving the electroencephalography (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 accuracy of classification of 80% was achieved. The present study suggests the merits and feasibility of applying EEG inverse solutions to BCI applications from noninvasive EEG recordings.**

***Index Terms*—Brain–computer interface (BCI), dipole source analysis, electroencephalography (EEG), inverse problem, motor imagery.**

I. Introduction

OVER the last three decades, the development of a technology called brain–computer interface (BCI), for review see [30] and [33], 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 for people suffering from severe motor disabilities but being cognitively intact.

In BCI systems, messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of nerves and muscles. The system directly reads out the patient's intent and translates it into physical commands that control the output devices.

Thus far, both invasive and noninvasive approaches have been used to acquire data (i.e., signals containing information about the user's intent) in order to establish an interface between the computer and the brain. Invasive approaches (which are usually called brain-machine interface) take advantage of better signal quality but for obvious reasons, their application for human is debatable. Electrocorticograms and single-neuron recordings [6], [19], [20], [26] are two examples of invasive methods. The major noninvasive method is the use of electroencephalography (EEG), which offers a relatively simple and inexpensive BCI [2], [3], [23], [29]–[34].

Manuscript received January 6, 2005; revised January 29, 2005; accepted February 1, 2005. This work was supported in part by the National Science Foundation (NSF) under Grant BES-0411898, in part by NSF CAREER Award BES-9875344, and in part by the National Institutes of Health under Grant R01EB00178.

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Digital Object Identifier 10.1109/TNSRE.2005.847386

Present-day EEG-based BCIs use various signals to detect subjects' intention. Some instances are slow cortical potentials, P300 potentials and μ or β rhythms [2], [3], [5], [18], [22]–[24], [29], [31], [33], [34]. In the present study, we focus on μ rhythm associated with left- and right-hand movement imagination (MI).

The μ rhythm is a part of α band and is traditionally defined as an 8–12-Hz rhythm recorded over the sensorimotor cortex which decreases or desynchronizes with movement. It has been demonstrated that this desynchronization also occurs during motor imagery [22].

The basic phenomenon which is exploited in this work is that, during unilateral hand movement imagery, an event-related desynchronization (ERD) appears on the contralateral hemisphere. So, if we extract the difference between the left- and right-hand MIs, we can distinguish them from each other, thus forming the basis for a binary type of BCI system.

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 one human subject undergoing left- or right-hand MI [25]. 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 [8], [12].

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. A. Osman of University of Pennsylvania [21], [27]. EEG data were recorded from 59 channels placed according to the international 10/20 system with a sampling rate of 100 Hz. Subjects were seated in front of a display screen and asked to imagine either left- or right-hand movement (each subject 180 trials, 90 left, 90 right). Each trial epoch lasted 6 s and started with a blank screen displayed 2 s as shown in Fig. 1. Two noticeable timing cues are *preparation cue* and *execution cue.* During the former, which starts at 3.75 s and lasts 0.25 s, a letter "L" or "R" appears on the screen indicating that which hand

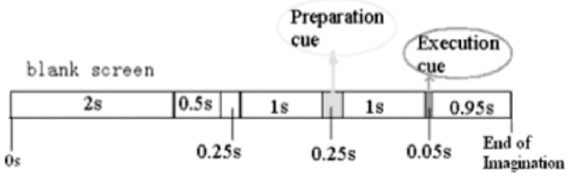

Fig. 1. Time sequence of one trial epoch of the experiment.

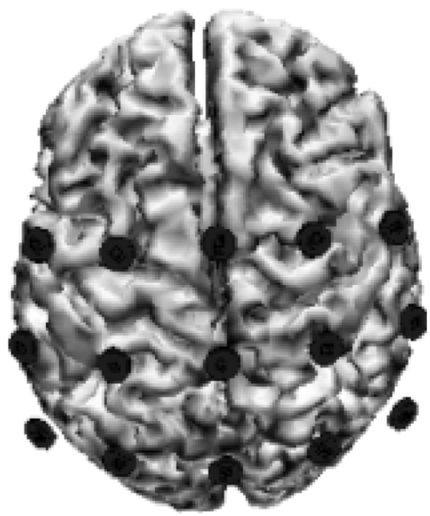

Fig. 2. Layout of the channels used in this study (channels FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, and CP4).

movement should be imagined. The latter begins at 5.0 s and displays an "X" for 0.05 s to tell the user to start imagination.

