COHERENT MEG/EEG SOURCE LOCALIZATION IN TRANSFORMED DATA SPACE

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Accepted 9 September 2009

ABSTRACT
In some cases, different brain regions give rise to strongly-coherent electrical neural activities. For example, pure tone evoked activations of the bilateral auditory cortices exhibit strong coherence. Conventional 2nd order statistics-based spatio-temporal algorithms, such as MUSIC (MUltiple SIgnal Classification) and beamforming encounter difficulties in localizing such activities. In this paper, we proposed a novel solution for this case. The key idea is to map the measurement data into a new data space through a transformation prior to the localization. The orthogonal complement of the lead field matrix for the region to be suppressed is generated as the transformation matrix. Using a priori knowledge or another independent imaging method, such as sLORETA (standard LOw REsolution brain electromagnetic TomogrAphy), the coherent source regions can be primarily identified. And then, in the transformed data space a conventional spatio-temporal method, such as MUSIC, can be used to accomplish the localization of the remaining coherent sources. Repeatedly applying the method will achieve localization of all the coherent sources. The algorithm was validated by simulation experiments as well as by the reconstructions of real bilateral auditory cortical coherent activities.

Keywords: MEG; sLORETA; AEF; Brain source localization; MUSIC.

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INTRODUCTION

Magnetoencephalography (MEG) and Electroencephalography (EEG) can be used to estimate the locations of neural activities within the brain, and it is of critical significance in clinical medicine and cognitive neuroscience research. In physics, from scalp MEG/EEG to estimate the underlying activated sources is an ill-posed inverse problem. That is, there are infinity source combinations in the brain can account for the identical Scalp MEG/EEG recordings. Nevertheless, some authors proposed different solutions to overcome the ill-posed inverse problem by employing a variety of reasonable assumptions. These algorithms fall into two categories: parametric and tomographic. According to whether the methods depend on the data correlation matrix or not, tomographic algorithms can also be classified into non-adaptive (for example, LORETA, \(^ {1} \) LORRETA \(^ {2} \) and LPISS \(^ {3} \) and variants of LORETA \(^ {4} \) and adaptive \(^ {5} \) (for example, MUSIC-type methods \(^ {6-8} \) and beamforming-type method \(^ {9-11} \) ). MUSIC-type methods, as a class of subspace based methods, have attracted considerable attention because of (1) its ability to accurately identify multiple independent or partially-correlated sources; (2) avoiding multidimensional nonlinear optimization procedure necessary in parametric methods, which is often trapped in local minima and cannot converge to global minima. Beamforming-type methods are also a popular neuroimaging tool due to its ability of brain source reconstruction with high spatial resolution \(^ {12} \).

However, while sources are fully-correlated (also called coherent), these correlation matrix based methods will encounter difficulties in resolving them. In this case, coherent sources usually merge into one equivalent source located somewhere between them since the measurement correlation matrix becomes rank-deficient. However, in practice, coherent sources widely-exist in MEG/EEG. For example, pure tones evoked activities in the left and right primary auditory cortices are often coherent with each other \(^ {13-15} \). Such a class of practical problems requires a method for coherent source localization.

Some authors have made efforts to solve the problem. In the improved variants of classical MUSIC, R-MUSIC, \(^ {7} \) a new concept, Independent Topography (IT) model, was proposed to identify highly-correlated sources by maximum \( V_{\text{N}} \) multidimensional search \( \left( V \right) \) indicates the number of the volume grids and \( N \) the number of the estimated dipoles). In R-MUSIC, each signal principal components can be taken as a spatiotemporal ITs and, again, each IT is considered to be a source comprising (Case 1) one true independent source or (Case 2) multiple synchronous sources which collectively have a single time course. The author gave a subspace correlation threshold-95% to determine which case the IT should be. In practice, fixed threshold is not suited to all the conditions. If the threshold is too large, the algorithm may mistakenly take Case 1 as Case 2 and trigger a multidimensional search for one more synchronous sources. Similarly, too small threshold may result in taking Case 2 as Case 1 and miss synchronous sources. Determining an appropriate threshold, which can distinguish between the two cases, is very difficult. Furthermore, even though the threshold is determined perfectly, the triggered multidimensional search is also time consuming. As the number of the synchronous sources increases, the process will be more complex.

