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Motor imagery classification by means of source analysis for brain–computer interface applications

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Abstract

We report a pilot study of performing classification of motor imagery for brain–computer interface applications, by means of source analysis of scalp-recorded EEGs. Independent component analysis (ICA) was used as a spatio-temporal filter extracting signal components relevant to left or right motor imagery (MI) tasks. Source analysis methods including equivalent dipole analysis and cortical current density imaging were applied to reconstruct equivalent neural sources corresponding to MI, and classification was performed based on the inverse solutions. The classification was considered correct if the equivalent source was found over the motor cortex in the corresponding hemisphere. A classification rate of about 80% was achieved in the human subject studied using both the equivalent dipole analysis and the cortical current density imaging analysis. The present promising results suggest that the source analysis approach could manifest a clearer picture on the cortical activity, and thus facilitate the classification of MI tasks from scalp EEGs.

(Some figures in this article are in colour only in the electronic version)

1. Introduction

People suffering from severe motor disabilities but being cognitively intact need an alternative method to interact with the environment. Over the past decades, the development of the technology of brain–computer interface (BCI) (see Wolpaw *et al* 2002 for review) has provided a novel and promising communication channel for these patients. It reads out the intents of the patients and translates them into physical commands which control the output devices. Both noninvasive and invasive approaches have been used to acquire data for BCI. The noninvasive methods include the use of electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI) and optical imaging. Among these, because EEG has relatively short time constants, which can function in most environments, and EEG acquisition systems are relatively simple and inexpensive, EEG-based BCI systems are currently widely used (Wolpaw *et al* 1991, 2002, Pfurtscheller and Neuper 1994, Pfurtscheller *et al* 1997, Birbaumer 1999, Babiloni *et al* 2000, 2001, Wang and He 2004, Vallabhaneni and He 2004, Vallabhaneni *et al* 2004). On the other hand, intracranial recording methods, such as electrocorticograms and single-neuron recordings, are invasive (Donoghue 2002, Nicolelis 2001, 2003, Rohde *et al* 2002) although these methods take advantage of better signal quality. For obvious reasons, it would be desirable if one can fully develop noninvasive methods to control BCI devices, thus avoiding brain implants in human subjects.

Present-day EEG-based BCIs use different signals to encode the subjects' intent, such as slow cortical potentials, P300 potentials and μ or β rhythms (Wolpaw *et al*

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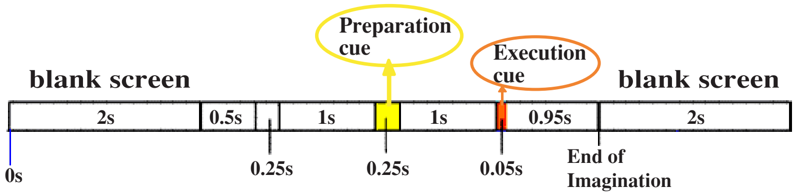

Figure 1. Time sequence of one trial epoch of the experiment.

1991, 2002, Pfurtscheller and Neuper 1994, Pfurtscheller *et al* 1997, Pfurtscheller 1999, McFarland *et al* 1997, Birbaumer 1999, Babiloni *et al* 2000, 2001, Wang and He 2004, Vallabhaneni and He 2004). In the present study, we focus on μ rhythms caused by motor imagination, i.e. left and right hand imagination. μ rhythm, a part of the α band, is traditionally defined as an 8–12 Hz rhythm recorded over the sensorimotor cortex that decreases or desynchronizes with movement, while it has recently been demonstrated that it also occurs with motor imagery (Pfurtscheller 1999). During unilateral hand movement imagery, an event-related desynchronization (ERD) appears on the contralateral hemisphere. So the difference in the scalp EEG with the different hand imagination can be used to generate different control signals for BCI systems (Pfurtscheller *et al* 1997, Babiloni *et al* 2000, 2001, Wang and He 2004, Vallabhaneni and He 2004).

The source analysis methods, which solve the inverse problem of EEG from noninvasively recorded scalp potentials, allow analysis of brain signals in the source space (He 1999, He and Lian 2004). The reconstructed source distribution over certain physical regions, e.g. brain cortex, within the human brain can be regarded as an alternative representation of intracranial recordings, which compensates the distortion and smearing effect caused by low conductive skull (He *et al* 2002, He 2004). From this point of view, the EEG-based source analysis methods would convert the signal space of noninvasive EEG measurement from the smeared scalp potential into the source distribution within the human brain, which is believed to have improved quality. In the present study, we test the hypothesis that the source analysis methods will aid the classification of motor imagination by revealing the activity of the brain, thus facilitating BCI from the scalp EEG.