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. Fig. 2 shows the locations of the electrodes used in the present source analysis study and their schematic relative positions with a brain model. Note that the electrodes are over the scalp instead of over the cortex, so Fig. 2 is just a schematic illustration.

B. Data Preprocessing

Preprocessing step consisted of Laplacian spatial filtering, time-frequency analysis, noise normalization, and independent component analysis. Details are described in the following.

1) Surface Laplacian Filtering: Scalp recorded EEG represents the noisy spatial overlapping of activities arising from very diverse brain regions. Spatial filter techniques attempt to accentuate localized activity and reduce diffusion in multichannel EEG. The surface Laplacian method [1], [11], [14], which derives the second spatial derivative of the instantaneous spatial potential distribution, could serve for such a high-pass spatial filtering purpose. Assuming that the distances from a given electrode to its four directional neighboring electrodes are approximately equal, the surface Laplacian can be approximated by subtracting the average value of the neighboring channels from the channel of interest [14]

$$M_j^{Lap} = M_j - \frac{1}{4}\sum_{k\in Sj} M_k \tag{1}$$

where M_j is the scalp potential EEG of the jth channel, and S_j is an index set of the four neighboring channels.

2) Time-Frequency Analysis: Each trial lasts 6 s, but not all time points of this 6-s period carry information about the difference between left- and right-hand MI; so it is not efficient to use the whole time range for source analysis. In addition, the desynchronization phenomenon during motor imagery tasks is highly frequency related. In the present study, the time-frequency (TF) representation was used to select the appropriate time window and frequency band for source analysis [25].

With the aid of TF representation, we can obtain the time-varying energy of the signal in each frequency band [28]. To reach this goal, we employed the wavelet transform with complex Morlet's wavelets $w(t, f_0)$

$$w(t, f_0) = A \cdot \exp\left(\frac{-t^2}{2\sigma_t^2}\right)\exp(2i\pi f_0 t) \tag{2}$$

where $\sigma_t = 1/2\pi\sigma_f$ and $A = (\sigma_t\sqrt{\pi})^{-1/2}$. As we know, in wavelet transform, there is a tradeoff between time and frequency resolution. To compromise between them, the ratio (f_0/σ_f) was chosen as 7.

The time-varying energy $[E(t, f_0)]$ of a signal at a specific frequency band is the squared norm of the convolution of a complex wavelet with the signal

$$E(t, f_0) = |w(t, f_0) * M(t)|^2 \tag{3}$$

where M is the Laplacian-filtered EEG. The result of convolution of the signal by a family of wavelets is a TF representation of the signal as shown in Fig. 3. The left column is the TF representation of EEG signals recorded at electrode C3 (on the left hemisphere), and the right corresponds to channel C4 (on the right hemisphere). The upper row is left-hand MI and the lower is right hand.

From Fig. 3, we can see that the μ rhythm has a clear energy decrease (ERD) on the contralateral hemisphere starting from 4 to 5.5 s, which also suggests that subjects would begin imagination right after the preparation cue instead of the execution cue.

With the help of TF representation, we chose the time window from 4 s to 5.5 s and frequency band from 8–12 Hz for source analysis because the largest difference between right- and left-hand MI appeared during this time window and frequency band. A fifth-order Butterworth filter was used for temporal bandpass filtering.

3) Noise Normalization: Noise normalization is one of the central tasks in preprocessing. In the present study, 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 [7]). The "20% percentile" method was utilized to estimate the noise level. That is, within the selected time range, 20% time points with lowest potential power are used to estimate the noise variance at each channel individually. 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. This was done by multiplying it by the inverse of the square root of the diagonal noise covariance matrix

