Imaging Brain Electric Sources by Means of a New Subspace Source Localization Approach – 3D-FINE

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***Abstract*- We have developed a new algorithm (3-dimensional first principle vectors, 3D-FINE) to enhance the spatial resolvability and localization accuracy for closely spaced sources, which are reconstructed from the scalp EEG using subspace source localization method. Computer simulations were conducted to evaluate the performance of the 3D-FINE algorithm in an inhomogeneous realistic geometry head model, in comparison to classic subspace source localization approach. The present results show that 3D-FINE could distinguish closely spaced sources, with distance as low as 8.5mm at signal-noise-ratio (SNR) of 12dB, simulated on the superficial gyrus and sources, with distance as low as 16.3mm at SNR of 12dB, simulated within the deep sulcus. The present computer simulation results indicate that 3D-FINE show improved source localization accuracy as compared with the MUSIC algorithm at various noise levels, i.e. SNR from 6 dB to 16 dB, for closely spaced sources.**

***Keywords*- subspace source localization, MUSIC, 3D-FINE, subspace, brain array manifold, EEG, source imaging**

I. INTRODUCTION

In the attempts to noninvasively localize electric sources from the scalp EEG, three-dimensional (3D) source localization is of increasing interest in both neuroscience research [1] and clinical applications [2-3]. The subspace source localization methods, e.g. MUSIC algorithm [4], have been successful in 3D source localization. The subspace approaches avoid difficulties of traditional least-squares source localization methods, i.e. multidimensional nonlinear optimization and initial value selection problems. Using a 3D search, they estimate multiple source locations at their cost functions' extrema through certain projection onto the estimated signal or noise subspaces, which are obtained from the noninvasive measurements. Different projection onto specifically designed subspaces can achieve different source localization features.

The advancement of MUSIC algorithm led to the recursively applied and projected MUSIC (RAP-MUSIC) algorithm [5], which uses a recursive procedure to find multiple source locations with each at one recursive step. It demonstrates the improved performance in two highly correlated sources [5]. We have recently developed a new algorithm in the framework of subspace source localization by investigating the use of the first principle vectors (FINE) to enhance the spatial resolution and improve the localization accuracy [6]. The capability of 3D-FINE for 3D source localization was demonstrated by several computer simulations in a three-concentric-sphere head model.

In the present work we visited the rationale of 3D-FINE algorithm by comparing its formulation with other algorithms in subspace source localization. We unified all projection formulations over noise subspace rather than signal subspace. We specifically developed the 3D-FINE incorporating the realistic geometry (RG) information of human head in order to diminish the errors caused by using an approximated three-concentric-sphere head model. A three-shell realistic geometry inhomogeneous head model, reconstructed from a human subject's MR images, was used and numerically solved by means of boundary element method (BEM). The performance of the newly developed RG 3D-FINE was systematically evaluated by computer simulations.

II. METHOD

A. 3D-FINE

In principle, subspace source localization methods scan the entire possible source space in a 3D grid and calculate the subspace correlation between subspace spanned by each scanned point, denoted as $A(\underline{r})$, and the entire noise subspace, denoted as E_n, estimated from a spatio-temporal matrix consisting of measured EEG data, and thus obtain estimates for multiple source locations at the extreme values. Alternatively, the similar procedure could be realized against the estimated signal subspace because it is orthogonal to the entire noise subspace. We unify the formulations of all the algorithms here using noise subspace in order to make them comparable. And we define subspace correlation as estimator and define the procedure to obtain estimator values over noise subspace as projection.

The above mentioned procedure is the classic subspace source localization, known as MUSIC algorithm. The detailed description of MUSIC can be found in [4] and the final form can be expressed as

$$J_{MUSIC}(\underline{r}) = \frac{1}{\lambda_{\min}\left[U_{A(\underline{r})}{}^{T} P_n U_{A(\underline{r})}\right]} \tag{1}$$

where $U_{A(\underline{r})}$ contains left singular vectors of $A(\underline{r})$, which is the subspace span by source point at $\underline{r}$. $P_n = E_n E_n{}^T$ is the projection matrix formed on entire noise subspace, E_n [4]. The denominator of the equation (1) calculates the subspace correlation between these two subspaces. The MUSIC estimator, $J_{MUSIC}(\underline{r})$, thus, identifies multiple source locations at the equation (1)’s maximal extrema, which are reciprocals of the subspace correlations. $\lambda_{\min}[\cdot]$ indicates the minimum eigenvalue of the subspace correlation matrix given in the bracketed items. The optimal source moment orientation is found as eigenvector associated with $\lambda_{\min}$.