2. Method

2.1. Data description

The EEG data consisting of synchronized imaginary movement experiments were made available by Dr Allen Osman of University of Pennsylvania (Osman and Robert 2001, Sajda *et al* 2003).

Scalp EEG data were recorded from 59 electrodes placed according to the International 10/20 System with a sampling rate of 100 Hz. The subjects were asked to imagine either right- or left-hand movement (180 trials, 90 left and 90 right) according to a highly predictable time cue.

Each trial (6 s) began with a blank screen. Two important timing cues that should be mentioned here are that at 3.75 s of a trial epoch, a cue (*preparation cue*, lasting 250 ms) of one letter (‘L’ or ‘R’) appeared on the screen indicating which hand movement should be imagined; and at 5.0 s another cue ‘X’ (*execution cue*, lasting 50 ms) appeared, indicating that it was time to make the requested response as shown in figure 1. However, an important thing that should be mentioned here is that even though the execution cue is set as the start point of imagination, subjects would begin imagining right after the preparation cue.

2.2. Data pre-processing

Data pre-processing consisted of Laplacian spatial filtering, time–frequency analysis, bandpass temporal filtering and independent component analysis. The raw EEG data were processed using each of these procedures, as described in detail below.

2.2.1. Laplacian spatial filtering. The surface Laplacian filter is a sort of spatial high pass filter, and it attempts to enhance neuronal activity which is close to the recording electrode (Hjorth 1975, Babiloni *et al* 1996, He 1999, He *et al* 2001), thus accentuating localized activity and reducing diffused activity (McFarland *et al* 1997). It could be approximately calculated by using the five-point approximation method (Hjorth 1975),

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

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

2.2.2. Time–frequency analysis. The time range of one trial is 6 s, while we cannot use the whole time range for source analysis since not all points during this period contain information of the difference between left- and right-hand movement imagination. Also, the correct frequency band should be chosen as event-related (de)synchronization (ERD/ERS) is highly frequency related. In the present study, the time–frequency (TF) representation was used to select the time window and frequency band for source analysis.

The TF representation provides a time-varying energy of the signal in each frequency band (Tallon-Baudry *et al* 1997). In the present study, the signal was convoluted by complex Morlet’s wavelets $w(t, f_0)$,

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

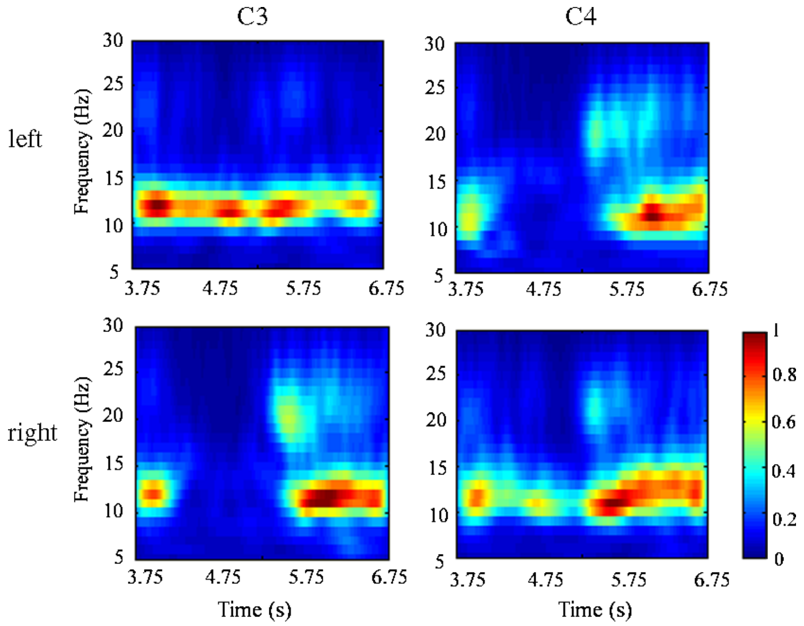

Figure 2. Averaged time–frequency (TF) representation of channels C3 and C4 during motor imagery in a subject. Left column refers to TF representation for C3 and right column for C4. The upper row refers to the TF representation of left-hand movement imagination and the lower refers to right-hand movement imagination. The time period shown here is 3 s from the preparation cue (3.75 s) and the frequency band is from 5 to 30 Hz.

with $\sigma_f = 1/2\pi\sigma_t$, $A = (\sigma_t\sqrt{\pi})^{-1/2}$. The trade-off ratio (f_0/σ_f) was chosen as 7 to create a wavelet family. This constant was used to determine the compromise between time and frequency localization.