Transformation of the original data into a new space may help to solve the problem. J. Gross and A. A. Ioannides \(^ {16} \) proposed a framework of linear transformations, which is designed to maximize some desired property of the signal coming from a region of interest. Alberto Rodriguez-Rivera et al. \(^ {17} \) suggested localizations of brain source in beamspace. In their work, beamspace transformations are optimally designed to preserve source activity located within a given region of interest and obtain substantial reduction of computation. In the present study, we investigated a new method designed for coherent source localization. The key idea of this method is the transformation of the original MEG/EEG data into a new data space to accomplish localization of the coherent sources. Different from the methods presented in literatures, \(^ {16,17} \) the linear transformation matrix in our method is designed not to directly enhance selected desirable properties of the data, but to suppress the activities within the coherent interfering source region and pass signals originating from other locations or orientations. This concept was initially introduced in the the field of array signal processing \(^ {18,19} \) to greatly improve the estimation of unknown signal information by incorporating known signal information. In the following paragraphs, for the simplicity of presentation, the proposed method is referred to as Localization In Space Transformed (LIST).

METHODS

MUSIC and its Inability for Coherent Sources

Assume that the scalp MEG recordings \( X(t) \) are collected from \( p \) dipole sources at a period \( t \), and G
is the lead field matrix, which relates dipole sources to the scalp measurements. The lead model can be expressed as,

\[ X(t) = GS(t) + N \]  

(1)

where \( G = [a_1, a_2, \ldots, a_s] \), \( a_s \) denotes the lead field of the \( s \)th dipole source, and \( N \) the additional Gaussian white noise matrix with independent distribution. The moment time courses of the \( p \) dipole sources are denoted by \( S(t) = [s_{1T}, s_{2T}, \ldots, s_{pT}] \), where superscript \( T \) denotes the transpose. The data correlation matrix can be expressed as

\[ R_{xx} = \langle X(t)X(t)^T \rangle \]  

(2)

where \( \langle \cdot \rangle \) denotes the ensemble average. \( R \) can be partitioned into the signal subspace \( \hat{\Phi} \) and the noise subspace \( \Phi_n \). The estimation of \( R \) can be denoted as \( \hat{R} \).

Naturally, the first \( p \) dominant eigenvectors of \( \hat{R} \) constitute the estimated signal subspace \( \hat{\Phi} \), and the remaining eigenvectors constitute the estimated noise subspace \( \hat{\Phi}_n \) (about the selection of the order \( p \), see discussion in Ref. 20). The MUSIC estimator can thus be defined on the noise subspace as,

\[ J(i) = \frac{1}{\lambda_{\min}[\hat{\Phi}_n^T \hat{\Phi}_n a_s]} \]  

(3)

where \( J(i) \) is the MUSIC estimator at the possible location index \( i \). \( \lambda_{\min} \) is the smallest eigenvalue of the given bracketed items \( [\cdot] \). Using \( J(i) \) scanning all the brain volume grid points, estimating the dipole locations become a task to find \( p \) maxima. 

However, MUSIC encounters difficulty in the presence of complete correlation between sources. Suppose there are \( M \) coherent sources, \( s_i, i = 1, \ldots, M \). Then the scalp EEG underlying these sources can be expressed as,

\[ X(t) = \sum_{i=1}^{M} (a_i)^T k_i s_i = a_s s_1 \]  

(4)

where \( k_i \) denotes the scaling factor between \( s_i \) and \( s_1 \). Here, \( a_s = \sum_{i=1}^{M} k_i a_{s_i} \), i.e., the weighted sum of all the lead fields of the coherent sources, which we call the generalized lead field matrix. Unfortunately, \( a_s \) doesn’t belong to the set of lead field matrix within brain volumes. As we know, when performing MUSIC, the optimal solution is searched within the whole lead field matrix. Thus, it is impossible to find a lead field matching the generalized lead field matrix \( a_s \) and to solve out the correct source locations. Instead, MUSIC will erroneously place a single source somewhere between them, which in fact is an equivalent false source of all the coherent sources, whose lead field should have the smallest subspace angle with \( a_s \).

Beamformer techniques encounter similar problems like MUSIC in localizing coherent sources.

Localization in Space Transformed (LIST)

Based on the reasoning in the above subsection, we conclude that MUSIC has difficulty in localizing coherent sources in original data space. By mapping the original data into a new space through a transformation, which is specially constructed so as to reject the contribution of sources in the suppression region while allowing for source construction at other specified regions, coherent sources may be localized. Suppose \( T \) is the transformation matrix, the new data space can be expressed as,

\[ Y(t) = T^TX(t) \]  

