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Spatio-temporal EEG Source Localization Using a Three-dimensional Subspace FINE Approach in a Realistic Geometry Inhomogeneous Head Model

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Abstract

The subspace source localization approach, i.e. first principle vectors (FINE), is able to enhance the spatial resolvability and localization accuracy for closely-spaced neural sources from EEG and MEG measurements. Computer simulations were conducted to evaluate the performance of the FINE algorithm in an inhomogeneous realistic geometry head model under a variety of conditions. The source localization abilities of FINE were examined at different cortical regions and at different depths. The present computer simulation results indicate that FINE has enhanced source localization capability, as compared with MUSIC and RAP-MUSIC, when sources are closely spaced, highly noise-contaminated, or inter-correlated. The source localization accuracy of FINE is better, for closely-spaced sources, than MUSIC at various noise levels, i.e. SNR from 6 dB to 16 dB, and RAP-MUSIC at relatively low noise levels, i.e. 6 dB to 12 dB. The FINE approach has been further applied to localize brain sources of motor potentials, obtained during the finger tapping tasks in a human subject. The experimental results suggest that the detailed neural activity distribution could be revealed by FINE. The present study suggests that FINE provides enhanced performance in localizing multiple closely-spaced, and inter-correlated sources under low signal-to-noise ratio, and may become an important alternative to brain source localization from EEG or MEG.

Keywords

Source localization; electrophysiological neuroimaging; subspace; MUSIC; FINE; brain mapping; inverse problem; EEG; MEG

I. Introduction

It is of increasing interest in neuroscience research [1,2] and clinical applications [3–5] to localize electric sources within the three-dimensional (3D) brain from the scalp EEG. Such interest is initiated by the needs from basic neuroscience research and clinical applications. It is further motivated by the report of scalp EEG and MEG observations of electrical activity from deep cortical structures including the hippocampus [6], cerebellum [7], and thalamus [8]. How to localize and characterize current sources in the 3D brain has, thus, become the motivation of many efforts to elucidate the neural activity from the scalp potential or magnetic field over the past decades. Both equivalent current dipole models [9–17] and distributed current source models [18–26] have been extensively investigated and have each proven useful in both EEG and MEG.

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The inverse problem with a 3D distributed current source model is highly underdetermined and thus necessitates the introduction of priors in order to obtain good source estimation. Typical priors are smoothness [18–20,25] or assumption of sparse focal clusters of electrical activity [22,24]. They lead to either rather coarse spatial resolution for smoothness prior or numerical issues for the more computationally intensive methods with sparse focal prior. On the other hand, least-squares source localization, which uses equivalent dipole source model, is limited by difficulties of multidimensional nonlinear optimization and practical initial-value selection in searching algorithms and is trying to be solved by global optimization method [27].

The subspace source localization approach, which was first reported as multiple signal classification (MUSIC) algorithm [15], has been shown that it can avoid such difficulties and giving estimates for multiple dipole locations using a concept of subspace correlation. In the subspace source localization approaches the entire possible source space in a 3D grid is scanned and subspace correlations between the subspace spanned by each scanned point and the estimated noise-only subspace from the measured EEG data are calculated to obtain the estimates for multiple source locations at the lower extreme values (approximate to 0). Further development of subspace source localization approach has led to recursive MUSIC (R-MUSIC) [28], recursively applied and projected MUSIC (RAP-MUSIC) [16], and noise covariance incorporated MEG-MUSIC algorithm [17].

We have recently proposed to use the first principle vectors (FINE) for 3D subspace source localization [29], and initially tested the feasibility of FINE in a three-concentric-sphere head model. In the present study, we extended our FINE approach by incorporation of the realistic geometry of the head model, performed systematic computer simulation studies with respect to the performance of FINE under a variety of conditions, and applied FINE to localize brain sources associated with motor potentials in a human subject.

