33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Task-Related MEG Source Localization via Discriminant Analysis

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***Abstract*—To investigate the neural activity corresponding to different cognitive states, it is of great importance to localize the cortical areas that are associated with task-related modulation. In this paper, we propose a novel discriminant pattern source localization (DPSL) method to analyze MEG data. Unlike most traditional source localization methods that aim to find "dominant" sources, DPSL is developed to capture the "differential" sources that distinguish different cognitive states. As will be demonstrated by the experimental results in this paper, the proposed DPSL method offers superior accuracy to identify the spatial locations of task-related sources.**

I. Introduction

Magnetoencephalography (MEG) is a noninvasive modality that measures the magnetic fields produced by the neural activity within the brain. To study and understand the neural activity based on MEG measurement, source localization has been identified as one of the most important tools [1]-[6]. The objective of source localization is to estimate the locations of electrical sources in the brain. During the past several decades, a large number of source localization algorithms have been developed, including dipole fitting [1], multiple signal classification (MUSIC) [2], beamforming [3], minimum norm estimation (MNE) [4], sLORETA [5], minimum current estimation (MCE) [6], etc.

While most traditional source localization algorithms aim to find electrical sources for a given cognitive state, we attempt to address a different source localization problem in this paper. Our goal is to identify the electrical sources that differentiate two or more different cognitive states. Such a problem is referred to as *task-related source localization* in this paper. It is an important tool that helps to study and compare the neural activity associated with different cognitive states.

Manuscript received March 23, 2011. Asterisk indicates corresponding author. This work was supported in part by the National Institutes of Health (5 UL1 RR024153, KL2 RR024154, 1R01EB007749 and 1R21NS056136), the National Science Foundation (EEEC-0540865), the Telemedicine and Advanced Technology Research Center (W81XWH-07-1-0716), the Craig H. Neilsen Foundation, and the University of Pittsburgh.

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Traditionally, inferential statistics have been applied to determine task-related electrical sources [7]. These techniques are typically composed of two phases. First, a source localization algorithm (e.g., MNE [4]) is used to find the electrical sources associated with each cognitive state. Next, statistical hypothesis testing is applied to determine if the electrical sources found from the first phase carry the information to distinguish different cognitive states. This approach heavily relies on the accuracy of the source localization algorithm that is applied during the first phase. In other words, the hypothesis testing in the second phase is meaningful, if and only if all electrical sources are accurately found in the first phase. In practice, it is well-known that the source localization problem is profoundly underdetermined due to the limited observability of MEG measurement [1]. Hence, it is almost impossible to perfectly find all electrical sources in the first phase, especially if the signal-to-noise ratio (SNR) is low. In most cases, a source localization algorithm can only capture the *dominant* sources which are *not* necessarily associated with the differential pattern for different cognitive tasks. For this reason, the traditional techniques based on inferential statistics do not guarantee to identify the electrical sources corresponding to task-related modulation. It, in turn, poses an immediate need to re-think the fundamental strategy of source localization and develop a new algorithm for the proposed task-related source localization problem.

Towards this goal, we propose a novel *discriminant pattern source localization* (DPSL) algorithm in this paper. DPSL consists of two major steps. First, discriminant analysis is applied to create a spatial filter that can optimally differentiate different cognitive states. Second, based on the forward model of the magnetic field, the task-related electrical sources are found by studying the response of the optimal spatial filter. Unlike most traditional source localization algorithms that capture the *dominant* sources, DPSL algorithm aims to identify the *differential* sources by applying an optimal discriminant analysis in the first step. Hence, DPSL can efficiently minimize the impact of both external noise (e.g., due to external magnetic sources) and internal interference (e.g., due to non-task-related neural activity).

The remainder of this paper is organized as follows. In Section II, we derive the DPSL algorithm and demonstrate its efficiency by the experimental examples in Section III. Finally, we draw our conclusions and discuss several theoretical and practical aspects of DPSL in Section IV.