(5)

where \( X(t) \) is the original data and \( Y(t) \) the transformed data. This transformation can be taken as a class of projection. The columns of \( X(t) \) are taken as a set of vectors in high dimensional space. By projecting \( X(t) \) onto \( Y(t) \) using projector \( T \), a new data space is constructed. For example, for a voxel \( i \) within brain volumes, whose lead field vector is \( a_i \), we set the transformation matrix to \( T = a_i a_i^T \), whose normalized version is \( T = a_i (a_i^T a_i)^{-1} a_i^T \). Then, \( T^T = T \), and the transformed data space is,

\[ Y(t) = T^T \left( a_i s_i + \sum_{j=1, j \neq i}^{N} a_j s_j \right) \]  

(6)

\[ = a_i s_i + T^T \sum_{j=1, j \neq i}^{N} a_j s_j \]

By this operation, the energy of voxel \( i \) is preserved. Naturally, in order to suppress the contribution of voxel \( i \), we may set \( T \) equal to the orthogonal complement matrix of \( a_i (a_i^T a_i)^{-1} a_i^T \), i.e.,

\[ T = I - a_i (a_i^T a_i)^{-1} a_i^T \]  

(7)

Then, invoking Eq. (7) into Eq. (5), the transformed data \( Y \) is

\[ Y(t) = \left[ I - a_i (a_i^T a_i)^{-1} a_i^T \right] \left( a_i s_i + \sum_{j=1, j \neq i}^{N} a_j s_j \right) \]

(8)

\[ = \sum_{j=1, j \neq i}^{N} \left[ a_j - a_i (a_i^T a_i)^{-1} a_i^T s_j \right] \]

(9)

Since \( I - a_i (a_i^T a_i)^{-1} a_i a_i = [0] \), the activation of voxel \( i \) can be completely suppressed by the transformation. Similarly, in order to suppress a region instead of a single voxel, one can set

\[ E = [a_{k_1}, \ldots, a_{k_s}] \]

\[ k_1, \ldots, k_s \in \Omega \]
where \( a_i \) indicates the lead field matrix of the voxels within the expected suppression region \( \Omega \). If the transformation matrix is equal to the orthogonal complement matrix of \( E \), i.e., \( T = I - E (E^T E)^{-1} E^T \), the contributions of the region will be suppressed. Since the coherent source region is suppressed, the conventional MUSIC can easily localize the remaining coherent sources in the transformation space. It should be noted that, when the MEG data is projected into the transformation space, the lead field matrix should also be projected by the projector \( T \) and become \( b_i = T^T a_i \). The noise subspace was also recalculated. Correspondingly, the cost function will become,

\[
J'(i) = \frac{1}{\lambda_{\min}(b_i \Phi_n \Phi_n^T b_i)}
\]

Algorithm Procedure

If the exact location of a coherent source is known to be at \( \theta_i \), source localization can be accomplished by simply using Eq. (8) to suppress the source activation. However, in practice, the precise location of a coherent source is seldom known a priori. Thus, a coherent source region must be defined. Neuroimaging methods such as fMRI and sLORETA can be used for this purpose. In this study, we adopt sLORETA to define the coherent source region. sLORETA constructs a non-adaptive spatial filter from the sensor configuration. It is therefore data-independent and its performance is not significantly degraded by any correlation of source time courses. After a broad coherent source region is defined by sLORETA, LIST is applied to accomplish the source localization. In summary, the LIST algorithm can be summarized as follows:

1. Apply MUSIC to ERF (Event Related magnetic Field)/ERP (Event Related Potential) for initial sources localization.
2. Apply sLORETA at all the temporal peaks of ERF/ERP and obtain the information about the approximate locations of all the active sources.
3. Incorporating the results from Step 1 and Step 2, analyze which sources are identified by two methods and which ones are identified by sLORETA, whereas not by MUSIC. The latter is commonly taken as coherent sources.
4. A broad suppression region encompassing the coherent interfering sources is defined according to the above results and analysis.
5. Construct the transformation matrix to suppress the activation from the coherent interfering region and transform original data into a new data space.
6. Apply MUSIC in the transformed data space to localize the coherent sources.
7. Repeat Steps 4 and 5 to sequentially localize all of the coherent sources. Derive the time courses of all the active sources and further confirm which sources are coherent sources according to their time courses.