II. Methods

A. Notation and Preliminaries

The subspace source localization approaches are based on the spatio-temporal current dipole model [15] and its standard model for spatial correlation matrix could be expressed as

$$R_{\Phi} = AR_s A^T + \sigma^2 I, \quad (1)$$

where Φ is the spatio-temporal data matrix, A is the lead field matrix, S is the source temporal behavior matrix, and N is the noise matrix, assuming it as a spatially and temporally Gaussian white process. For an M -dimensional electrode space and p current dipole sources that are not fully correlated R_s ($p \times p$) is non-singular. If eigen-decomposition is applied to R_{Φ} , it can be partitioned into p -dimensional signal subspace, $E_s = [e_1, e_2, \dots, e_p]$ and $M-p$ -dimensional noise-only subspace, $E_n = [e_{p+1}, e_{p+2}, \dots, e_M]$ [30]. The projection matrix onto the column space of E_s and its complement E_n can be formed by $P_s = E_s E_s^T$ and $P_n = I - P_s$. Let $A(\underline{r})$ be the lead field vectors corresponding to the array manifold for the location $\underline{r}$. The subspace correlation between $A(\underline{r})$ and E_n could be calculated as the projection of $A(\underline{r})$ onto E_n , i.e. $P_n A(\underline{r})$, known as residual vectors. If the current dipole source at $\underline{r}$ is the true source and if it is rotating in three freedoms, the Frobenius norm of residual vectors should be

$$\|f_s(\underline{r})\|_F = \|A(\underline{r})^T P_n A(\underline{r})\|_F \approx 0. \quad (2)$$

If the dipole orientation is restricted by some conditions, e.g. the fixed orientation, equation (2) will not equal to zero because part of array manifold spanned by $A(\underline{r})$ is not in the signal subspace. However, the residue vector at its true moment orientation should be a zero vector [15].

$$\lambda_{\min} \begin{bmatrix} A(\underline{r})^T P_n A(\underline{r}), & A(\underline{r})^T A(\underline{r}) \\ - & - \end{bmatrix} \approx 0 \quad (3)$$

where $\lambda_{\min} [\cdot, \cdot]$ indicates the minimum generalized eigenvalue of the matrix pair given in the bracketed items. The true moment orientation is found as the eigenvector associated with $\lambda_{\min}$.

B. MUSIC, RAP-MUSIC, and FINE

In the MUSIC algorithm, the estimates of dipole location are obtained by calculating the subspace correlation over the entire noise-only subspace. Similar as equation (3), it can be expressed as

$$J_{MUSIC}(\underline{r}) = \lambda_{\min} [A(\underline{r})^T P_n A(\underline{r}), A(\underline{r})^T A(\underline{r})], \quad (4)$$

where $J_{MUSIC}(\underline{r})$ is the MUSIC estimator at possible source location $\underline{r}$. The estimator could be further simplified using singular value decomposition (SVD) [15] by transforming a generalized eigenvalue problem into a simple eigenvalue problem,

$$J_{MUSIC}(\underline{r}) = \lambda_{\min} \begin{bmatrix} U_{A(\underline{r})}^T P_n U_{A(\underline{r})} \\ - \end{bmatrix}, \quad (5)$$

where $U_{A(\underline{r})} (M \times 3)$ contains left singular vectors of $A(\underline{r})$.

The first recursion of RAP-MUSIC estimator [16] is the same as the MUSIC estimator. From the second recursion, it can be expressed as

$$J_{RAP-MUSIC}(\underline{r}) = \lambda_{\min} \begin{bmatrix} U_{A(\underline{r})}^T \Pi_{A_{k-1}}^\perp P_n' \Pi_{A_{k-1}}^\perp U_{A(\underline{r})} \\ - \end{bmatrix}, \quad (6)$$

where $\Pi_{A_{k-1}}^\perp = (I - A_{k-1} (A_{k-1}^T A_{k-1})^{-1} A_{k-1}^T)$, and A_{k-1} is the set of lead field vectors from the previous $k-1$ recursions. A new projection matrix P_n' is formed via reorthogonalization [31] at each step, $P_n' = I - P_s'$, where $P_s' = \Pi_{A_{k-1}}^\perp E_s E_s^T \Pi_{A_{k-1}}^\perp$.