II. Discriminant Pattern Source Localization

A. Discriminant Analysis

Without loss of generality, we consider two cognitive states that are labeled as "State-A" and "State-B", respectively. We further assume that MEG signals are recorded from M channels. We use a vector $\mathbf{x} \in R^M$ to represent the MEG features corresponding to these M channels, where $x_m \in \mathbf{x}$ denotes the mth feature associated with the mth MEG channel. Here, the feature vector $\mathbf{x}$ can be a collection of MEG signals from M different channels at a particular time t. Alternatively, if a linear transformation (e.g., short-time Fourier transform, wavelet transform, etc.) is applied, the feature vector $\mathbf{x}$ can be a set of transformed signals in the frequency or wavelet domain. Several examples of representing the measured MEG signals as a feature vector $\mathbf{x}$ can be found in Section III.

With the feature vector $\mathbf{x}$, the objective of discriminant analysis is to find a decision function $F(\mathbf{x})$ that can appropriately distinguish the two cognitive states:

$$F(\mathbf{x}) = \begin{cases} \geq 0 & (\text{if "State-A"}) \\ < 0 & (\text{if "State-B"}) \end{cases}. \tag{1}$$

The aforementioned discriminant analysis is essentially a binary classification problem. A large number of machine learning techniques, such as linear discriminant analysis (LDA), support vector machine (SVM), common spatial pattern (CSP), logistic regression, etc., can be used to construct the binary discriminant function $F(\mathbf{x})$ in (1).

Taking the linear L1-norm SVM as an example, it takes the MEG features collected from repeated trials as the input. Given the feature vectors $\{\mathbf{x}_{l,1};\ l = 1,2,\ldots,L\}$ and $\{\mathbf{x}_{l,2};\ l = 1,2,\ldots,L\}$ from L different trials of "State-A" and "State-B" respectively, a linear L1-norm SVM aims to find the following discriminant function to distinguish two different cognitive states [8]:

$$F(\mathbf{x}) = \mathbf{w}^T \cdot \mathbf{x} + c \tag{2}$$

where $\mathbf{w} \in R^M$ and $c \in R$ stand for the SVM coefficients and they can be found by solving a convex optimization problem:

$$\begin{array}{lll} \min\limits_{\mathbf{w},c,\xi} & \sum\limits_{l=1}^{2\cdot L} \xi_l & \\ \text{s.t.} & \|\mathbf{w}\|_1 \leq \lambda & \\ & \mathbf{w}^T \cdot \mathbf{x}_{l,1} + c \geq 1 - \xi_l & (l = 1,\ldots,L) \\ & -(\mathbf{w}^T \cdot \mathbf{x}_{l,2} + c) \geq 1 - \xi_{l+L} & (l = 1,\ldots,L) \\ & \xi_l \geq 0 & (l = 1,\ldots,2\cdot L) \end{array}. \tag{3}$$

In (3), $\|\mathbf{w}\|_1$ denotes the L1-norm of the vector $\mathbf{w}$, $\{\xi_l;\ l = 1,2,\ldots,2\cdot L\}$ are slack variables and λ is a regularization parameter that can be determined by cross-validation [8]. Since SVM is a well-known technique, we do not discuss its technical details here. The background of L1-norm SVM can be found in [8].

While we use the linear L1-norm SVM as an example to illustrate the basic idea of discriminant analysis, many other classification techniques [11] can also be applied to find the discriminant function $F(\mathbf{x})$ in (1)-(2). In addition, the aforementioned discriminant analysis can be extended to more than two cognitive states, e.g., by using a multi-class classification algorithm [11].

The discriminant function $F(\mathbf{x})$ in (2) is the linear combination of multiple MEG features $\{x_m;\ m = 1,2,\ldots,M\}$. Remember that the mth feature x_m is associated with the mth MEG channel. It, in turn, implies that the discriminant function $F(\mathbf{x})$ in (2) can be conceptually viewed as a spatial filter $\mathbf{w}^T\cdot\mathbf{x}$ that extracts the discriminant information from all MEG channels to distinguish different cognitive states. For this reason, the spatial filter $\mathbf{w}^T\cdot\mathbf{x}$ should *amplify* the MEG signals generated by task-related electrical sources and simultaneously *attenuate* the signals coming from non-task-related sources. Based upon these observations, we will next describe our proposed source localization algorithm that aims to reveal the differential pattern inside the brain corresponding to different cognitive states.