SIMULATION EXPERIMENTS

Simulation Configuration

A series of numerical experiments were conducted to test the effectiveness of the proposed method. The sensor configuration of the 275-channel CTF Omega 2000 biomagnetic measurement system (VSM MedTech, Coquitlam, BC, Canada) installed at the University of California, San Francisco was used. The source space was based on a real subject’s head shape from an anatomical MRI scan. The brain volumes is partitioned into 17102 voxels with 5 mm grid spacing. Two classes of functions were used to simulate the source time courses: (1) \( s(t) = \exp([-|t-t_0|^2/r^2]\sin[2\pi f(t-t_0)] \) (Simulation Function 1, SF1) and (2) \( s(t) = \sin[2\pi f(t-t_0)] \) (SF2). The parameters will be specified in the corresponding sections. Data were simulated and processed using in-house programs implemented in MATLAB (MathWorks, Natick, MA, USA). We used the sLORETA algorithm implemented in NUTMEG (http://bil.ucsf.edu).²³

Evaluation Indexes and Definition of the Ratio of Signal to Noise

Localization Bias (LB) and normalized blurring Index (NBI) in region of interest (ROI) were used to measure the localization accuracy and spatial resolution ability of the proposed methods, respectively. LB measures the distance between simulated sources and the estimated sources of maximum power within a sphere neighbor of the simulated sources. NBI was introduced firstly in Ref. 24, which is defined as,

\[
NBI_i = \frac{\sqrt{\sum_r |a_k - r_k|^2 J^T(\delta)}}{\sum_v |r_v|^2 J^T(\delta) \sum_k 1}
\]

where the subscript \( i \) refers to a grid point of the discrete solution space in the 3D model. For the reconstructed distributions, it is selected as the point with maximum power within a sphere neighbor of the corresponding simulated source. The subscript \( k \) refers to the neighboring points within the spherical ROI.
surrounding the point \(i\). The \(e_k\) and \(v_i\) are the spatial location vectors corresponding to the grid points \(k\) and \(i\), respectively. NBI can exhibit the distribution of sources ROI. Generally, the smoother the sources spread in ROI, the closer to 1 the NBI is; otherwise, if the sources are sharply distributed, NBI is close to zero. Obviously, a smaller NBI is expected.

In this study, The Ratio of Signal to Noise (SNR) was defined as the ratio of the Frobenius norm of the MEG data matrix to that of the noise matrix. Referring to the Eqs. 1 and 5, SNR in original and transformed data space can be written as,

\[
SNR = \frac{\|GS\|_F}{\|N\|_F} \quad \text{in original data space}
\]

\[
SNR = \frac{\|T^*GS\|_F}{\|T^*N\|_F} \quad \text{in transformed data space}
\]

where \(\bullet \| \bullet \|_F\) indicates the calculation of the Frobenius norm.

**Simulation Tests**

**Reconstruction of two coherent sources**

This simulation was conducted to test LIST using point source suppression techniques. Two identical synchronous sine wave sources (SF2: \(t_0 = 0, f = 10\)) were placed at \((0, 30, 40)\) mm and \((0, -30, 40)\) mm with coordinates defined as Fig. 1.

A sensor lead field was calculated using a single-layer spherical volume conductor as the forward model and the Omega 2000’s sensor geometry, with 5 mm grid spacing. Gaussian white noise was added to the generated data such that the SNR was equal to 2. Conventional MUSIC erroneously placed a diffuse “source” centered at \((-5, -5, 40)\) mm (Fig. 2(A)) with scanned subspace correlation values 0.975. Applying point suppression to the coordinates of one source (LIST) resulted in a highly focal and accurate localization of the other source (see Figs. 2(B) and 2(C)) with the estimated subspace correlation values 0.996 and 0.994, respectively.

If we employed R-MUSIC with a fixed subspace correlation threshold 0.95 as suggested in Ref. 7, R-MUSIC will mistakenly take the false source as an actual source and end the search for coherent sources. The recommended fixed threshold 0.95 is too low to trigger a multidimensional search for coherent sources in this head model.

**Sequential localization of multiple sources**

A total of three sources were synthesized to test the region-based suppression techniques. Two of these sources were synchronous, located at \((-40, 30, 40)\) mm and \((-40, -30, 40)\) mm, respectively, while the third was with a different frequency located at \((-60, 0, 40)\) mm. The waveforms of the two coherent sources (SF1: \(t_1 = 0.218; \Omega = 0.0678; f = 9.5\); \(t_0 = 0.139\)) and the independent source (SF2, \(f = 22.8\); \(t_0 = 0.1\)) are shown in top-right and middle-right subplot of Fig. 3(A), respectively. The SNR was set to 2. The simulated scalp MEG was shown in Fig. 3(B). As expected, Conventional MUSIC localizes the independent source with zero localization bias, but fails to resolve either of the synchronous sources (The reconstruction profile was shown in the left of Fig. 3(A)). Furthermore, the recovered waveform of the independent source (shown in the bottom-right subplot of Fig. 3(A)) was seriously distorted, whose correlation coefficient with the original waveform is 0.76. Below, we try to localize the coherent sources by LIST. According to the above described LIST, if one knows the approximate position of a correlated source, the remaining source might be localized by LIST. This priori information might often be achieved from anatomical information, data-independent inverse problem algorithms, or imaging results from another modality (e.g., fMRI). One convenient method to estimate the approximate position of the coherent sources is sLORETA. We employed sLORETA to all the peaks and got the source approximate distribution at each temporal peaks. The results collectively indicated that there were three active sources. Figures 4(A) and 4(B) show the typical results of sLORETA for the peaks at two different latencies, 220 ms and 376 ms. Considering both the results of conventional MUSIC (Fig. 3) and sLORETA (Figs. 4(A) and 4(B)), one can conclude...
that,

