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Sparse Electromagnetic Source Imaging using EEG and MEG

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Abstract— **The present study proposed the combined use of EEG and MEG data in a new sparse electromagnetic source imaging (ESI) technique, i.e., variation-based sparse cortical current density (VB-SCCD) method. Monte Carlo simulations were conducted to investigate the performance of the proposed approach in multiple extended brain activations (up to ten) that were randomly generated. Experimental EEG and MEG data from a face recognition task were further used to evaluate the performance of VB-SCCD. The present results indicate that the proposed approach can accurately reconstruct multiple brain activations and their spatial extents. The source imaging results from real data further demonstrate it is capable to recover networked brain activations involving multiple cortical regions, which are consistent with results from functional magnetic resonance imaging in same task paradigm. The present results further indicate the capability of the proposed approach in reconstructing deep brain sources and temporal dynamics of brain sources at millisecond resolutions. It thus suggests that sparse ESI using combined EEG and MEG is a promising technique probing detailed spatiotemporal brain activations.**

I. Introduction

Electromagnetic source imaging (ESI) techniques based on noninvasive scalp electroencephalogram (EEG) and/or magnetoencephalogram (MEG) signals are able to achieve high spatiotemporal imaging of coordinated brain electrical activity [1]. It has millisecond temporal resolutions that allow explorations of dynamic neural processes and their causal connectivity, while it also provides source estimates of localized spatial extents with crucial information regarding where in the brain such processes take place. This technique has been widely applied to study human brain functions in both normal and diseased conditions. However, compared with other noninvasive neuroimaging technology, such as functional magnetic resonance imaging (fMRI), its capability in imaging complex brain networks is still very limited.

One way to enhance spatial resolution and localization characteristics of ESIs is to combine EEG and MEG data, which have different sensitivities to different brain sources. Due to its biophysical property, MEG is mainly limited by less sensitivity to radially oriented cortical sources [2]. Since deep brain sources are nearly radial, the sensitivity of MEG to deep sources drops rapidly [3]. Alternatively, EEG reflects current sources of all orientations. However, when field gradient distributions are concerned, electrical field gradient is smoothed by low-conductive skull, which makes EEG signals more vulnerable to noise than MEG. Since EEG and MEG provide complimentary information regarding brain activations, combining multi-modal measurements in ESI may achieve better detection and inverse reconstructions of brain sources, especially for complex networked activations.

Previous studies have reported several ESI methods to integrate EEG and MEG for brain source reconstructions. Methods involving multiple steps were proposed to localize tangential and radial components of sources separately [4-5]. In contrast, most methods [6-9] implemented combined analysis of EEG and MEG yielding estimations of all source parameters at the same time. Both simulations [6,8] and experimental data [6-7] obtained from these studies have indicated superior performance using combined EEG and MEG data compared to EEG or MEG data alone. However, most of these studies focused on cases involving only one or two brain sources. Yet a complex network with multiple sources has not been systematically investigated and it is unknown whether the advantage of multimodal integration may yield success under such complicated brain dynamics.

Recently, we have developed several sparse ESI (sESI) techniques using distributed source models [10-11], which reconstruct EEG/MEG sources via exploring sparseness in solutions. Based on compressive sensing (CS) theory [12], we have proposed a novel sESI technique, i.e., variation-based sparse cortical current density (VB-SCCD) method [11], to reconstruct brain sources with the use of sparse representations in a transformed domain. The performance of this new technique has been demonstrated in localizing multiple distributed brain sources and reconstructing their cortical spatial extents using EEG [11] and MEG [13-14]. Thus we hypothesize that combining EEG and MEG in VB-SCCD can further improve its performance.

To test this hypothesis, in the present study, we developed an approach to simultaneously analyze EEG and MEG data in VB-SCCD. We conducted a systematic Monte Carlo simulation that involved different numbers of sources (i.e., 1, 2, 5 and 10). Particularly, we investigated brain sources of fairly large size (~8 cm^2). We also examined the performance of the approach in imaging complex networked brain activity from experimental data in a face recognition task.

II. Methods

A. Simultaneous EEG and MEG Forward Model

Let the vector $\bar{s}$ represent N elemental dipole moments in cortical current density (CCD) model. Vectors $\bar{v}$ and $\bar{b}$ denote potentials and magnetic fields measured in EEG and MEG, respectively. $A_v = (\bar{a}_{v,1}, \bar{a}_{v,2}, \cdots, \bar{a}_{v,N})$ is the gain matrix calculated by boundary element method (BEM) and each

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column specifies potentials on electrodes from a unity dipole, while $A_b = (\bar{a}_{b,1}, \bar{a}_{b,2}, \cdots, \bar{a}_{b,N})$ is the corresponding gain matrix for magnetic fields. Both $\bar{n}_v$ and $\bar{n}_b$ denote background and measurement noises in EEG and MEG. Then the forward problem can be expressed in the following vector notation:

$$\bar{v} = A_v\bar{s} + \bar{n}_v \text{ and } \bar{b} = A_b\bar{s} + \bar{n}_b. \tag{1}$$