B. Task-Related Source Localization

Once $F(\mathbf{x})$ in (2) is known, the key idea of DPSL is to identify the locations of the electrical sources that are "selected" by the spatial filter $\mathbf{w}^T\cdot\mathbf{x}$. These electrical sources should carry the differential information that distinguishes different cognitive states. On the other hand, if an electrical source is "filtered out" by the spatial filter $\mathbf{w}^T\cdot\mathbf{x}$, it should be weakly correlated with the task-related modulation.

To derive the proposed DPSL algorithm, a human brain is first partitioned into a number of voxels. Each voxel contains a current dipole that models the electrical source within the brain. Such a voxel-based model has been widely adopted by many source localization algorithms [1]-[7]. In this paper, we apply a similar model with N voxels and, hence, N current dipoles:

$$\mathbf{q}_n = r_n \cdot \mathbf{v}_n \quad (n = 1,2,\cdots,N) \tag{4}$$

where $\mathbf{q}_n \in R^3$ denotes the moment of the nth dipole, $r_n \in R$ stands for the magnitude of the dipole, and $\mathbf{v}_n \in R^3$ is a unit vector representing the orientation of the dipole.

The N current dipoles in (4) generate the magnetic fields that are measured by M MEG channels. Given the dipole model in (4), the MEG feature vector $\mathbf{x} \in R^M$ collected from M channels is a linear combination of the dipole moments [1]:

$$\mathbf{x} = \sum_{n=1}^{N} \mathbf{A}_n \cdot \mathbf{q}_n + \mathbf{n} \tag{5}$$

where $\mathbf{A}_n \in R^M$ is the leadfield matrix of the nth dipole and $\mathbf{n} \in R^M$ is a vector containing the measurement noise of all MEG channels. The leadfield matrix $\mathbf{A}_n$ models the influence of the nth dipole on the measured MEG signals. It can be calculated according to the geometrical structure and the conducting medium of the human head [1].

Next, we consider the discriminant function $F(\mathbf{x})$ in (2) which is essentially a spatial filter applied to the MEG feature vector $\mathbf{x}$. Substituting (5) into (2) yields:

$$F(\mathbf{x}) = \sum_{n=1}^{N} \mathbf{w}^T \cdot \mathbf{A}_n \cdot \mathbf{q}_n + \mathbf{w}^T \cdot \mathbf{n} + c\ . \tag{6}$$

As previously discussed, the optimal spatial filter $\mathbf{w}^T\cdot\mathbf{x}$ should amplify the MEG signals generated by task-related current dipoles and simultaneously attenuate the signals coming from non-task-related dipoles. Based upon these observations, we propose to calculate the gain of the spatial filter $\mathbf{w}^T \cdot \mathbf{x}$ for each dipole and use it as a quantitative metric to assess the contribution of each dipole to the discriminant function $F(\mathbf{x})$:

$$g_n = \left| \frac{\mathbf{w}^T \cdot \mathbf{A}_n \cdot \mathbf{q}_n}{r_n} \right| \quad (n = 1, 2, \cdots, N). \tag{7}$$

Substituting (4) into (7), we get a further simplified representation:

$$g_n = \left| \mathbf{w}^T \cdot \mathbf{A}_n \cdot \mathbf{v}_n \right| \quad (n = 1, 2, \cdots, N). \tag{8}$$