(1) the estimated source in Fig. 3(A) is an actual one;

(2) it is possible that the coherent source cancelation phenomenon takes place since sLORETA indicates two sources exist while conventional MUSIC cannot identify either of them.

According to the earlier analysis and the sLORETA results, a broad suppression region (40 × 40 × 40 mm, \(-60 \leq x \leq -20, -50 \leq y \leq 10\) and \(20 \leq z \leq 60\)) is defined surrounding one of the diffuse sources found with sLORETA, leaving two sources in the region of interest.

As shown in Fig. 5(A), both sources of interest, a independent source and a coherent source, were resolved; the peak of the reconstructed coherent source and the independent source was reconstructed perfectly with zero localization bias. Similarly, defining a suppression region (40 × 40 × 40 mm, \(-60 \leq x \leq -20, 10 \leq y \leq 50\) and \(20 \leq z \leq 60\)) containing the identified coherent source results in a peak at the location
At left, the reconstruction profile of the three simulated sources on the plane $z = 40$ mm, using conventional MUSIC. The circles indicate the two coherent sources and the diamond indicates the independent source. At right, the time series of the two coherent sources (top). The true (middle) and reconstructed (bottom) time series of the independent source.

The imaging results of sLORETA on the plane $z = 40$ mm at timeinstant (A) 220 mins and (B) 376 mins. And the displaying threshold is set to 50%.

As shown in Figs. 5(C) and 5(D), the reconstructed waveforms of the two coherent sources are nearly identical, with mutual correlation coefficient 0.99. The correlation coefficients between both of them and the respective original waveforms are 0.985 and 0.988. In contrast to the reconstructed result in Fig. 3, the reconstructed time series of the independent source (Fig. 5(E)) was much less
Fig. 6 The reconstruction of the three sources by the proposed method. The reconstruction profile on the plane $z = 40$ mm with suppression of the region $(-40 \times 40 \times 40$ mm, $-60 \leq x \leq -20, -50 \leq y \leq 10$ and $20 \leq z \leq 60$) (A) and $(-40 \times 40 \times 40$ mm, $-60 \leq x \leq -20, 10 \leq y \leq 50$ and $20 \leq z \leq 60$) (B), respectively. The reconstructed time courses of the three sources located at $(-40, 30, 40)$ mm, at $(-40, -30, 40)$ mm and at $(-60, 0, 40)$ mm were shown in subplot (C), (D) and (E), respectively.

Source reconstruction using conventional MUSIC shows a failure typical of simultaneous bilateral activation, placing a low amplitude, diffuse “source” mislocated at $(-5, -15, 70)$ mm, approximately centered between the two actual auditory cortex sources. Note that the reconstructed time course appears to be reasonable and does not show obvious symptoms of failure (see Fig. 6).

To determine whether the localized peak was due to an actual source or was an artifact caused by multiple coherent sources, sLORETA was performed. Figure 7 shows the reconstruction results by sLORETA. The left plot of Fig. 7 shows the superimposed time courses at the plane $z = 40$ mm reconstructed by sLORETA. In the time instant for the peak source, imaging was performed by sLORETA and the result was shown at the right of Fig. 7. The sLORETA reconstruction reveals that there are two sources at the left and right temporal cortices at the temporal peak of 91.7 ms.

In order to apply our proposed technique to real data, auditory evoked field data was acquired from a 24-year-old female using pure tones. Data was acquired with a 275-channel whole-head MEG device from CTF Systems (VSM MedTech, Coquitlam, BC, Canada). The recordings were collected in accordance with the ethical standards of the UCSF Institutional Review Board and Helsinki Declaration of 1975, as revised in 1983. The auditory stimuli consisted of 1-kHz pure tones of 400 ms duration. The interstimulus interval was randomly varied between 1.5–1.6 s. The sampling frequency was set at 1200 Hz. The spherical head model was generated and partitioned into 17,102 voxels using a development version of NUTMEG. A digital filter was used to highpass the data at 1 Hz. After visual rejection of trials containing eyeblink and movement artifacts, a total of 112 trials were averaged.