In order to combine EEG and MEG, they have to be converted into a common basis. The signal-to-noise ratio (SNR) transformation is used as proposed in previous studies [6], which converts all channel data into the SNR domain and makes both EEG and MEG data unit-free measurements. In details, standard deviations σ of noise are estimated for EEG/MEG at single channels and then EEG/MEG data are normalized by their individual standard deviation of noise:

$$\hat{v}_{i,j} = v_{i,j}/\sigma_{v,i} \text{ and } \hat{b}_{i,j} = b_{i,j}/\sigma_{b,i}, \tag{2}$$

where i indicates the i-th channel, j indicates the time point. EEG/MEG gain matrices are also adjusted accordingly:

$$\hat{A}_{v,i,\bullet} = A_{v,i,\bullet}/\sigma_{v,i} \text{ and } \hat{A}_{b,i,\bullet} = A_{b,i,\bullet}/\sigma_{b,i}. \tag{3}$$

Finally, the combined forward problem can be expressed as:

$$\bar{m} = \begin{bmatrix} \bar{\hat{v}} \\ - \\ \hat{b} \end{bmatrix} = \begin{bmatrix} \hat{A}_v \\ \hat{A}_b \end{bmatrix} \bar{s} + \begin{bmatrix} \bar{\hat{n}}_v \\ - \\ \hat{n}_b \end{bmatrix} = A\bar{s} + \bar{n} \tag{4}$$

where A is the combined gain matrix.

B. VB-SCCD Algorithm

The optimization problem proposed to solve in VB-SCCD is developed based on the theory of sparse source imaging [10]. It can be mathematically stated as

$$\min \|V\bar{s}\|_1 \qquad \textit{subject to} \quad \|\bar{m} - A\bar{s}\|_2 < \beta \tag{5}$$

where V is a matrix operator to obtain variation maps of cortical current density distributions. The variation vector is thus defined as $V\bar{s}$. The penalty function is designed to minimize the L1-norm of variation of inverse solutions, which is equivalent to maximize the sparseness in the variation domain. Each element in this vector represents a coefficient within the variation map over a triangular edge and its value indicates current density difference between two triangular elements sharing the same edge (see [10] for details).

Equation (5) is solved by the second-order cone programming [15]. The regularization parameter β can be estimated by applying the discrepancy principle [16]. We choose it to be high enough so that the probability of $\|\bar{n}\|_2 \geq \beta$, where $\bar{n} = \bar{m} - A\bar{s}$, is small. When noise is Gaussian white, $(1/\sigma^2)\|\bar{n}\|_2^2$, where σ^2 denotes noise variance, has the χ_m distribution, i.e., $(1/\sigma^2)\|\bar{n}\|_2^2 \sim \chi_m^2$. In practice, the upper bound of $\|\bar{n}\|_2$, i.e., β, is selected such that the confidence interval [0, β] integrates to a 0.99 probability [10]. In the analysis of real data, noise data can be selected from recordings considered as signal free (e.g., pre-stimulus data).

C. Monte Carlo Simulation

Accuracy of inverse solutions is location-dependent [6,17], since EEG/MEG has various sensitivities to sources at different locations with different orientations. Monte Carlo simulations with a large number of randomly sampled source locations were thus performed. Specifically, cortical sources were generated by randomly selecting seed elements on the CCD model and gradually growing into patches by iteratively adding neighboring elements. Dipole moment on each triangle was computed as the multiplication of triangular area and dipole moment density (i.e., 100 pAm/mm^2). To evaluate the performance of the proposed approach in reconstructing large cortical sources, we simulated source sizes to be ~8 cm^2 (7.83 ± 1.11 cm^2). Different brain activities were simulated with different number of cortical sources (i.e., 1, 2, 5, and 10). Simulations were repeated for 200 times to cover most parts of the brain in this random sampling procedure. Metrics, receiver operating characteristic (ROC) curve and area under the ROC curve (AUC), from detection theory [18] were used to evaluate performance of VB-SCCD.

The CCD model used in simulation was generated by the BrainSuite software [19], which segmented the interface between white and gray matters from a human head magnetic resonance imaging (MRI) data. The volume conductor was modeled by a three-shell boundary element model with three major tissues (the scalp, skull, and brain) of different conductivity (0.33/Ω.m, 0.0165/Ω.m, and 0.33/Ω.m) [20]. EEG electrode locations and MEG sensor locations and orientations were adapted from realistic EEG and MEG systems. For EEG, 120 channels were selected from a realistic 128-electrodes EGI system (Electrical Geodesics, Inc., Eugene, OR) by removing face electrodes. For MEG, there were 151 MEG sensors from a 151 channel CTF Omega system. Simulated EEG/MEG data were then contaminated by real noise recorded from a person in resting conditions and calibrated to a 10 dB SNR.