Kaveh and Barabell [32] also reported a Minimum-Norm subspace estimator as a subspace source localization approach in direction searching problem, which demonstrates a lower spatial resolution threshold than MUSIC. The Minimum-Norm estimator calculates the projection of lead field vectors onto the specific row (i.e. first row) of projection matrix, P_n , whereas the MUSIC estimator averages the projections of lead field vectors onto all the rows of P_n . Due to averaging, the spatial behavior of the MUSIC estimator is smoothed, which means its ability to distinguish closely-spaced sources is decreased. On the other hand, the MUSIC estimator has smaller variance, which could be defined as a measure of the stability of estimator, than that of Minimum-Norm subspace estimator. Furthermore, an estimator formed by a row in P_n , such as Minimum-Norm subspace estimator, tends to exhibit a false peak [33]. Thus, it is desirable to find a subset in noise-only subspace to form a projection matrix which combines the merits of the MUSIC estimator and Minimum-Norm subspace estimator. Here, we introduce FINE as a new formulation of subspace approach.

In the FINE algorithm, for each scanned point, a region Θ , which surrounds the scanned point, is found by dividing the entire brain volume [29] and a small set of vectors in the noise-only subspace, denoted by FINE vector set F_Θ , could be identified as an intersection set between the noise-only subspace and the array manifold spanned by the specific region Θ based on the concept of principal angles [31,33]. The array manifold of the specific region Θ could be mathematically described by a spatially extended source representation matrix,

$$R_\Theta = \int_\Theta A(r)A(r)^T dr \quad [29],$$

which is the integral of array manifold spanned by current dipole sources, i.e. their lead fields $A(r)$, within the region Θ . Employing eigen-decomposition on the representation matrix we obtain a set of representative vectors which virtually spans the same subspace spanned by the array manifold for region Θ , denoted as $V_\Theta = [v_1, v_2, \dots, v_D]$. The number of representative vectors is selected such that the summation of the D largest eigenvalues is not less than 99 percent of the summation of all eigenvalues.

The FINE vectors F_Θ define the intersection subspace between E_n and V_Θ , i.e. $F_\Theta = E_n U_\Theta$, where $U_\Theta ((M-p) \times D)$ contains the left singular vectors of $E_n^T V_\Theta$ and F_Θ is a $M \times D$ matrix. The new projection matrix is formed as $P_\Theta = F_\Theta F_\Theta^T$. The FINE estimator can be expressed as

$$J_{FINE}(r) = \lambda_{\min}[U_{A(r)}^T P_\Theta U_{A(r)}] \quad (7)$$

If the column dimension of FINE vectors $D = M - p$, the FINE estimator becomes the same as the MUSIC estimator. On the other hand, if $D = 1$, the FINE estimator approaches the other extreme point where the Minimum-Norm subspace estimator is an example. Thus, the parameter D determines the performance of FINE estimator by a trade-off between the estimator's sensitivity and stability. The value of D is generally decided by size of surrounding region. Furthermore, FINE finds a specific subset from noise-only subspace for each scanned point instead of a universal vector, e.g. as in Minimum-Norm, or a universal set of vectors to perform 3D source scanning, which helps to reduce the chance to generate false peaks and, thus, improve the stability of the estimator.

C. Simulation Protocols and Human Experimentation

Computer simulations were conducted to evaluate the FINE algorithm in comparison to MUSIC and RAP-MUSIC. A three-shell realistic geometry inhomogeneous head model [34] was used. The boundary head model was constructed from high-resolution T1-weighted 3D MRI images of a subject using Curry software (NeuroScan Labs, TX). The conductivity ratio used for forward solution computation is 1:0.0125:1 for scalp:skull:brain [35–36]. The values of estimators were scanned on a discrete cubic grid with more than 160,000 grid points. The inter-grid distance was 2 millimeter (mm). Furthermore, a small local refined cubic grid was formed at each identified peak with an inter-grid distance of 0.5 mm and a local scan on the high-density grid was performed.