To determine whether the localized peak was due to an actual source or was an artifact caused by multiple coherent sources, sLORETA was performed. Figure 7 shows the reconstruction results by sLORETA. The left plot of Fig. 7 shows the superimposed time courses at the plane $z = 40$ mm reconstructed by sLORETA. In the time instant for the peak source, imaging was performed by sLORETA and the result was shown at the right of Fig. 7. The sLORETA reconstruction reveals that there are two sources at the left and right temporal cortices at the temporal peak of 91.7 ms.

Applying the proposed method, we defined the suppression region to be a broad volume ($70 \times 40 \times 60$ mm, $-45 \leq x \leq 25, 20 \leq y \leq 60$ and $10 \leq z \leq 70$) encompassing the coherent interfering source localized distorted, whose correlation coefficient with the simulated waveform is 0.981.

**APPLICATION TO AUDITORY EVOKED MEG DATA**

In order to apply our proposed technique to real data, auditory evoked field data was acquired from a 24-year-old female using pure tones. Data was acquired with a 275-channel whole-head MEG device from CTF Systems (VSM MedTech, Coquitlam, BC, Canada). The recordings were collected in accordance with the ethical standards of the UCSF Institutional Review Board and Helsinki Declaration of 1975, as revised in 1983. The auditory stimuli consisted of 1-kHz pure tones of 400 ms duration. The interstimulus interval was randomly varied between 1.5–1.6 s. The sampling frequency was set at 1200 Hz. The spherical head model was generated and partitioned into 17,102 voxels using a development version of NUTMEG. A digital filter was used to highpass the data at 1 Hz. After visual rejection of trials containing eyeblink and movement artifacts, a total of 112 trials were averaged.

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Applying the proposed method, we defined the suppression region to be a broad volume ($70 \times 40 \times 60$ mm, $-45 \leq x \leq 25, 20 \leq y \leq 60$ and $10 \leq z \leq 70$) encompassing the coherent interfering source localized
by sLORETA. As shown in Fig. 8, a plausible location for right primary auditory cortex on the superior temporal plane clearly emerges. The peak location is located at $(0, -45, 50)$ mm. Similarly, selecting a suppression region $(70 \times 30 \times 60$ mm, $(-45 \leq x \leq 25$, $20 \leq y \leq 60$ and $10 \leq z \leq 70)$ containing the other coherent interfering source region results in a peak at a plausible location for left primary auditory cortex (Fig. 9). Furthermore, no spurious activations near the center of the model sphere were observed. The left source was located at $(-10, 50, 50)$ mm. The correlation coefficient between the reconstructed waveforms of the two sources was 0.92. The localization is consistent with results from the same MEG data shown in Dalal et al.15

![Figure 6](image6.png)

**Fig. 6** Conventional MUSIC reconstruction of AEF data exhibiting failure due to correlated sources. The spatial activation shown is at FWHM (Full Width at Half Minimum). The time course shown is for the spatial peak.

![Figure 7](image7.png)

**Fig. 7** The reconstruction of sLORETA at the plane $z = 40$ mm. At left, the superimposed x-axis-component time courses obtained by sLORETA at that plane. The peak point at 91.7 mins is indicated by an arrow. At right, the source imaging at the plane $z = 40$ mm at the indicated peak point. The spatial activation shown is at the threshold of 60% of the maximum energy.

![Figure 8](image8.png)

**Fig. 8** Reconstruction of AEF data with suppression of the left temporal cortex identified by sLORETA. Right auditory cortex is revealed, along with its time course. The spatial activation shown is at FWHM.
DISCUSSION AND CONCLUSION

The Selection of the Eigenvector Components in Suppression Region

We also study the effect of chosen eigenvector components in the suppression region on the performance of coherent source localization. The given suppression region Σ usually consists of several thousand voxels, making the product $E^T E$ a highly-singular matrix since some columns of the lead field of close-spaced voxels will be nearly linearly dependent and, therefore, difficult to invert accurately. To solve this problem, singular value decomposition (SVD) may be applied to $E^T E$; the most significant components can be chosen to improve the condition number of this matrix.

