ITERATIVE MUSIC FOR HIGHLY CORRELATED EEG/MEG SOURCE LOCALIZATION

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ABSTRACT
This study presented an iterative MUSIC (Multiple Signal Classification) for highly correlated EEG source localization. By suppressing the equivalent false source, the approximate true source location information was obtained. And then, by iteratively suppressing source found in the last iteration, eventually, both of the sources were identified. The method is designed to tackle highly correlated sources, for example, bilateral activations at primary auditory/auditory cortices, at which cases conventional MUSIC has difficulty. Compared with other similar methods, the presented one needs less computation load since it utilizes the minor difference between sources, as can be adequately explained by a theoretical model for correlated sources. Simulation and real data test confirmed its effectiveness.

Keywords: MUSIC; MEG; Source localization; Inverse problem.

INTRODUCTION
Electroencephalography (EEG) and Magnetoencephalography (MEG) 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 EEG/MEG 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 EEG/MEG 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 nonadaptive [for example, sLORETA, LPISS, and 3SCO (Refs. 2-4)] and adaptive (for example, MUSIC-type methods5-7 and beamforming-type methods8). MUSIC-type methods, as a class of subspace based methods, have attracted considerable attention because of: (i) its ability to accurately identify multiple independent or partially-correlated sources; (ii) avoiding multidimensional non-linear optimization procedure necessary in parametric methods, which is often trapped in local minima and cannot converge the global minima. However, while sources are highly 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 EEG/MEG. For example, pure tones evoked activities in the left and right primary auditory cortices are often coherent with each other and conventional MUSIC has difficulty in identifying them.\(^9-^{11}\) Such a class of practical problems requires a method for coherent source localization.

In this study, we proposed an iterative MUSIC method (iMUSIC) to image highly correlated sources. Theoretical analysis, Simulations and real data test show the effectiveness of the methods.

**METHOD**

**Subspace-Based Methods: MUSIC**

The EEG data \(Y(t)\) generated by current dipole sources can be modeled as

\[
Y(t) = AX(t) + n(t),
\]

where \(A\) is the gain matrix relating the measured signals to the dipole amplitudes, rows of \(X(t)\) are the time courses of the current dipoles, and \(n(t)\) is additive noise. Assuming that \(n(t)\) is uncorrelated across the channels, that the variance of the noise on each channel is \(\sigma^2\), and that the signal and noise are uncorrelated, the correlation matrix of the MEG data is

\[
R = \langle Y(t)Y(t)^T \rangle = \text{APA}^T + \sigma^2I,
\]

where \(P = \langle X(t)X(t)^T \rangle\).

Using the singular value decomposition (SVD) of \(R\), we obtain the ordered singular values \(\{\lambda_i; i = 1, 2, \ldots, k, \lambda_i \geq \lambda_{i+1}\}\) and corresponding singular vectors \(\{e_i; i = 1, 2, \ldots, k\}\), where \(k\) is the number of MEG sensors. Assuming that the number of dipoles \(p\) is known \textit{a priori}, we can construct the signal subspace \(E_s = [e_1, e_2, \ldots, e_p]\) and noise subspace \(E_n = [e_{p+1}, e_{p+2}, \ldots, e_k]\).

Where \(a(\theta)\) is the signal vector produced by a dipole at location \(\theta\), the cost function in classical MUSIC is as follows:\(^6,^{12}\)

\[
J(\theta) = \text{subcorr}(a(\theta), E_s)^2.
\]

In practice, the following calculation method is used to obtain the cost function,

\[
J(\theta) = \lambda_{\max}\{U_L^TP_EU_L\},
\]

where \(U_L\) contains the left eigenvectors of \(a(\theta)\), and \(\lambda_{\max}\) is the maximum eigenvalue of enclosed expression. Locations of the sources are found as the \(p\) maxima of this cost function across dipole locations.

**The Proposed Method**

Assume there are two highly correlated sources located at \(\theta_1\) and \(\theta_2\) with highly similar waveforms \(s_1\) and \(s_2\). The common component of source 1 and source 2 is \(s\).