Seven different source configuration settings (from S1 to S7) in different cortices were investigated (Fig. 1). S1 and S2 are in the occipital lobe, corresponding to the functional visual cortex. S3 and S4 are in the temporal lobe, corresponding to functional auditory cortex. S5 and S6 are in the frontal lobe, the region related to the higher order cognitive functions. S1, S3, and S5 are close to the epicortical surface of brain, at which gyri sit; on the other hand, S2, S4, and S6 are in the deep portion of lobes as sulci. We used two source configuration settings in each lobe with different depths (e.g. S1 and S2) in order to investigate the depth dependence of FINE. Finally, S7 is in the thalamus, which is the deepest functional brain structure investigated in the present study.

In each source configuration, two closely spaced current sources were simulated in order to study the spatial resolvability of FINE by varying the distance between them. Both sources had damped sinusoid waveforms with frequencies of 5 Hz and 7.5 Hz. The time interval was 200 ms and the sampling frequency was assumed to be 1 kHz. A 128-electrode configuration was used and all the electrodes are homogeneously distributed over the upper hemisphere. Gaussian white noise (GWN) with certain SNR was added to the generated scalp potentials to simulate the noise contaminated measurements. A range of SNR from 4 to 16 decibels (dB) was investigated for each source configuration. Source correlations are also considered using the above described simulation settings. The parameters of such computer simulations will be described in the corresponding parts in the Results section for convenience. Finally, all computer simulations for each set of parameters were repeated 40 times using randomly generated GWN. It gives us a reasonable size of population of results and reduces uncertainty and bias during the realization of a random process.

Motor potential (MP) experiments were conducted in a human subject to evaluate the performance of the proposed FINE algorithm. In MP experiments, one healthy subject who gave written informed consent was studied in accordance with a protocol approved by the IRB. The subject was asked to perform fast repetitive unilateral finger movements which were cued by visual stimuli generated by the STIM system (Neuro Scan Labs). 94-channel signals referenced to right earlobe were amplified and recorded by the Synamps (Neuro Scan Labs), and were digitally processed by using SCAN 4.1 software (Neuro Scan Labs). 10 blocks of 2 Hz thumb and index finger oppositions for both hands were recorded, with each 30 second blocks of finger movement and rest. The EEG signals were recorded with a bandpass filter (0.3–100 Hz) and a sampling rate of 250 Hz. The electrode locations were measured using Polhemus Fastrack (Polhemus Inc.). Furthermore, EMG, which was used to determine the onset of finger movement event in each single trial for averaging MP signals, was recorded from surface electrodes positioned over the flexor digitorum muscle. The sampling rate and filter setting of EMG recording were the same as EEG.

III. Results

A. Simulation Results

We used the localization error as the major index to evaluate the performance of FINE. It is defined as the distance between the simulated source location and estimated source location. A trial is defined as a successful trial only if two simulated sources are both identified. The detection rate (DR) is defined as the number of successful trials divided by 40. Only simulation results in which DR is not less than 0.75 are reported. Standard deviation (STD) is also calculated as an index of the stability of FINE. The thresholds of subspace correlation for all three algorithms were chosen as 0.05 against the noise-only subspace [28].

Effects of Distance between Sources—Fig. 2 shows the localization errors of MUSIC, RAP-MUSIC, and FINE, while varying the distance between two simulated sources, at the SNR level of 12 dB in both S1 (Fig. 2(a)) and S2 (Fig. 2(b)). The localization errors shown are the errors averaged over two simulated sources. Generally, RAP-MUSIC outperforms MUSIC. The increased accuracy of RAP-MUSIC over MUSIC is achieved during its second recursion because of the fact that the first recursion of RAP-MUSIC is the same as MUSIC. The performance of RAP-MUSIC is much more enhanced in comparison with MUSIC when sources become closer and closer. Similar phenomenon is also observed in the discussion below considering the SNR effect. The accuracy of FINE is similar to MUSIC and RAP-MUSIC when sources are well separated. However, when sources become closer, the accuracy of FINE becomes better than MUSIC and RAP-MUSIC in both S1 and S2. Especially in cases when the distance is 8.5 mm on S1 and 16.3 mm on S2, the localization errors of FINE are much

smaller than those of RAP-MUSIC. Furthermore, in these cases, MUSIC cannot successfully identify two sources (or $DR < 0.75$).