Another subspace source localization method, Minimum-Norm algorithm [7], has higher spatial resolution than MUSIC. The estimator of Minimum-Norm is formed by using the first row of the projection matrix, P_n, which is denoted by $\underline{h}^T$, and could be expressed as

$$J_{MN}(\underline{r}) = \frac{1}{\lambda_{\min}\left[U_{A(\underline{r})}{}^T \underline{h}\underline{h}^T U_{A(\underline{r})}\right]} \tag{2}$$

Comparing the MUSIC and Minimum-Norm algorithms, the difference is that Minimum-Norm calculates the projection onto the specific row (i.e. first row) of projection matrix, whereas MUSIC averages the projections onto all the rows of projection matrix. Because of averaging, the spatial resolution of MUSIC is smoothed, which means its sensitivity to detect closely spaced sources decreases. On the other hand, the merit of MUSIC lies in smaller variance, which is a measure of the stability of estimator, than that of Minimum-Norm, which is practically unstable and exhibits false detection [8]. We develop the 3D-FINE algorithm in order to improve the spatial resolvability for closely spaced sources while keeping the estimates as stable as MUSIC. The 3D-FINE algorithm introduces the brain regional organization concept into the formulation of estimator and uses a specific subset of noise subspace for each brain region, instead of the entire noise subspace as in MUSIC and one limited row as in Minimum-Norm, to form projection matrix. It is thus enriched with both merits from above two algorithms, which could reveal brain electrical activity at high spatial resolution.

In the 3D-FINE algorithm, the entire brain could be divided into a number of regions due to its organization, and for a specific region Θ, its mathematic representation, termed as spatially extended source representation matrix, can be expressed as

$$R_\Theta = \int_\Theta w(\underline{r}) \cdot A(\underline{r}) A(\underline{r})^T d\underline{r} \tag{3}$$

where $w(\underline{r})$ is a weighting function and $\underline{r}$ indicates current source location within the brain region Θ. Employing the eigen-decomposition on the representation matrix we obtain a set of representative vectors that virtually spans the same subspace as spanned by the array manifold for region Θ.

$$V_\Theta = [\underline{v}_1, \underline{v}_2, \cdots, \underline{v}_D] \tag{4}$$

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. A small set of vectors in the noise subspace, denoted as FINE vector set, F_Θ, could then be found as the intersection subspace between the noise subspace and the span of representative vectors based on the concept of principal angles [8] and used to form a new projection matrix. For different brain regions different FINE vector sets are used [6].

$$J_{FINES}(\underline{r}) = \frac{1}{\lambda_{\min}[U_{A(\underline{r})}{}^T P_\Theta U_{A(\underline{r})}]} \tag{5}$$

B. Forward Solution

In the present study, the computation of the forward solution was realized in a three-shell realistic geometry inhomogeneous head model using BEM [9].

The boundary head model was acquired and constructed from high-resolution T1-weighted 3D MRI images in a subject using Curry software (NeuroScan Labs, TX). It consists of three conductivity boundaries between air and the scalp, the scalp and skull, and the skull and brain, and three compartments with different conductivity values, i.e. scalp, skull, and brain. The conductivity ratio used for forward solution computation is 1:0.0125:1 for scalp:skull:brain [10-11]. The purpose of using the realistic geometry head model is to reduce the influence from co-registration error of generally applied approximated three-layer concentric sphere head model and evaluate the performance of 3D-FINE in a complex irregular shaped volume conductor.