The simulation setting is the same as the section ‘Sequential localization of multiple sources’ in the. The SNR was set to 0.5. The suppression region ($40 \times 60 \times 40$ mm, $-60 \leq z \leq -20$, $-50 \leq y \leq 10$ and $20 \leq z \leq 60$) was defined. Figure 10(A) shows the eigenvalues spectrum of the lead field matrix in the suppression region. As the number of the chosen eigenvectors (donated by $M$) increase, the NBI, LB and SNR changes. When $M$ rises to 7, NBI of the coherent source get the minimum value (Fig. 10(B)). When $M$ change from 4 to 30, LB remain zero (Fig. 10(C)). It is obvious that choosing 7 most significant eigenvectors will get zero localization bias and sharpest peak and therefore, is optimal. Using such selection of the M, we also calculate the variation of the Frobenius norm of the lead field matrix for the three simulated sources in the transformed space as the number of the chosen eigenvectors increases. The result was shown in (Fig. 10(D)). The symbols star, circle and diamond indicate the Frobenius norm of the lead field at the positions of the simulated coherent source, interfering one and independent one, respectively. While 7 eigenvector components were chosen, the Frobenius norm of the transformed lead field at the coordinates of the interfering one, of the coherent source and of the independent one decreases to 4%, 67% and 85% of that of the original lead field, respectively. And in this case, the 7 dominant components explains 85% of the total variance (energy). The transformation matrix constructed by such selection of the eigenvector components almost completely suppress the activation at the position of the interfering source while retaining most of the activation at the position of the sources expected to be localized. Therefore, in transformed space, the coherent source and independent source can be localized since most of the interference is removed.

We also study the changes of SNR, defined in Eq. (12), with the increase of $M$. Figure 11 shows the variation of the SNR of the simulated MEG in transformed space as a function of eigenvector components selected for the lead field of the suppression region. As the eigenvector components increase, the SNR decreases. When the chosen components is 7, the SNR is near 0.3, decreasing 35%.

The simulations indicate that too few components cannot represent the region sufficiently and lead to the degradation of the localization performance; too many components will also greatly suppress other sources external to the given suppression region. In addition, too many components can decrease the effective SNR significantly. An appropriate selection of the eigenvector components can reach a compromise between (1) the given suppression region can be represented sufficiently; (2) the sources beyond the suppression region can be suppressed as small as possible; and (3) the reduction of the effective SNR is as little as possible. In this study, we recommend the selection of 7 largest eigenvectors to construct the transformation matrix. In practice, according to our experience, the chosen dominant components should explain at least 85% of the total variance. In case that the components increase...
Coherent MEG/EEG Source Localization in Transformed Data Space

Fig. 10 (A) Eigenspectrum of the lead field of the suppression region. The NBI of the coherent source and the independent source (B), LIL of the coherent source (C), and the Frobenius norm of the lead field at the coordinates of the three simulated sources (D) as a function of eigenvector components selected for the lead field of the suppression region.

Fig. 11 SNR as a function of eigenvector components selected for the lead field of the suppression region.
whereas the cumulated variance does not increase significantly, such increase of the eigenvector components may be of no significance and will lead to performance degradation. One useful strategy is to localize the sources using a coarse selection of M firstly, and then select an appropriate number of components like this simulation. Finally, the source positions can be further adjusted according to the M chosen in the second time. Such study is in principle straightforward but the details are beyond the main scope of this paper.

Effect of Source Positions Within the Suppression Region on Localization Accuracy

This simulation would assess how well an interfering source is suppressed depending on its position within the suppression region. The simulated data from the section ‘Reconstruction of two coherent sources’ was used. A $70 \times 30 \times 40$ mm suppression region ($-35 \leq x \leq 35, 15 \leq y \leq 45$ and $20 \leq z \leq 60$) was defined. One source was fixed at $(0, -30, 40)$ mm, while the algorithm was evaluated with the other source at each of 105 locations throughout the suppression region. Figures 12(A) and 12(B) show the localization bias of the source of interest as a function of the locations of the interfering source within the suppression region when the SNR was set to 0.25 and 0.5, respectively. When the SNR was 0.25, the LB of the fixed source was 3.8 mm, with 85% of locations within the suppression region yielding LB of 5 mm (equal to one voxel) or less. Similarly, when the SNR was 0.5, LB of the fixed one was 0.6 mm, without locations within the suppression region yielding LB larger than 5 mm. This simulation shows that the variation of the position of the sources within the suppression region has little effect on the localization ability of the proposed method.