Effects of SNR—Fig. 3 compares the effects of SNR on the performance of MUSIC, RAP-MUSIC, and FINE in term of averaged localization errors over two sources. Fig. 3(a) and (b) show the results on S1 with a large distance (14.1 mm) between two simulated sources, and a small distance (11.3 mm), respectively. Fig. 3(c) and (d) show the results on S2, also with two distances (23.3 mm, large; 16.3 mm, small). When the SNR levels are relatively high (e.g. 16 dB and 14.5 dB), the localization errors of FINE are similar to MUSIC and RAP-MUSIC in the large distance cases (Fig. 3(a), (c)). In the small distance cases (Fig. 3(b), (d)), it is close to RAP-MUSIC, but better than MUSIC. In contrast, in the cases with low SNR values (e.g. 8 dB and 6 dB), the performance of FINE is better than both MUSIC and RAP-MUSIC. The deep sources (Fig. 3(c), (d)) obviously have larger biases as compared with superficial sources (Fig. 3(a), (b)), which also indicates the difference on their spatial source resolvability as discussed below.

Effects of Depths—The effects of depths could be observed in both Fig. 2 and Fig. 3. The superficial sources (in S1) had less localization errors than the deep sources (in S2) for the three algorithms when either varying the distance (Fig. 2) or the SNR (Fig. 3). Also, it is obvious that FINE has higher spatial resolvability for the superficial sources than for the deep sources. For example, in Fig. 2, the two simulated sources could be identified as close as 8.5 mm in S1. On the other hand, in S2, only two sources with distance above 16.3 mm could be distinguished. Furthermore, on the plots for different SNR values (Fig. 3), a pair of sources with distance of 11.3 mm from S1 has lower source localization errors comparing the pair with larger distance of 16.3 mm from S2. The same phenomena are also observed for other two subspace source localization algorithms. All of these show source localization ability of subspace source localization algorithms, including FINE, is depth-dependent.

Standard Deviation (STD) of Solutions—Fig. 4 presents the summary of STD values of FINE as the ratio between MUSIC and FINE and the ratio between RAP-MUSIC and FINE. All values are averaged over all considered distances and SNR levels and two simulated sources. The first and second two columns are the ratios of STD for S1 and S2, respectively. The three algorithms show only slight difference in the values of STD, which indicates that FINE is as stable as MUSIC and RAP-MUSIC.

Performance of FINE under Various Simulated Source Settings—Fig. 5 presents the mean values of localization errors of FINE in the cases of the superficial sources in dashed lines (S1, diamond; S3, triangle; S5, square), deep sources in solid lines (S2, diamond; S4, triangle; S6, square), and simulated deepest sources in a dotted line with circles (S7). The vertical bars represent the STD values and the varying gray scales correspond to from S1 to S7. The results shown are mean and STD values of source localization errors averaged over two simulated sources. We choose the distance of 14.1 mm for the superficial sources (S1, S3, and S5) and 18 mm for the deep sources (S2, S4, S6, and S7).

A two-phase structure is observed for all curves which are plotted against SNR levels (from 16 dB to 4 dB). The first phase is close to a flat line where the localization error is steady, while in the second phase the source localization error increases as SNR decreases. The turning point is around 12 dB. When SNR is lower than 12 dB, the dependence of source localization error on SNR becomes obvious. At the extremely low SNR value (i.e. 4 dB), the DR for FINE decreases, and it is below 0.75 in several cases (e.g. S1, S2, and S7). The values of STD generally share the similar trend as the mean values. The curves for deep sources (i.e. S2, S4, and S6) have very similar shapes and the deepest sources (S7) have a shape similar to those from the other deep sources, but with larger error values in low SNR. In the cases of superficial

sources, the curves for S1 and S5 have very similar shapes, but not for S3. The source localization errors at the temporal superficial sites are much higher than other two superficial sites in high SNR. This is because the temporal sites are not well covered by the electrodes as other two sites. In low SNR, the effect of SNR is dominant over the effect of electrode coverage. Therefore, the source localization errors for the three superficial sites have the similar level. The larger STD values with high SNR values (e.g. 16 db, 14.5 db, and 12 db) at temporal site as comparison with occipital and frontal sites also indicate that the site is not well covered by the electrodes.