D. Experimental Protocol and Data Analysis

To evaluate the performance of the proposed approach with empirical data, we performed VB-SCCD analysis on a face processing event-related potentials (ERPs) and fields (ERFs) data. Experimental details and the full dataset can be found at www.fil.ion.ac.ik/spm/data/mmfaces.html. Briefly, EEG and MEG data were recorded in a subject performing a face recognition task [21]. The subject made symmetry judgments on faces and scrambled faces, which were presented every 3.6 s and each stimulus lasted for 0.6 s. EEG data were acquired on a 128-channel ActiveTwo system, sampled at 2,048 Hz, while MEG data were sampled at 625 Hz from a 151-channel CTF Omega system. Epochs were created from -200 ms to 600 ms for both EEG and MEG and then averaged to produce event-related data. The subject's T1-weighted MRI was obtained in a 1.5T Siemens Sonata with voxels of 1x1x1 mm^3, using a whole body coil for RF transmission and an 8-element phased array head coil for signal reception. The registration was performed among subject's head shape, EEG electrode locations, and MEG sensors using a surface-fitting algorithm [22].

I. Results

Fig. 1 shows the AUC values for different number of cortical sources (i.e., 1, 2, 5, and 10) using combined EEG and MEG data. Multiple sources up to ten were active. Also note that the sources were simulated to be of fairly large sizes (7.83

± 1.11 cm^2). As indicated by the general trend in Fig. 1, when the number of sources increases, the AUC metric decreases. However, the overall reconstruction accuracy in these conditions is considered high since most of AUC values are higher than 0.8 [18], even when there are ten simultaneously activated and randomly located sources.

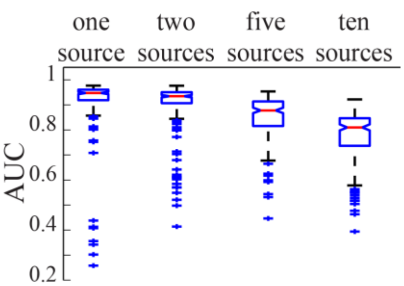

Figure 1. Whisker plots of AUC metric values for VB-SCCD using EEG+MEG with different numbers of sources (1, 2, 5, and 10).

Examples of reconstructed sources are illustrated in Fig. 2 in reference to corresponding simulated ones for different number of sources. These reconstructed distributions were uniformly thresholded at 20% of their own maximal values. When there are only a few simulated sources (1 or 2), the reconstructed distributions are almost exactly recovered in terms of location and spatial extent. When the number of sources increases to five, all cortical sources can still be resolved, and their localizations are accurate. Meanwhile, these sources start to exhibit larger extents than simulated ones under 20% thresholding. Notably, when the number of sources to reconstruct is ten, the reconstructed cortical sources have consistent distributions and many closely located sources are still able to be resolved, while more cortical sources have enlarged spatial extents. Since the chance for randomly selected sources being close becomes higher when the number of sources increases, some of the closely located sources may be fused. These examples demonstrate the remarkable resolvability of VB-SCCD using combined EEG and MEG data in localizing multiple sources (up to 10). The reduced performance for increased number of sources is also suggested in these examples as shown in Whisker plots of AUC values (Fig. 1).

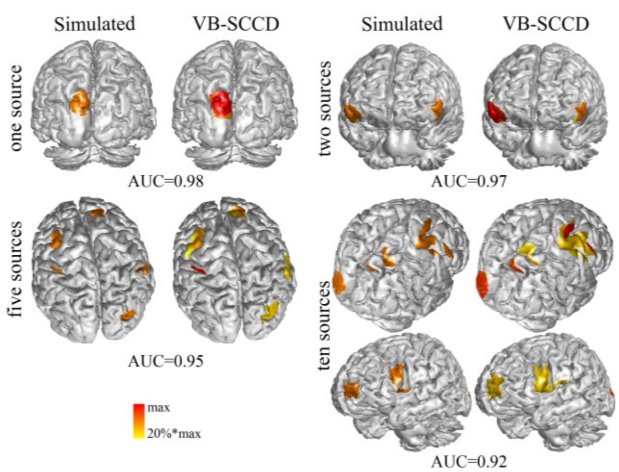

Figure 3. Illustration of four examplar reconstructions in different numbers of sources (1, 2, 5, and 10). Two different views are provided for the example of ten sources.