$$\tilde{M} = \frac{1}{diag\sqrt{C}} M \tag{4}$$

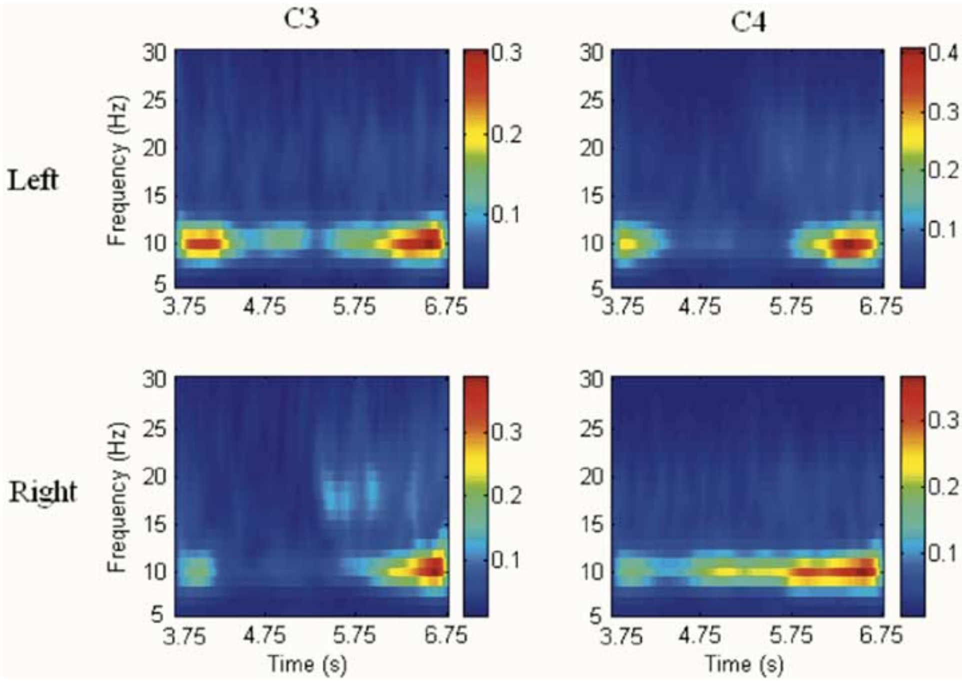

Fig. 3. TF representation of channels C3 and C4 in a human subject. Left column refers to TF representation for C3 and right column for C4. The upper row refers to the TF representation of left-hand MI and the lower refers to right-hand MI. The time period shown here is 3 s from the preparation cue (3.75 s) and frequency band is from 5 to 30 Hz.

where M is the spatially and temporally filtered EEG, and $\tilde{M}$ consists of the SNR values after noise normalization.

4) Independent Component Analysis (ICA): ICA is a statistical method for finding underlying components from multidimensional data that are statistically as independent from each other as possible [4]. Here, we briefly describe the basic concepts and estimation principles of ICA.

The goal is to find a coordinate system in which the data are maximally statistically independent

$$\tilde{M}_{n\times t} = A_{n\times n} \cdot S_{n\times t} \tag{5}$$

where $\tilde{M}$ is the n (number of channels) by t (time points) matrix of SNR values, A is the mixing matrix and S is a matrix whose components are mutually independent.

Solving the ICA problem is to find a matrix W iteratively so that the linear transformation of the data $\tilde{M}$ yields to components that are as mutually independent as possible

$$\hat{S} = \hat{W} \cdot \tilde{M}. \tag{6}$$

In the present study, a fixed-point algorithm was used for ICA [15]. Before implementing ICA, singular value decomposition (SVD) was used for denoising. This procedure can speed up the iteration process of ICA by setting all singular values which are below a certain threshold to zero. It was realized as

$$\tilde{M} = U\Sigma V^T \tag{7}$$

where Σ is a diagonal matrix containing singular values of $\tilde{M}$, U contains the orthogonal, normalized spatial patterns and V^T contains the normalized time courses.

After noise normalization, we have changed our signal data to SNR values; all the time courses with singular value less than a certain value were regarded as noise subspace and discarded. Assuming that V_c and Σ_c are subsets of V^T and Σ corresponding to singular values above threshold, which is regarded as the signal subspace, ICA can be computed and realized only on this signal subspace. Then, (6) can be changed to

$$\tilde{S} = \tilde{W}.V_c \tag{8}$$

where $\tilde{W} = \tilde{W}U\Sigma_c$, then the mixing matrix A in (5) can be obtained by the following equation:

$$A = U\Sigma_c\tilde{W}^{-1}. \tag{9}$$

Sorting mixing matrix A by its column norms, independent components can be obtained from (5) in a decreasing order.