Effects of Source Correlation—In Fig. 6, we compare the effect of the different levels of source correlation on the localization accuracy of FINE with MUSIC and RAP-MUSIC. The distance between the two simulated sources, in S1, is 14.1 mm and correlation between them ranges from 0 to 0.75 for 16 dB SNR and from 0 to 0.5 for 12 dB SNR. The three algorithms show better abilities in distinguishing two correlated sources in the relatively high SNR case (16 dB, Fig. 6(a)) than in the low SNR case (12 dB, Fig. 6(b)). MUSIC cannot successfully detect two sources with the correlation value of 0.75 in the 16 dB SNR case. Furthermore, its performance is much degraded to detect two sources with the correlation values of 0.25 and 0.5 in the 12 dB SNR case. RAP-MUSIC indicates great improvement over MUSIC by increasing the detection ability for the second source in a separate recursion. But the localization errors increase dramatically when the correlation becomes significant. FINE shows its ability to distinguish correlated sources, as presented in Fig. 6(a) and (b), with smaller localization errors. In the low correlation cases (e.g. 0, 0.1, and 0.25) with high SNR value (e.g. 16 dB), RAP-MUSIC shows slight low localization errors as comparing with FINE in terms of both mean and STD values for source localization errors. However, in the high correlation cases (e.g. 0.5 and 0.75) or relatively low SNR value (e.g. 12 dB), its localization errors are higher than those from FINE.

B. Human Experimental Results

The MP data generated by fast repetitive unilateral finger movements was analyzed using FINE, MUSIC, and RAP-MUSIC. During the source localization analysis, several noisy channels were rejected by visual inspection. In the time domain, total 126 time samples, which are 500 ms data (pre-onset, 300ms; post-onset, 200ms), were used. Activities are both observed in the pre-onset interval and the post-onset interval. The estimates of noise-only subspace were based on the SVD [15]. The thresholds of subspace correlation for all three algorithms were set to an exact same value, i.e. 0.05 [28], which was also the value used in computer simulations.

The results for both left hand and right hand are given in Fig. 7–8. Fig. 7(a) (for left hand) and Fig. 7(b) (for right hand) display the results of a 2 mm grid FINE scan (left column(s)) and MUSIC scan (right column(s)). Each subimage represents an axial (Fig. 7(a)) or a sagittal (Fig. 7(b)) slice of the brain in 4 mm increments along the z-axis or the x-axis in the interest region, which is illustrated in the MRI picture (top of Fig. 7). In each 2D subimage, the inter-pixel distance is 2 mm along both directions. In Fig. 7(a), each subimage has 20×20 pixels. In Fig. 7(b), each subimage has 16×30 pixels. Fig. 8 displays the peaks for both hands with a head geometrical background reconstructed from the MRI images in order to guide the interpretations of the identified peaks with the brain structural information.

Two peaks (LP1 and LP2) are identified in FINE result of Fig. 7(a) for left hand. LP1 is in the fifth slice and LP2 is in the ninth slice. In Fig. 8(a) with the brain structural information, it can be seen that LP1 appears to be located on the precentral gyrus within the premotor cortex while LP2 in the deep site of the precentral sulcus. As a contrast, the MUSIC result shows only one peak (LP), which is in the neighboring slice to the LP1 from FINE. Because the first recursion of RAP-MUSIC is same as MUSIC, the RAP-MUSIC identifies the first peak at the same

location as MUSIC. In the second recursion, the identified peak has a correlation value of 0.3361 indicating there are no additional identifiable sources present [28].

FINE also identifies two peaks (RP1 and RP2) in Fig. 7(b) for MP due to the right hand finger movement. RP1 is in the third sagittal slice and RP2 is in the sixth slice. RP2 is three slices (12 mm) medial from RP1. It can be seen from Fig. 8(b) that RP1 appears to be located on the anterior wall of the precentral sulcus, and RP2 on the medial wall within the supplement motor area (SMA). MUSIC still locates only one peak (RP) for the right hand, which is located in the slice neighboring to RP1. Again, in the second recursion of RAP-MUSIC, the correlation rises to 0.4498, indicating there are no additional identifiable sources present [28].