The time-varying energy, $E(t, f_0)$, of the 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 refers to Laplacian-filtered scalp-recorded EEG data. The convolution of the signal by a family of wavelets constructs a TF representation of the signal as shown in figure 2. Figure 2 shows the averaged TF representation of all trials. The left column is the TF representation for EEG signals recorded at electrode C3 (on the left hemisphere), while the right is for channel C4 (on the right hemisphere). The upper row corresponds to left-hand movement imagination, and the lower to right-hand movement imagination.

From figure 2, we can see that the μ rhythm has a clear energy decrease or ERD on the contralateral hemisphere starting from 4 s to 5.75 s, which also suggests that the subject would begin to imagine right after the preparation cue instead of the execution cue. With the help of TF representation, we chose the time window from 4.5 s to 5 s and frequency band from 11–12 Hz for source analysis due to the observation of the largest difference appearing during this time window and the frequency band.

2.2.3. Bandpass temporal filtering. The Laplacian-filtered EEG data were then bandpass filtered in the α band (11–12 Hz) using a fifth-order Butterworth temporal filter. As previously reported, μ rhythm ERD emerges over the contralateral central region from the start of the movement imagination (Pfurtscheller and Neuper 1994, Pfurtscheller *et al* 1997, Pfurtscheller 1999), which means that the μ rhythm is blocked on the contralateral side; we can anticipate that using source analysis methods, the equivalent sources estimated using dipole localization method or cortical current density imaging should be stronger on the ipsilateral side of the brain.

2.2.4. Noise estimation. The 20% time points with lowest mean global field/potential power (MGFP) were selected as noise. After getting the noise covariance matrix C, the original data were transformed to SNR values by

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

where M are the spatial and temporally filtered EEG data and only the diagonal value in matrix C was used.

2.2.5. Independent components analysis (ICA). The ICA method is a statistical method for transforming an observed multi-dimensional vector into components that are statistically as independent from each other as possible (Jutten and Herault 1991, Comon 1994, Hyvärinen and Oja 1997). The goal is to find a coordinate system in which the data are maximally statistically independent:

$$\tilde{M} = A \cdot S \tag{5}$$

where $\tilde{M}$ is the SNR value of n (channel number) by t (time points), 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 components that are as mutually independent as possible.

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

In the present study, the fixed-point algorithm was used for ICA (Hyvärinen and Oja 1997). 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 to zero which are below a certain threshold. It was realized as

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

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 estimation, 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 is the subset of time courses from V^T 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, equation (6) can be changed to

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

Replacing V^T in equation (7) by V_c from equation (8), the mixing matrix A in equation (5) can be obtained by the following equation

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

Sorting mixing matrix A by its column norm, independent components can be obtained from equation (5) in non-decreasing order.

2.3. Source analysis

Source analysis is a widely used technique to estimate the source signals from scalp-recorded EEG data. Such an approach has been used extensively to localize neural sources that generate the scalp EEG (He 1999, He and Lian 2004). 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, both the equivalent dipole analysis and cortical current density (CCD) imaging approaches were used. The equivalent dipole model assumes that the neural sources corresponding to a particular event or task can be approximated by one or a few current dipoles that are movable within the brain (He *et al* 1987, He and Lian 2004). The cortical current density model assumes that neural sources can be approximated by a layer of current dipoles distributed over the cortex (Dale and Sereno 1993). The 3-concentric sphere head model (Rush and Driscoll 1968) contains three concentric layers with different electrical conductivities, which represent the cortex, skull and scalp, respectively.

Because we are only interested in the activity in the motor cortex, channels on the frontal and occipital parts were removed—only the electrodes around the sensorimotor cortex (FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4) were chosen for source analysis. In the present study, only the first component of ICA was used for source reconstruction, by setting all but the first column of A to zero. The time point with the largest amplitude in this first component of ICA was used for source reconstruction, which consists of 15 data points over the corresponding sites of the scalp.

In the equivalent dipole analysis, to find the location and moment of the dipole is to minimize the residual error (He *et al* 1987),

$$\Delta^2 = \|Lj - \tilde{M}\|^2 \tag{10}$$

where L is the lead field matrix, j is the dipole moment and $\tilde{M}$ represents the first component of ICA. The simplex method (Kowalik and Osborne 1968) was used to solve this problem.

CCD is defined as dipole moment per volume with the unit μA mm mm^{-3}. A CCD is discretized into a large number of elementary dipoles which are distributed over the cortical surface. The weighted minimum norm (MN) method was used to solve the inverse problem,

$$\Delta^2 = \|Lj - \tilde{M}\|^2 + \lambda\|Qj\|^2 \tag{11}$$

where L is the lead field, j is the cortical current density vector, $\tilde{M}$ is the first component of ICA, Q is a weighting matrix with depth information, and λ is the regularization parameter, which was determined by the L-curve criterion (Hansen 1992).