In the present study, 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 nature and anatomical locations of electrical sources generating the scalp EEG by solving a so-called inverse problem [9]. Due to the nature of the inverse problem, it could be solved by inverse modeling but it is necessary to assume a model of the source and a model of the head volume conductor for estimation of the neural sources. In the present study, the head volume conductor was represented by the three-spherical volume conductor model. The two-equivalent-dipole source model [35] was used to approximate brain electrical sources induced by motor imagery. Dipole source analysis hypothesizes that the neural sources which are generating electrical measurements on the scalp, can be approximated by a set of current dipoles. Each dipole is movable within the brain and is characterized by six 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 [13], [35]

$$\Delta^2 = \left\| H(L)j - \tilde{M} \right\|^2 \tag{10}$$

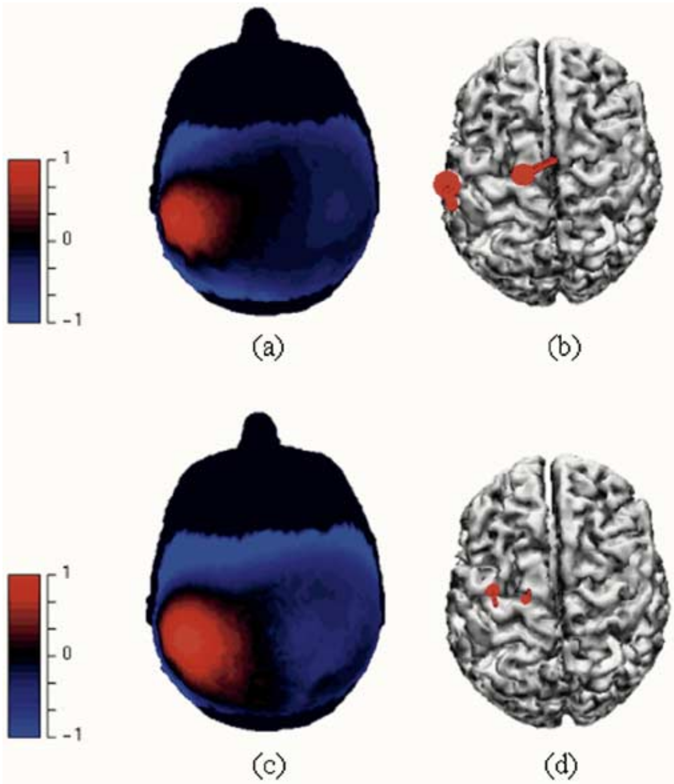

Fig. 4. Examples of the scalp measurements [(a) and (c)] and the estimated two-equivalent-dipole solutions [(b) and (d)] corresponding to two individual trials of left-hand MI. The color maps on the left column code the noise-normalized scalp data. The equivalent dipoles are shown by red dots (locations) and arrow (moments) on the right column.

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.

Due to its nonlinear nature, it is known to be problematic to localize more than two moving dipoles, and the resulting long computation time is not acceptable for BCI application. Therefore, we focused on localizing two moving dipoles and Simplex method [17] was used to solve this problem.

D. Classification Criteria

As we 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 (i.e., if the subject is imagining to move his/her left hand, the power decrease appears on the right side of the brain). Since we used noise-normalized data for source analysis, such decrease of power on the contralateral side of the scalp turned 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 MI is correspondent to that side (Fig. 4) (i.e., if both dipoles locate on the left side of the brain, we conclude that it is left-hand MI). 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. 4 shows two examples of the scalp data, processed according to the series of procedures described above, and the estimated equivalent dipoles. Each row in the figure corresponds to one single trial. Fig. 5 shows examples of the two-equivalent-dipole solutions of the left- 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 were obtained directly from the source analysis without training. Table I shows the total classification accuracy for each of these four subjects and the average classification accuracy for all. 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.

We have performed the source analysis of the recorded scalp EEG signals from four human subjects by means of equivalent dipole localization method. The classification was based on the phenomenon that during motor imagination, a desynchronization appears in the contralateral μ rhythm. Thus, the normalized scalp data distribution should reflect an equivalent ipsilateral dominance. Our equivalent dipole analysis has supported this notion that equivalent dipoles have been estimated on the ipsilateral hemisphere of the brain. We have classified the left- or right-hand movement based on the anatomic locations of the equivalent dipoles. 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 did not have any training involved and all the 180 trials provided by the University of Pennsylvania database, have been used without rejecting any "bad" trial. Yet, in practice, subjects cannot always concentrate well. Sometimes they get distracted or imagine nothing. The performance would be further improved if these "bad" trials could be rejected based on online feedback. In a real-time online experimental setting, we can reject the trials by observing EEG or EMG recordings and detecting the artifacts that may unexpectedly bias the classification. The online feedback will also help subjects adapt to think in the way that could generate "better" signals for classification.