IV. Discussion

In the present study, we have systematically investigated the source localization performance of the FINE algorithm by conducting a series of computer simulations in a realistic geometry inhomogeneous head model by means of the boundary element method. We studied many factors, e.g. location, spatial distance, temporal correlation, and so on, which have substantial influence on the subspace source localization algorithm and, furthermore, we compared the source localization ability of FINE to handle these influential factors in comparison with the previously reported subspace source localization algorithms, i.e. MUSIC and RAP-MUSIC. We have, then, evaluated the FINE algorithm in an experimental setting during fast repetitive unilateral finger movement using the subject-specific realistic geometry head model and compared the results with those from both MUSIC and RAP-MUSIC.

As discussed by Mosher et al. [15], in general, the MUSIC algorithm may fail when the noise is of sufficient strength to corrupt the estimates of the noise-only subspace, or when the source time series is strongly correlated, or when the sources are closely spaced. In our proposed subspace source localization approach, i.e. FINE, a subset of noise-only subspace for each scanned point is identified and denoted as FINE vectors, which is used to calculate the subspace correlation instead of using the entire noise-only subspace as in the classic MUSIC algorithm. Through our computer simulations, we have found that the use of FINE vectors in the above-mentioned conditions enhances the 3D source localization ability of the subspace approaches. First, FINE shows a much lower spatial threshold to separate the closely-spaced sources (Fig. 2). Recently, other reported 3D source estimation methods [18–20,25] show smoothed estimations with low spatial source resolvability, which needs to be enhanced. In Fig. 3, FINE indicates much stronger source detection ability in the low SNR conditions as compared with other subspace source localization algorithms (e.g. 8 dB and 6 dB). In event-related potential (ERP) studies, it usually requires experiments to be repeated many times in order to obtain high SNR signals via averaging. However, long time running of the experiments will make subjects hard to follow the same experimental protocol and increase the recording efforts. Even with the averaging procedure, there is a limit on the best SNR of ERP because of the inter-trial difference. The performance of FINE in low SNR conditions may be useful for source localization in cases when a small number of trials is desirable. Furthermore, several discussions and efforts from R-MUSIC [28] to RAP-MUSIC [16] in literatures have been made to address the source correlation, which is originated from the observation of the synchronization phenomenon in the brain electrical activity [37–39]. From the data of the present study, it shows that FINE is able to distinguish strongly-correlated sources successfully when MUSIC cannot (Fig. 6). Our simulation studies also confirmed that RAP-MUSIC shows higher source localization accuracy and stronger spatial resolvability than MUSIC. While RAP-MUSIC can always separate two simulated sources, it has larger source localization error comparing with FINE. However, in the presence of perfectly synchronized sources, all three algorithms fail in our computer simulations (not shown).

The source localization ability in the different brain structures, such as gyri, sulci, and deep cortex thalamus, which is the largest component of the diencephalons and comprises a number of subdivisions relaying information to the cerebral cortex from other parts of the brain, has been examined using seven source configurations (S1-S7), which have different locations, electrode coverage, and depths. As other source localization algorithms, the performance of FINE is also dependent to the source depth. Source localization errors are larger for the deep sources than for the superficial sources. The spatial resolvability of closely-spaced sources is decreased in the deep brain (Fig. 2, Fig. 3, and Fig. 5). Electrode coverage also seems to play a role in source localization accuracy. The superficial sources in the temporal site (Fig. 5, S3) are a typical example because it is not well covered by the electrodes. Those source sites well covered by the electrode montage have shown better localization accuracies. Furthermore, the variance of FINE is shown by data (Fig. 4) at the similar level with MUSIC and RAP-MUSIC, which appeared to be much more stable than the Minimum-Norm algorithm. It may be because of two reasons. First, a subset from the noise-only subspace with larger column dimensions is used in FINE and, second, a specific projection matrix is formulated by choosing the subset for each scanning point instead of a universally same projection matrix for every scanning point in Minimum-Norm. However, in some well conditioned cases (e.g. Fig. 2(b)), a slight increase of source localization errors from FINE as compared with the results from MUSIC may be due to the possible increasing of variance.