The waveform of source 1 can be further written as \(s_1 = s + s_1'\). That of source 2 as \(s_2 = s + s_2'\), where \(s_1'\) denotes a small remaining independent component of \(s_1\) and \(s_2'\) denotes that of \(s_2\). The scalp EEG due to source 1 and source 2 will be

\[
Y = (a(\theta_1) + a(\theta_2))s + (a(\theta_1)s_1' + a(\theta_2)s_2').
\]

Obviously, from the view of space-time source model, the two coherent source problem factually is treated as three independent source problem: one strong source and two minor sources. When MUSIC scan is conducted, one location \(\theta_c\), whose gain matrix best matches the combination of gain matrix \(a(\theta_1) + a(\theta_2)\) will be identified. Due to \(s_1'\) and \(s_2'\) being small components, in the final imaging results, they could usually not be resolved. This is the reason why classical MUSIC has difficulty in identifying highly correlated sources and instead, misplaces an equivalent false source somewhere between the true ones.

Based on above analysis, it is straightforward that removing the common component \((a(\theta_1) + a(\theta_2))s\) will let two small components be most likely to show up in the imaging results. In this study, we remove the common component by constructing a suppression matrix \(H\) to suppress the activation from the location \(\theta_c\). One way to design \(H\) is as follows:

\[
H = I - a(\theta_c)(a(\theta_1)^Ta(\theta_1))^{-1}a(\theta_1)^T,
\]

where \((a(\theta_1) + a(\theta_2)) \approx a(\theta_c)\). Left multiplying two sides of Eq. (5) with Eq. (6), the common component will be removed, as shown by the following equation:

\[
H^TY = [0]s + (H^Ta(\theta_1))s_1' + (H^Ta(\theta_2))s_2'.
\]

Since \(H\) is orthogonal complementary matrix of \(a(\theta_c)\), the first term in the right side of Eq. (5) will be attenuated. However, due to noise interference and the remaining component being small, in the final imaging results, only the approximate source regions of two sources \(\Sigma_1\) and \(\Sigma_2\) are indicated. By constructing a matrix \(H_1\) (see Refs. 13 and 14 for how to construct a region suppression matrix) in the similar way as Eq. (6), the source region \(\Sigma_1\) can be suppressed and source 2 can
be identified. Similarly, suppressing $\Sigma_2$ will lead to the accurate localization of source 1. In such an iterative way, sources 1 and 2 can be accurately identified eventually. It should be noted that in each iterative computation process, the gain matrix correspondingly become $a^T(\theta) = H^T a(\theta)$ since suppression matrix is already applied to the measured EEG $Y$.

In summary, the steps to perform IMUSIC are as follows:

(i) employ conventional MUSIC on measured EEG, which suppose to be generated by one pair of highly correlated sources within brain volume, and find the peak location of the cost function;
(ii) suppress the activation from peak location by designing a suppression matrix. Observe the imaging results and underline the most possible correlated source regions $\Sigma_1$ and $\Sigma_2$;
(iii) suppress one of source region $\Sigma_1$, and identify the other source $\theta_2$ using MUSIC;
(iv) suppress the identified source $\theta_2$ and identify the first source $\theta_1$;
(v) if necessary, repeat Steps (iii) and (iv) until the source locations keep unchanged.

SIMULATION

Simulation Settings

In the simulations, the spherically symmetric EEG forward model was employed. The source space had a spherical shape (radius $= 90$ mm) with a $10$ mm spacing between sources. The simulated sensor array comprised 129 arranged in a hemispheric array on a sphere with 100 mm radius. The SNR was defined as the ratio of the Frobenius norm of the data matrix to that of the noise matrix.

Simulation 1: Two equally strong dipole sources were simulated: dipole 1 was located at $(10, 60, 0)$ mm (location index 144) and dipole 2 was at $(10, -60, 0)$ mm (location index 132). The distance of the sources was thus 120 mm. The waveforms of the two sources were 10 Hz sine functions with different phase and 500 ms duration. The sampling frequency was 1000 Hz. The correlation coefficient ($r$) between the two sources was set to 0.98 by adjusting the phase difference between the waveforms. Uncorrelated white Gaussian noise was added to all data points scaled such that SNR was 1. Point suppression is iteratively applied to the simulated data until the source locations were kept unchanged.