3. Results

The effect of source analysis is illustrated in figure 3. Figure 3(*a*) depicts the scalp EEG map of one single trial, after Laplacian spatial filtering and bandpass temporal filtering, while figure 3(*b*) shows the equivalent dipole solution and cortical current density distribution (only those larger than 80% of the largest current strength are plotted.). From figure 3(*a*), it is hard to tell whether the activity originates on the left or right hemisphere of the brain, while it is clear from the source space as shown in figure 3(*b*).

Figures 4 and 5 show the equivalent dipole solutions and cortical current density distribution of five trials for both left- and right-hand movement imagination respectively. As we have mentioned above, in μ rhythm, an ERD appears on the contralateral side of the brain during motor imagination, thus the equivalent dipole and CCD should appear or be stronger on the ipsilateral side. These two figures support this hypothesis.

For now, a simple classification rule can be defined based on source analysis results:

(a) For equivalent dipole analysis, the classification is correct if the equivalent dipole is located on the ipsilateral side with the imaginary hand.
(b) For CCD, all currents larger than 80% of the largest sum up. If the summation is larger on the ipsilateral side than on the contralateral side, we judge the classification correct, otherwise wrong.

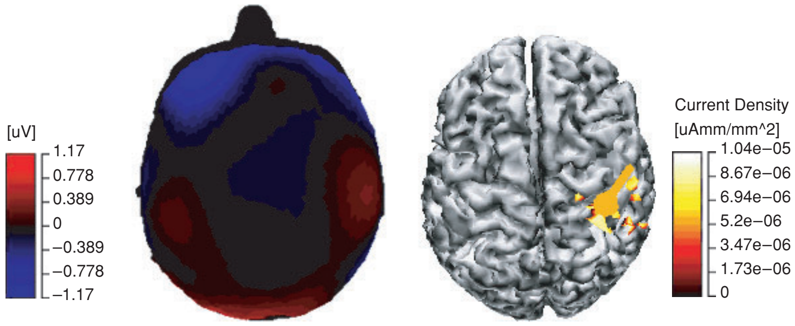

Figure 3. Illustration of the effect of source analysis. The left panel (*a*) illustrates the surface Laplacian and temporal-bandpass filtered scalp EEG map of a single trial, and the right panel (*b*) depicts the equivalent dipole solution and cortical current density distribution estimated from it.

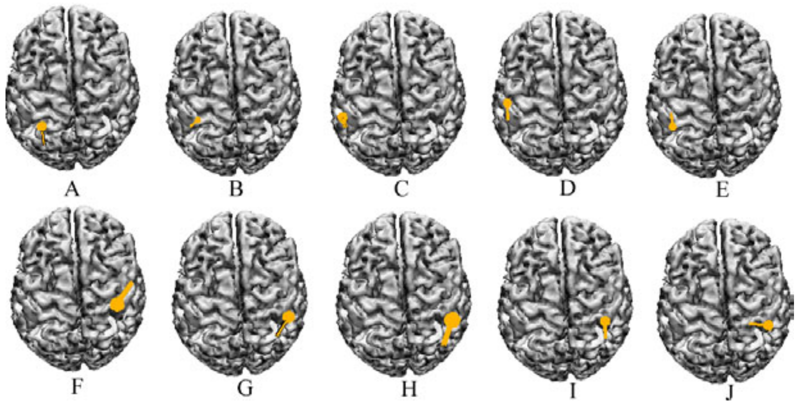

Figure 4. Examples of equivalent dipole solutions of different trials in a human subject during imagination of left or right hand in α band. (A, B, C, D, E—left-hand movement imagery; F, G, H, I, J—right-hand movement imagery.) Results were estimated from single trial scalp EEG data. See text for detailed procedures to obtain single trial inverse solutions.