III. Computer Simulation

In the present study, computer simulations were conducted to evaluate the 3D-FINE algorithm as compared with the MUSIC algorithm in a three-shell realistic geometry inhomogeneous head model. Two source configurations, one on the gyrus to simulate superficial source and one on the sulcus to simulate deep source, were investigated. In each source configuration, two closely spaced current sources (D1 and D2) were simulated in order to study the spatial resolvability by varying distance between them. Both sources had damped sinusoid waveforms with frequency of 5Hz for D1 and 7.5Hz for D2. The time interval was 200ms long and the sampling frequency was assumed as 1 kHz. Gaussian white noise (GWN) with varying SNR was added to the calculated scalp potentials to simulate the noise contaminated measurements. All computer simulations for each simulated condition were repeated 40 times using randomly generated GWN. Data with more than 30 trials successfully distinguishing two simulated sources was presented to keep them reliable and comparable. A 128-electrode configuration was used and all the electrodes were distributed over the upper hemisphere of the head.

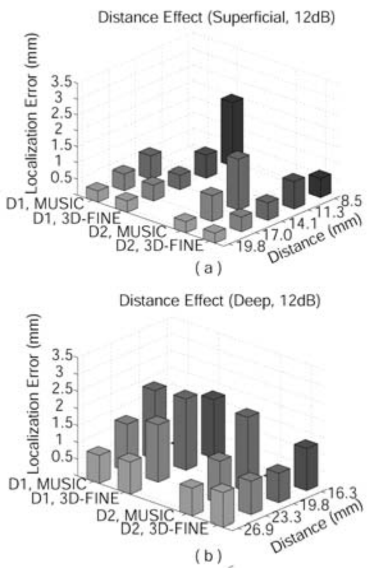

Fig. 1 Source localization error versus distance at SNR=12dB. (a) superficial source; (b) deep source.

Fig. 1 shows the localization errors of MUSIC and 3D-FINE due to different distances between two sources at the SNR level of 12dB for both superficial (Fig. 1(a)) and deep (Fig. 1(b)) sources. The results show that both MUSIC and 3D-FINE have better resolution in localizing superficial sources than deep sources. The localization errors for superficial sources are also much lower. For example, in the case with distance of 19.8mm, the average localization error across two algorithms and two sources is below 0.5mm for superficial sources, but as large as 2mm for deep sources. The difference between MUSIC and 3D-FINE could also be observed. When D1 and D2 are well separated, the accuracy of 3D-FINE is similar with MUSIC. However, when D1 and D2 become closer and

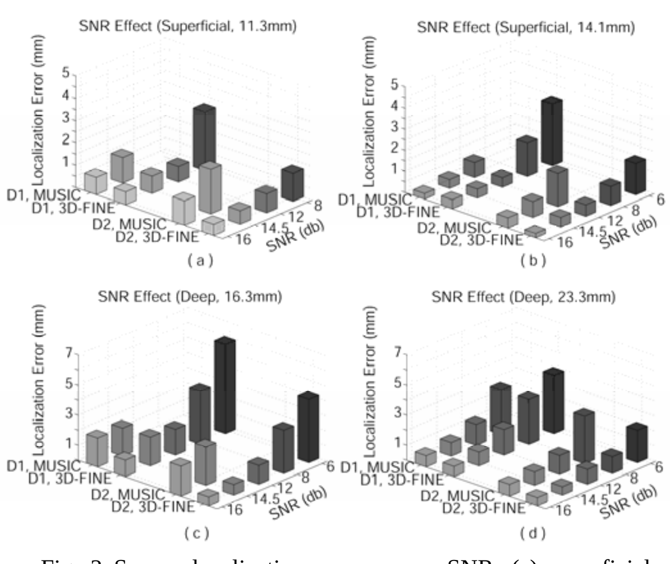

Fig. 2 Source localization error versus SNR. (a) superficial source, distance=11.3mm; (b) superficial source, distance=14.1mm; (c) deep source, distance=16.3mm; (d) deep source, distance=23.3mm.

closer, for both superficial and deep sources, the accuracies of 3D-FINE become better and better. Especially in cases with distance of 8.5mm and 11.3mm for superficial sources and with distance of 16.3mm for deep sources, MUSIC couldn't successfully identify two sources while 3D-FINE still works well.