If the value of g_n in (8) is large, it implies that the nth dipole $\mathbf{q}_n$ is "selected" by the spatial filter $\mathbf{w}^T \cdot \mathbf{x}$ and, hence, it carries the differential information for different cognitive states. On the other hand, if the value of g_n is small, it means that the nth dipole $\mathbf{q}_n$ is "neglected" by the spatial filter $\mathbf{w}^T \cdot \mathbf{x}$ and, hence, it is weakly correlated with the task-related modulation. *By calculating the gain values $\{g_n;\ n = 1,2,\ldots,N\}$ for different dipoles, we can identify the spatial locations of the task-related electrical sources.*

Studying (8), one would notice that we must know the orientation $\mathbf{v}_n$ for each dipole in order to calculate the gain g_n. In this paper, we consider the case where the dipole orientation $\mathbf{v}_n$ is parallel to the vector $\mathbf{A}_n^T \cdot \mathbf{w}$ and, hence, the gain g_n reaches the maximum possible value:

$$g_n = \left\| \mathbf{w}^T \cdot \mathbf{A}_n \right\|_2 \quad (n = 1, 2, \cdots, N). \tag{9}$$

It should be noted that other approaches may be used to determine the dipole orientation $\mathbf{v}_n$. Different choices of dipole orientation lead to different source localization results. Hence, it is extremely important to appropriately interpret the results when different dipole models are applied.

III. Experimental Studies

A. Experimental Setup and Data Pre-processing

In our experiment, a healthy human subject performs a four-target center-out task with his right wrist holding an MEG-compatible joystick [10]. During each trial, visual signals are presented on a screen in front of the subject. The subject is instructed to move the cursor from the center to one of the four locations (i.e., up, down, left or right) by making wrist movements (i.e., radial deviation, ulnar deviation, flexion and extension) while keeping the rest of the body in a relaxed position. In addition, the subject is instructed to keep their gaze at the center of the screen, and only attend to the targets using his peripheral vision. A successful repetition is characterized by reaching one of the four peripheral targets within a pre-specific time window after the onset of the target and holding the cursor position there without overshooting. Only successful repetitions are used for our off-line data analysis.

During the experiment, MEG data are acquired by using a 306-channel whole-head MEG system (Elekta Neuromag®) with 1 kHz sampling frequency. During a separate visit, the subject takes a standard head structural MRI scan. The MRI data are co-registered with the MEG data for source localization.

In our data analysis, we consider the MEG data for two movement directions: left and right (i.e., two different cognitive states). There are 123 trials collected for each movement direction. In this study, although the MEG signals are measured by 306 channels, only 204 gradiometer channels are used for the following analysis. The other 102 magnetometer channels carry large noise and, hence, are removed due to their low SNR.

B. Source Localization

Previous neuroscience research on MEG movement decoding demonstrates that significant power modulation related to movement directions can be observed in low-frequency band (≤ 7 Hz) [9]. In addition, the important neural activity that carries movement information can be found during a short time window [9]. For these reasons, we only consider the low-frequency band for the time window $t \in$ [150 ms, 450 ms], where $t = 0$ represents target onset. We apply discrete wavelet transform (DWT) with second-order Symlet wavelet function [12] to decompose the MEG signals from each channel and each trial to multiple resolution levels. The aforementioned DWT results in five wavelet coefficients corresponding to five selected time-frequency windows for each channel. Here, each time-frequency window is around 60 ms in length and covers the low-frequency band (≤ 7 Hz).

Next, we apply DPSL to find the electrical sources for each time-frequency window separately. Such an analysis allows us to study and compare the source locations over different time and/or frequency. In each DPSL run, the MEG feature vector $\mathbf{x}$ contains 204 wavelet coefficients corresponding to 204 gradiometer channels. Fig. 1 shows the source localization results, i.e., the spatial maps of the spatial filter gain estimated by DPSL.