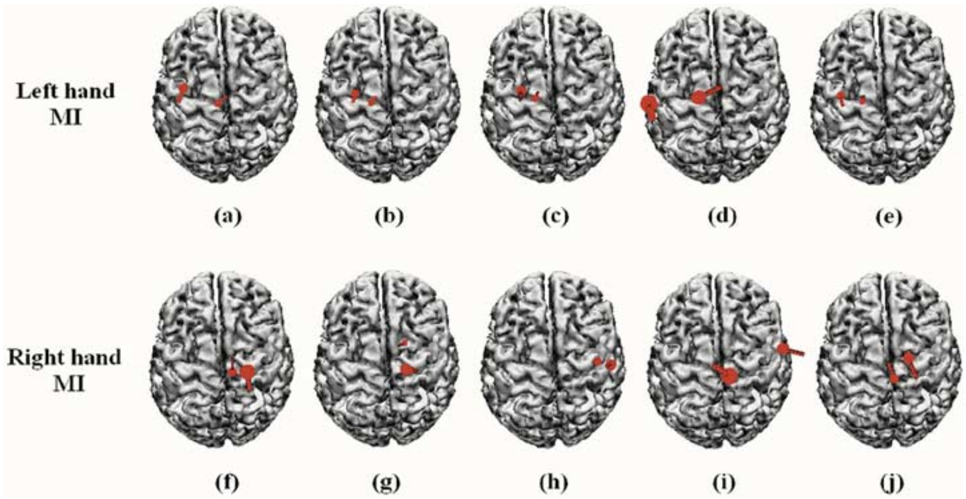

Fig. 5. Examples of estimated two-equivalent-dipole solutions corresponding to trials of left-hand MI (top row) and right-hand MI (bottom row). Note that the locations and moments of the equivalent dipoles varied from trial to trial, due to the low SNR of single trials.

TABLE I
CLASSIFICATION ACCURACY OF TWO EQUIVALENT DIPOLES PROCEDURE IN CLASSIFYING MI IN HUMAN SUBJECTS

Subject	Left hand MI	Right hand MI	Average
1	83.33%	85.56%	84.44 %
2	87.78%	67.78%	77.78 %
3	86.67%	66.67%	77.22 %
4	88.89%	72.22%	80.56 %
Average	86.67%	73.06%	80.00 %

Another important factor that plays a major role in classification is the chosen time window and frequency band. For different subjects, the clearest ERD may occur at different frequency bands and at different time points [24], [31]. In this study, with the help of TF representation, we have manually selected two fixed intervals for all subjects since the focus of the present study is to develop and evaluate the two-moving-dipole approach for BCI applications. While it is beyond the scope of the present study to find an adaptive way to choose the most suitable frequency band and time window for each subject (e.g., based on training data), it should be further explored for online experiments in future investigations.

The single equivalent dipole model has been previously reported to provide reasonable results in classification of hand MI in one human subject [25]. In the present study, we have proposed the two-moving-dipole approach and compared the two-dipole model with the single-dipole model. Our experimental results suggest that the two-dipole model worked better than the single-dipole model in general. However, we have used a combined classification procedure integrating the two-dipole and single-dipole models in the present analysis. When the estimated two dipoles appear on both hemispheres, the single-dipole model helped to reduce the dimensionality of data and sometimes provided correct classification from the localization of single-dipole source.

Note that while we have tested the feasibility of the proposed two-dipole-approach for classifying motor imaginary tasks in a simple setting of imagining of left- or right-hand movement, the proposed approach should be in principle applicable to discriminate among different grasping tasks, and other more complicated motor imagery tasks. The time necessary to detect the kind of task and to switch from one task to another shall only be corresponding to the analysis of inverse computation. Such time required is depending on the forward model being used and the platform on which the source analysis is carried out. In principle, such inverse source analysis should be applicable for real-time applications, while further efforts are needed in practical implementation.

V. CONCLUSION

We have further refined our source analysis approach for classification of motor imagery tasks for BCI applications, and found that the two-dipole-source-analysis approach works well for classifying hand movement imagery tasks in a group of four human subjects. The present promising results suggest that source analysis provides an alternative means of aiding the classification of motor imagery tasks by converting scalp EEG's into source signals, and merits further investigation.

ACKNOWLEDGMENT

The authors are grateful to Dr. A. Osman of University of Pennsylvania for making his data available. They would also like to thank L. Qin and L. Ding for useful discussions in the data analysis.

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