Results from experimental data in a face recognition task are shown in Fig. 3. Averaged event-related MEG and EEG data in face conditions are plotted, showing the characteristic positive peak P100 at ~100 ms and the negative peak N170 at ~170 ms. The spatiotemporal dynamics of underlying brain activities are presented by reconstructing the sources at multiple consecutive time points from 135 ms to 195 ms in intervals of 10 ms focusing on N170 component. Each individual cortical map was uniformly thresholded at 30% of its own maximal value. Dominant activities are observed in the bilateral fusiform and lateral ventral occipital regions, which start early (i.e. 145 ms). Brain areas then show significant activities within the frontal lobe including the medial superior frontal gyrus, orbital part of inferior frontal gyrus, and medial orbitofrontal gyrus at relatively late time (e.g. 165 ms) (Fig. 3). These observations are consistent with the fMRI data reported in [21] in terms of locations. The results further indicate the sequence of multiple brain activations involving multiple cortical regions due to the high temporal resolutions of EEG and MEG data.

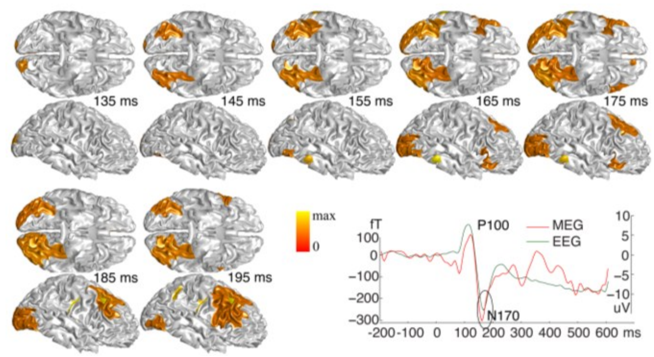

Figure 2. Dynamic patterns of source reconstructions within P100/M100 and P170/M170 components from a face recognition task.

II. Discussion

In the present study, we demonstrated that a new sparse ESI technology (i.e., VB-SCCD) is able to reconstruct complex brain activations (up to ten sources) via combining EEG and MEG data. Reconstructed cortical brain sources in both simulations and experimental data provided not only precise source locations, but also accurate source spatial extents. The present experimental results further suggest that VB-SCCD with combined EEG and MEG data is promising to noninvasively estimate multiple brain activations as well as their temporal dynamics.

Our previous investigations [11,14] examined the performance of VB-SCCD using EEG- or MEG-alone data and compared with other widely used ESI techniques, e.g., weighted minimum norm estimate (wMNE) [23] and cortical low resolution electromagnetic tomography (cLORETA) [24]. Although VB-SCCD showed superior performance than other two techniques, the AUC metric in conditions with multiple sources evidently dropped from that of single source using single-modality data. However, our present study demonstrated that, using EEG and MEG together in VB-SCCD, the performance of VB-SCCD in conditions with two sources is as good as that in condition with single source. Furthermore, at conditions of more number of sources (five or ten), AUC still maintains above 0.8, which is considered high [18]. The performance of VB-SCCD with combined EEG and MEG data at conditions with five or ten sources is even better than most of investigated methods with single-modality data in conditions of small number of sources. These results strongly suggest the advantage of integrating complementary information of EEG and MEG in inverse source reconstructions. Particularly, such advantage was fully utilized in VB-SCCD which, based on the CS theory, was especially suited for handling increased independent measurements.

A Monte Carlo protocol with the number of sources up to ten was exploited in our present study, which is one of the few EEG/MEG studies, to our knowledge, using randomly generated multiple source (more than five) schemes [17]. Despite the large number of sources and the fairly large size of sources, overall the present simulation data suggest that VB-SCCD is capable of reconstructing complex cortical activations. The results from experimental EEG/MEG data in a face recognition task also demonstrated a consistency between source imaging results and activations obtained from fMRI data [21]. It is important to note that experimental source imaging results indicate multiple activations in different cortical regions at each time instant, which demonstrates the capability of VB-SCCD with combined EEG and MEG data in reconstructing complex brain activations in real data. Furthermore, reconstructed cortical sources involve not only areas close to epicortical surfaces (e.g., frontal cortex), but also deep areas (e.g., fusiform regions), which demonstrates the capability of the proposed approach in recovering deep brain sources that is usually much more difficult than superficial brain sources.

In the present study, sources of fairly large sizes, i.e., (~8 cm^2, were investigated. This further challenges the performance of ESI techniques in addition to large number of sources. However, sources of large size are commonly observed in brain activity under various tasks, e.g., the face recognition task examined here, and in many neurological or psychiatric disorders, e.g., the epilepsy. Nonetheless, the VB-SCCD method with combined use of EEG and MEG data can achieve accurate estimates of source locations and extents. Our results strongly suggest that the sparse ESI method VB-SCCD using combined EEG and MEG is a promising technique that can probe detailed spatiotemporal processes from complex and dynamic brain activity, and can be applied noninvasively to study large-scale brain networks of high clinical and scientific significance.

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