Simulation 2: For real data application, the sources is not always point-like, and usually is less or more extended. Therefore, small region suppression is more practical than point suppression. In this simulation, a region suppression strategy was applied while the other settings are the same as in the simulation 1. The suppressed region encompassed a sphere with radius 20 mm. The eigenvectors corresponding to the largest eigen values were used to construct the suppression matrix $H$.

Simulation 3: Other simulation is the same as in simulation 1, only the SNR was set to 0.5, 0.8, 1 or 2. This simulation studied the performance of IMUSIC under various SNR cases.

Simulation 4: To identify which estimated source is false, this simulation was conducted. The settings were the same as in simulation 1. Among two localized sources, any two of three sources were suppressed and then the MUSIC was applied to the modified dataset to conduct localization.

RESULTS

Figure 1 shows source imaging result employing classical MUSIC to the simulated EEG data with SNR = 1. Clearly, at given SNR and intersource correlation, conventional MUSIC failed to resolve two sources [Fig. 1(A)]. Instead, it misplaced a false equivalent source at the midline between two true sources. To obtain approximate information about true sources, the false source was suppressed and two approximate source regions were shown up [Fig. 1(B)]. Suppressing the peak location in Fig. 1(B), the down source was localized [Fig. 1(C)] with 10 mm bias (one voxel). Iteratively suppressing the peak location, two sources were accurately localized [Figs. 1(D) and 1(E)]. The norm distribution of suppressed gain matrix (the right column in Fig. 1) intuitively proved that the suppression almost completely attenuate the gain from coherent interferer and therefore, block its activations.

The results for simulation 2 were similar with that in Fig. 1 since the simulated sources were point-like ones. Extended sources suppression discussion is beyond the scope of this study and therefore, here did not be extensively studied. Simulation 2 was designed to show that small region suppression of point-like source got as good performance as that in point source suppression. In real data section, we will apply region suppression to conduct localization.

Figure 2 shows the iterative process of implementation of IMUSIC at various SNRs. When SNR was 1 or 2, two sources were localized accurately when the source location indices kept unchanged. When SNR was 0.5 or 0.8, one source was localized with bias 10 mm (one voxel).
Fig. 1  The imaging result obtained by the presented IMUSIC on the plane $z = 0\, \text{mm}$, the white stars indicate the true simulated source locations. SNR = 1. The left column shows the imaging results after the suppression matrix $H$ was employed and the right column show the Frobenius norm distribution of transformed gain matrix $a'(\theta)$ after the suppression matrix $H$ was applied to $a(\theta)$ at each location (for (A), $H$ may be regarded as identity matrix). (A) The imaging results obtained by the first MUSIC scan. (B) The Frobenius norm distribution of the gain matrix $a(\theta)$ on the plane $z = 0\, \text{mm}$. (C) MUSIC imaging results after suppressing the peak location in (A) using suppression matrix $H_1$. (D) The Frobenius norm distribution of transformed gain matrix $a'(\theta) = H_1 a(\theta)$. (E) Imaging results after suppressing the peak location in (C) using $H_2$. (F) The norm distribution of $a'(\theta) = H_2 a(\theta)$. (G) Imaging results after suppressing the peak location in (E) using $H_3$. (H) The norm distribution of $a'(\theta) = H_3 a(\theta)$. (I) Imaging results after suppressing peak location in (G) using $H_4$. (J) The norm distribution of $a'(\theta) = H_4 a(\theta)$. 

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Figure 3 showed the results for simulation 4. The range of color bar was fixed at $[0, 1]$, which indicates the largest subspace correlation between gain matrix at each scanning point and signal subspace of data correlation matrix. Clearly, when two estimated sources (located at true simulated source locations) were suppressed, the cost function distribution is very flat and all the imaging index is very low (the maximum is 0.1 or so), suggesting that there hardly exists any sources in this case. However, when one of the sources located at two simulated source positions and the middle source identified in the first MUSIC scan [Fig. 1(A)] were suppressed, the other simulated source still were able to be identified. Based on such results, we can conclude that the middle source obtained by the first MUSIC scan was a false equivalent source. Figure 4 also further showed that there are only
two main activations and no activation at the location which the first MUSIC can regarded as sources. These sLORETA results also facilitate to make sure that the source identified by the first MUSIC scan was false sources.