Studying Fig. 1, we notice that the task-related sources are activated in the following order: (1) the primary visual area in Fig. 1(a), (2) the parietal area in Fig. 1(b), (3) the contralateral somatosensory area in Fig. 1(c)-(d), (4) the contralateral motor cortical area in Fig. 1(d)-(e), and (5) the visual area in Fig. 1(e). These observations are consistent with the results of neuroscience studies. During the experiment, the subject first receives the visual stimulus on a screen and, hence, the primary visual cortex is activated [13]. Next, during the motor planning phase, the parietal cortex and the pre-motor cortex are activated [14]. Afterwards, the motor cortical area is activated to execute the movement. Finally, after the movement is completed, the subject attends to the visual target on the screen and the visual cortical area is activated again. It is important to note that strong modulation is observed in the contralateral primary somatosensory cortex from 270 ms to 390 ms, as shown in Fig. 1(c)-(d). We believe that such strong modulation is related to the role of somatosensory cortex in sensorimotor integration, as discussed in [15]-[16].

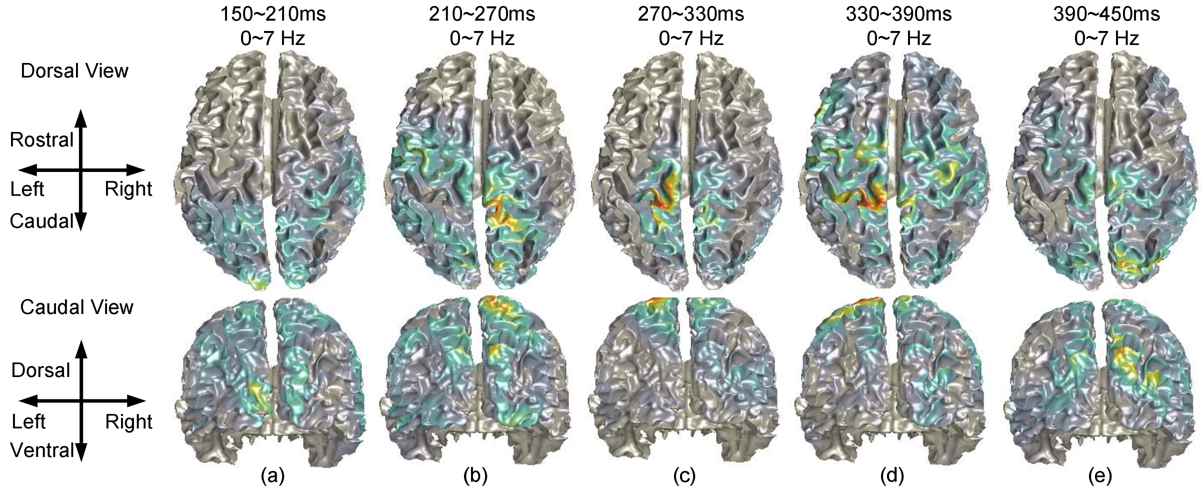

Fig. 1. Spatial maps of the spatial filter gain estimated by DPSL for different time-frequency windows.

IV. Conclusions and Discussions

In this paper, we propose a new discriminant pattern source localization (DPSL) method to identify task-related electrical sources corresponding to different cognitive states. The proposed DPSL algorithm consists of two major steps. First, discriminant analysis is applied to find a spatial filter to distinguish different cognitive states. Next, the gain of the spatial filter is calculated for each voxel to reveal the locations of the task-related sources. DPSL can be conceptually viewed as a post-processing step for the traditional cognitive state decoding. It is an important tool to identify the locations of the discriminant sources that differentiate cognitive states.

Finally, it is worth mentioning that there remain a number of open questions related to the proposed DPSL method. First, our current implementation of DPSL is limited to linear spatial filters. In general, the proposed methodology can be possibly extended to nonlinear spatial filters for discriminant analysis. Second, similar to other source localization methods, the spatial resolution of DPSL is limited by the small number of MEG channels. Given the limited resolution, DPSL cannot accurately distinguish task-related and non-task-related sources that are close to each other. Third, DPSL may not accurately detect the electrical sources that are deep in the brain, since the spatial filter gain can be extremely small for these deep sources. This is a well-known issue for many other traditional source localization algorithms. These open questions will be carefully studied and further addressed in our future research.

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