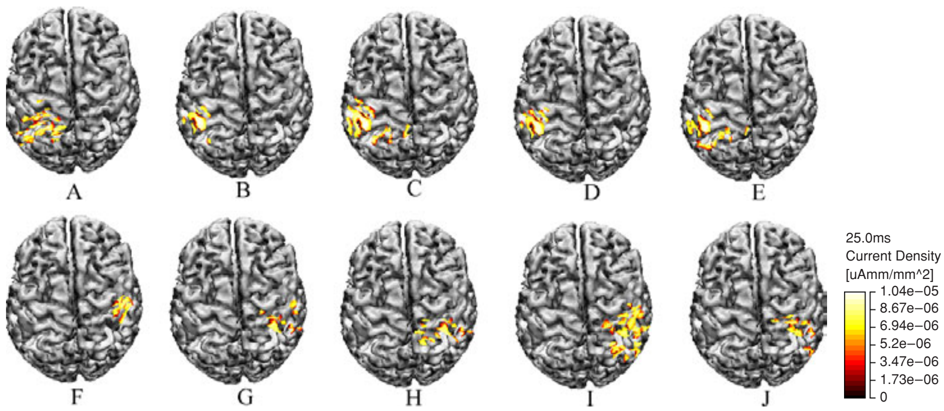

Figure 5. Examples of cortical current density distributions of different trials in a human subject during motor imagination. (A, B, C, D, E—left-hand movement imagery; F, G, H, I, J—right-hand movement imagery.) Results were estimated from single trial scalp EEG data. See text for detailed procedures to obtain single trial inverse solutions.

The classification accuracy was defined as the ratio of the number of trials the present source analysis method for which the motor imagery was classified correctly over the total number of trials. Based on these two criteria, we obtained 78.9% and 80.6% classification accuracy in the human subject studied. This result is quite promising because it is based on a single trial, not averaged values. We also did not use any training procedure and all data analysis was performed based on only one frequency component. So using more frequency bands and a better classifier may further improve the results as obtained from the source analysis.

4. Discussion

In the present pilot study we have initially tested the hypothesis that source analysis methods such as dipole localization and cortical imaging can be applied to classification of motor imagery tasks for BCI applications. The promising results we have obtained in this pilot study suggest that the source analysis approach has the unique characteristics of detecting the activity within the human brain thus substantially reducing the distortion or smearing problem caused by the low conductivity of the skull and making the motor imagery classification easier.

We have performed the source analysis of the recorded-scalp EEG signals in a human subject by means of two representative source reconstruction methods: equivalent dipole localization and cortical imaging. The classification was based on the phenomena that during motor imagination, contralateral μ rhythm ERD always appears, and thus the corresponding equivalent source distribution should show dominating phenomena on the ipsilateral side. By means of the signal processing strategy we have developed and tested in the present study, our results show that a reasonable classification rate can be achieved by this simple classification rule. Note that, not only the contralateral ERD can be found, a significant ipsilateral ERS has also been observed, which may make this classification more accurate. However, the classification rule we have adopted in the present study is totally based on the contralateral ERD. If some subjects have different topography of ERD, this rule may not be so effective. A better classifier with some training procedure could be introduced to further improve the approach (Babiloni *et al* 2000, 2001, Pfurtscheller *et al* 1997, Wang and He 2004, Vallabhaneni and He 2004).

Previously reported methods showed about 80% classification accuracy for the ten-fold cross-validation protocol with training (Wang and He 2004, Vallabhaneni and He 2004), while the present method achieved about 80% classification accuracy using all trials without training. The unique feature of not requiring a training process appears to be one of the advantages of the present approach, where the physical relationships between the neural sources and scalp EEG are taken into consideration. The obtained source signals have better SNR than the scalp EEG data and can be well related to cortical regions that are involved in the motor imagery tasks. ICA appears to play an important role in extracting the useful information, enabling effective source estimation to identify the imagined hand movements by revealing the origins of the brain activities so as to manifest the difference between mental tasks directly. The present 80% single trial based classification accuracy indicates that the use of source analysis methods in facilitating discrimination of left- or right-hand movement imagination is quite positive. It is worth pointing out that a full scale human study in a large group of subjects should be conducted before any final conclusion can be drawn. However, the present results do suggest the feasibility of using source analysis for classifying motor imagery tasks.

In the present study, all the 180 trials that are provided by the UPenn database are used for testing without rejecting any 'bad' trial. However, in the practical experiment, subjects could not always concentrate and perform well on every trial. Sometimes they might be distracted and thought nothing. The performance would be further improved if these 'bad' trials could be rejected based on online feedback. Although we have tested the present approach in offline data, the approach itself could be implemented in online BCI application with little alteration.

Note that the frequency band and time window are also essential for classification because we know, for different subjects, the clearest ERD may occur at different frequency bands and at different time points (Pfurtscheller *et al* 1997, Wang and He 2004). In this study, we have selected the two parameters manually with the help of TF representation. How to find a better way to choose the suitable frequency band and time window for source analysis is another issue that should be further explored.

In summary, we have developed a source analysis approach in combination with signal pre-processing for classification of motor imagery, and tested the present approach in a human subject. The present results obtained in the pilot study suggest that the source analysis provides an alternative means of aiding the classification of motor imagery tasks by converting scalp EEGs into source signals.

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