Selection of the Size of the Suppression Region

In this simulation, we study the effect of the size of the suppression region on the localization ability of LIST. In order to study the suppression effect, we also calculate the Frobenius norm of the lead field in the transformed space for different sizes of the suppression region. The simulation settings were the same as in the section ‘Sequential localization of multiple sources’. The results were shown in Fig. 13. As the size of the suppression region increased gradually, the distance between the coherent source and the suppression region was closer and closer. From Figs. 13(A) to 13(F), the distance between the coherent source and the above side of the suppression region was 40 mm, 30 mm, 20 mm, 10 mm, 5 mm and 0 mm, respectively. Obviously, while the distance between them was less than 10 mm, the coherent source can hardly localize since, in such situation, the coherent source was also trapped in the greatly suppressed area (see the below subplots from Figs. 13(D) to 13(F), which demonstrate the Frobenius norm of the lead field at the same plane after different transformation) and its energy was attenuated largely enough to have difficulty in localizing it. For the given head model in this study, a distance, less than 10 mm, will lead to the sources near the suppression region are hardly identified.

Transformation Matrix Design

To remove the effect of the coherent sources on each other, we consider a transformation of mapping the original data into another data space. It is straightforward that the transformation should be specially designed so that in the process of the transformation, the coherent interfering source region can be suppressed. Naturally, the effect will be removed. In order to enhance sources in some region, the transformation can be calculated as the integral of the lead

![Fig. 12](image-url) Reconstruction bias of the source at $(0, -30, 40)$ mm as a function of position of the source within the suppression region while the SNR was set to 0.25 (A) and 0.5 (B), respectively.
Fig. 13 The reconstruction profile on the $z = 40$ mm plane with suppression of the outlined region. In each subplot, the imaging profile was shown above and the Frobenius norm of the corresponding transformed lead field on the same plane shown below. The three simulated sources configuration was the same as in Sec. 3.2.2. From (A) to (F), the suppression region became larger and larger gradually, and the distance between the coherent source (located at $(-40, 30, 40)$ mm) and the above side of the suppression region was $40$ mm (A), $30$ mm (B), $20$ mm (C), $10$ mm (D), $5$ mm (E) and $0$ mm (F), respectively.

field matrix of the volume expected to focus on. It is straightforward that, to suppress the activation within a region, the orthogonal complement of the integral of the region’s lead field matrix can be calculated as the transformation matrix. Such a transformation matrix can suppress the activations within coherent interfering region and thus, can identify the sources beyond the suppression region. Linear transformation designed
to enhance some regions\textsuperscript{17} cannot be used as the preprocessor for coherent source localization. Because, although the activation of coherent source region is enhanced, it still has high correlation with the coherent interfering sources. As a result, such transformation only changes the location of the false equivalent sources, since the energy ratio between sources within enhancement region and within coherent interfering source region is changed. The coherent cancelation phenomena still exists. The proposed linear transformation can almost completely remove the effect of the coherent interfering sources on the localization of the coherent sources by suppressing the activations within coherent interfering source region.

The selection of the eigenvector components for the suppression region, the position of the suppressed sources within the suppression region and the size of the suppression region can influence the localization performance of LIST. Such parameters should be carefully selected when the presented method was applied to real data. The strategies of selection of related parameters have been discussed in the above paragraphs.

\section*{Data Postprocessing After Transformation}

After transformation of the measurement data into another data space by specially designed transformation matrix, we use MUSIC to conduct the subsequent source localization. In fact, any other source localization algorithms, i.e., adaptive beamformers, as long as it relies upon estimating the second order statistics of the measured data or related quantities, can be used as the subsequent source localization algorithms. Dalal \textit{et al.}\textsuperscript{15} demonstrated a closely related idea of adding null constraints to the vector-based adaptive beamformers to suppress correlated activity. In this study, we used MUSIC to perform theoretical analysis and the experiments of simulation data and real data to illustrate our concept. We define the approximate active region by sLORETA in this study. In practice, any other methods, as long as they can determine the approximate location of the sources and are not influenced significantly by the source correlation, can be used for this goal.

\section*{CONCLUSION}

Overall, We use sLORETA to estimate the approximate region of the coherent sources and MUSIC to accomplish high resolution localization in transformed space. A transformation matrix is designed using the integral of the lead fields from a specified region. It is then straightforward to define a transformation to suppress that region by using its orthogonal complement. By transformation of the original data space into a new data space, the method significantly reduces the norm of the lead field matrix within the given suppression region encompassing the coherent interfering sources and thus, suppresses the activation from that region. When applied to the original data, this transformation matrix will remove contributions from coherent sources. Subsequently, in transformed data space, MUSIC can localize the coherent sources. Computer simulations on real head model were conducted to validate the effectiveness and accuracy of the proposed method. Real AEP data analysis provided further evidence that LIST can localize coherent sources with high-resolution.

\section*{ACKNOWLEDGMENT}

SSD was supported in part by NIH grant F31 DC006762. The work was supported by NSFC No. 60778029 and 30525030, and the 863 project 2009AA02Z301.

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