**REAL DATA STUDY**

**Experiment**

In order to test the effectiveness of the method, we applied these techniques to human brain EEG data consisting of the mismatch negativity (MMN) of evoked potentials, a negative event-related potential (ERP) component originally found in the oddball paradigm where infrequent (deviant) sounds are presented among frequent (standard) ones. The EEG (bandpass 0.01–100 Hz, sampling rate 500 Hz) was recorded with a cap of 64 Ag-AgCl electrodes connected according to the extended 10/20 system while stimuli were presented binaurally through headphones at an intensity level of 70 dB SPL. Rare sounds deviating in consonant identity occurred in a sequence of repetitive, homogeneous consonant-vowel syllables with an offset to onset interval of 500 ms. The EEG data were further filtered (0.01–30 Hz) and corrected for ocular artifacts. Epochs of 700 ms, including a 200 ms pre-stimulus interval for baseline correction, were averaged stimulus category (standard and deviant). Generally, two kinds of electrode reference techniques (average reference and REST\(^\text{15,16}\)) can readily be used and here we used average reference technique. The MMN was delineated by subtracting the waveform to the standard from that to the deviant. A grand average ERP (\(N = 7\)) was shown in Fig. 7. The grey-line box indicates the ERP segment selected for IMUSIC source analysis.

**Results and Analysis**

As predicted, conventional MUSIC misidentified a false source located at the midline (location coordinate: (0, 10, 30) mm) between two true sources. According to the theoretical model and simulation study, to obtain approximate information on source locations, the activations from peak location in Fig. 6(A) was suppressed and as a result, Fig. 6(B) was obtained. A region suppression of peak location in Fig. 6(B) led to the imaging result shown in Fig. 6(C), where the right source was located at (80, 10, 10) mm. Similarly, suppression of source region...
identified in Fig. 6(C) led to identification of the left source located at \((-80, 0, 30)\). IMUSIC successfully identified two sources at the bilateral temporal cortices, which was consistent with the results reported by other group. Figure 7 showed the sLORETA imaging results at the time point indicated by the red arrow in Fig. 5. The result by IMUSIC was consistent with that of sLORETA.

**DISCUSSION**

High correlation between sources usually gives rise to source cancellation phenomenon. Such cases are frequently encountered in the practice of identifying bilateral auditory, visual, somatosensory cortices. Here we proposed a novel method for such cases, based on a theoretical model for coherent sources. Since two sources have high similar waveforms we in any cases are able...
to obtain their common component and respective remaining one. This signal decomposition strategy is core of IMUSIC. The common signals at two distinct locations will merge into one component [described in Eq. (5)] if we observe the measured spatio-temporal MEG from the view of sensor level. Applying conventional MUSIC to conduct inverse problem, only one equivalent source will be obtained since the remaining components at two true source locations is quite small such that in the final image they cannot be resolved. One straightforward way to let them show up is suppressing the common component which is represented explicitly by the equivalent source and naturally the small component will have a chance to be resolved with rather large bias since they are so small. As shown in Fig. 1(C) (simulations) and Fig. 6(B) (real data), the information on source approximate locations is highly likely to be obtained by this means. Based on such biased source location information, further iterative process is necessary. One important problem that will rise is how to determine the source first found is a false one. One method is to utilize a priori information about source locations (for example, for primary auditory cortices related ERP, sources generally are also located there and the middle source is a false one), or the source location information from other modalities [for example, fMRI, PET or other imaging methods, MNE, sLORETA (used for real data analysis in Fig. 7)]. Another method likely to be used for this goal is suppressing any two sources of three found sources and the source disappearing after such process may be regarded as false source, as was demonstrated in Fig. 3.

One advantage of IMUSIC is light computation load: several time whole brain scan can accomplish source localization. Other authors (for example, Refs. 10 and 17) also presented significant solutions for such cases and got limited success, however, the computation load is very heavy and often an exhaustive search is needed. Assuming N is the voxel number in solution space, a N(N+1)/2 searches are needed while IMUSIC need LN searches (L <= 10).

CONCLUSION

To identify highly correlated sources within brain, iterative MUSIC was developed. Unlike other method, in which, either source location information is required to known as a prior, or extremely heavy computation load is need (an exhaustive search is necessary), this one utilizes the information, inherent to exist in the original data, to perform source localization. Such process is based on a theoretical model, which was validated to be effective by simulation and real data analysis.

REFERENCES