The performance comparison between MUSIC and 3D-FINE due to the effect of SNR is presented in Fig. 2. Similar phenomena observed in Fig. 1 under the consideration of distance also could be observed in Fig. 2 under the consideration of SNR level. When the SNR levels are relatively high (e.g. 16dB and 14.5dB), the localization errors of 3D-FINE are similar with MUSIC in large distance cases (Fig. 2(b), (d)). In small distance cases (Fig. 2(a), (c)), 3D-FINE clearly outperforms MUSIC. In contrast, in the cases with low SNR values (e.g. 8dB and 6dB), 3D-FINE demonstrates the excellent spatial resolvability which MUSIC can't achieve. Furthermore, by comparing Fig. 2(a) with (b) and (c) with (d), at all levels of SNR, the localization accuracy will decrease dramatically when distance between D1 and D2 decreases.

Fig. 3 displays 2D mesh plots from the two algorithms, MUSIC and 3D-FINE, at simulated sources plane (all values are normalized to 64 grayscale levels). More specifically, Figs. 3(a) and 3(b) were obtained from

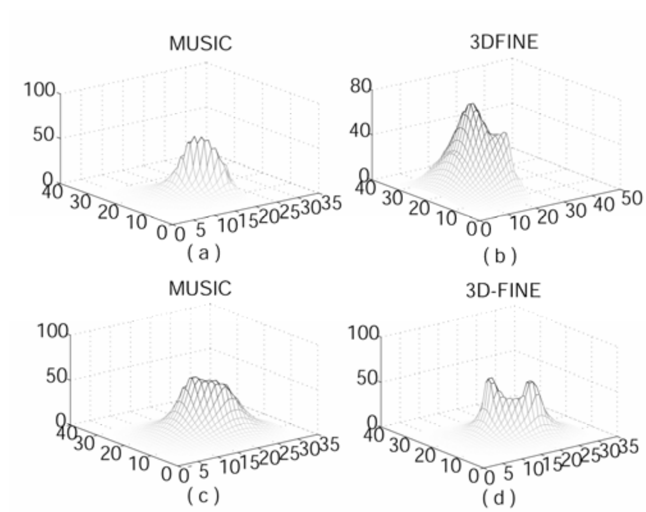

Fig. 3 2D mesh plots of two algorithms to illustrate the enhanced spatial resolution of 3D-FINE. (a) and (b): superficial source, SNR=12dB, distance=11.3mm; (c) and (d): deep source, SNR=12dB, distance=19.8mm.

superficial simulated sources with distance of 11.3mm at SNR=12dB, and Figs. 3(c) and 3(d) were obtained from deep simulated sources with distance of 19.8mm at SNR=12 dB. When MUSIC only shows a big lump for superficial source configuration in Fig. 3(a), 3D-FINE could successfully distinguish two simulated sources with distance of 11.3mm (Fig. 3(b)). For deep source configuration, both algorithms are able to provide dipole location estimates while 3D-FINE appears to show sharper peaks (Figs. 3(c)-(d)).

The ratio of standard deviation (STD) between 3D-FINE and MUSIC is 0.8540 for superficial source configuration, and it is 0.8016 for deep source configuration.

All values are averaged over all considered distances, all considered SNR levels, and two sources in each simulated case for both superficial and deep sources. They indicate the STD values of 3D-FINE even lower than those of MUSIC although such difference is not obvious, which, at least, shows 3D-FINE estimator is as stable as MUSIC estimator.

V. DISCUSSION

We have developed a novel algorithm in the framework of subspace source localization by applying projections over a subset of noise subspace instead of entire noise subspace. The new 3D-FINE enhances the performance of classic subspace source localization method, i.e. MUSIC, in many conditions as shown in the conducted computer simulations. First, 3D-FINE shows much lower spatial threshold to separate closely spaced sources (Fig. 1). It also indicates much stronger source detections in low SNR conditions (Fig. 2). Furthermore, it maintains similar stability as MUSIC while appreciates above mentioned merits.

In summary, the excellent performance of the 3D-FINE algorithm for EEG based 3D source localization problems in a realistic geometry head model is demonstrated via computer simulations. The present promising results of 3D-FINE in localizing closely spaced sources at low SNR suggest that 3D-FINE will provide an important alternative to brain source localization and imaging.

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