The contralateral activities within the premotor areas and supplemental motor areas revealed by FINE in the motor potential data analysis for both the left hand and the right hand data in a human subject are consistent with the neurophysiology knowledge. While the results from MUSIC show smoothed pattern over the motor-related cortices, which may indicate the source, i.e. the maximal point of the pattern, will only gain the information about the gravity of activity, the FINE algorithm appears to be able to pinpoint out the difference among the functional brain structures for motor control, such as, the activities on the precentral sulcus and the gyrus for the left hand (Fig. 7–8(a)) and the activities on the premotor and supplementary motor area for the right hand (Fig. 7–8(b)). These activities are consistent with the findings reported by other investigators using EEG and functional MRI [2]. The RAP-MUSIC algorithm also did not gain detailed activity distribution in the present finger movement experiment in the subject, which may be due to the combination effects of closeness and correlation of sources. Both effects result in the estimate bias for MUSIC, which is also same for the first recursion of RAP-MUSIC, and the peak, as it indicated by the data, always appear in the middle of two peaks identified in FINE for both hands. The removed array manifold, estimated from the results of first recursion, for the second recursion of RAP-MUSIC may, thus, cover the patterns for both sources and result in the loss of the second peak.

In summary, we have investigated the source localization performance of FINE in a realistic geometry inhomogeneous head model by both extensive computer simulations and human experimentation. The present study has demonstrated the excellent performance of FINE to localize closely-located sources and sources with high correlations. Its promising performance for 3D source localization suggests that it may become an important alternative for 3D source localization of neural sources from EEG and MEG, and merits further investigations.

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Figure 1. Illustration of the simulated source locations within the seven different brain regions. S1: superficial occipital lobe; S2: deep occipital lobe; S3: superficial temporal lobe; S4: deep temporal lobe; S5: superficial frontal lobe; S6: deep frontal lobe; S7: deep brain cortex, thalamus.

Figure 2. Comparison of source localization errors using the three algorithms at different distances between simulated sources. (a) S1, SNR = 12 dB; (b) S2, SNR = 12 dB.

Figure 3. Comparison of source localization errors using the three algorithms at different values of SNR. (a) S1, distance = 14.1 mm; (b) S1, distance = 11.3 mm; (c) S2, distance = 23.3 mm; (d) S2, distance = 16.3 mm.

Figure 4. Ratio of STD between MUSIC and FINE or RAP-MUSIC and FINE for S1 and S2. S1: left two columns; S2: right two columns.

Source Localization Errors in Seven Settings

Figure 5. Mean and STD values of source localization errors over seven simulation settings (S1–S7) at different values of SNR. For superficial locations (S1, S3, and S5), the distance between sources is 14.1 mm and it is 18 mm for deep locations (S2, S4, S6, and S7).

Figure 6. Comparison of source localization errors using the three algorithms at different correlation between simulated sources. (a) SNR = 16 dB; (b) SNR = 12 dB.

Figure 7.

FINE and MUSIC results for motor potentials induced by left hand finger movement (a, axial slices) or right hand finger movement (b, sagittal slices) in the interest region. Each subimage is a 2D slice in the x-y plane (a) or z-y plane (b) with grid increment of 2 mm (a: 20×20 pixels; b: 16×30 pixels). The increment between slices is 4 mm. Top: view of one slice MRI image and the interest region marked by a box; Left column(s): FINE results; Right column(s): MUSIC results. (Bottom/Top: the lowest/highest slice along z-axis; LP1, LP2: peaks identified by FINE for left hand; LP: peak identified by MUSIC for left hand; Left/Right: the most left/right slice along x-axis; RP1, RP2: peaks identified by FINE for right hand; RP: peak identified by MUSIC for right hand)

Figure 8.

Peaks identified by FINE for motor potential induced by left hand finger movement (a) or right hand finger movement (b) in a healthy human subject and displayed with brain structural information reconstructed from the subject's MRI images. (LP1, LP2, RP1, RP2: as defined in Fig. 7).