Comparison and Improvement of Inverse Techniques for MEG Source Connectivity Network Reconstruction

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Abstract — Recent studies on bio-electromagnetic inverse problems have shown that a satisfactory understanding of source mechanisms requires to perform source connectivity analyses. This paper focuses on the comparison of inverse techniques for reconstructing the source connectivity network. The results confirm that the noise effect for linear estimation technique is direct, while, for spatial filtering technique the effect is indirect. Linear estimation is advantageous for the connectivity reconstruction of high quality MEG data, while, the benefit for the case of spatial filter is low SNR environments. This paper also proposes a method to improve the source connectivity reconstruction by using the correlation gram matrix. The results show that the proposed method can increase the reconstruction accuracy, decrease the error fluctuation and enhance the representation for profiles of the original source connectivity network.

I. INTRODUCTION

Magnetoencephalography (MEG) uses an array of sensors positioned over the whole head that are extremely sensitive to the minuscule changes in the magnetic fields produced by the electrical activity in the brain. The traditional studies of the MEG source reconstruction have been proposed to localize the activities and study such activity-specific changes in isolation, however, this isolated study is insufficient. A satisfactory understanding of the source mechanisms requires performance of relationship analyses between activities. Many methods for connectivity analyses have been proposed, e.g. synchrony, coherence, and Granger. Among these methods, synchrony and coherence are used to assess undirected connectivity. Granger, which can reveal information about direction and degree of connectivity, and is widely used by several groups. One power of MEG is that it can extract the time courses of the sensor level measurement with excellent temporal resolution. MEG is, therefore, a very promising tool to investigate the sensor level connectivity. However, MEG measurement is sensitive to the field spread effect, the connectivity analyses at the sensor level cannot generate straightforward interpretations at the source level. Another power of MEG is that it can localize activities with good spatial resolution. Therefore, MEG source connectivity network reconstruction is becoming main issues in the bio-electromagnetic inverse computation researches recently. Although inverse techniques are constantly being improved and different methods have been comprehensively compared, most comparisons mainly focus on localization bias or spatial resolution instead of fully comparing unique source connectivity reconstruction characteristics. Thus, a complete and rigorous comparison of the performance of inverse techniques for MEG source connectivity network reconstruction is placing increasing demands [1]-[5].

This paper evaluated inverse techniques, with respect to the effectiveness of the MEG source connectivity network reconstruction. By considering two factors, the effect to the connectivity strength and the violation by the measurement noise, a thorough comparison is performed. This paper also suggested a modified spatial filter with a proposed correlation gram matrix to improve the reconstruction result. Finally, through simulations, some guidelines were proposed for a consensus on using inverse techniques of the source connectivity network reconstruction.

II. METHODS

MEG source reconstruction is an inverse problem of the form $\mathbf{b}=\mathbf{Ls}$, where $\mathbf{b}$ is the MEG sensor measurement, $\mathbf{s}$ is the unknown source and $\mathbf{L}$ is the leadfield matrix. The inverse operator $\mathbf{W}_{mn}$ according to linear estimation is

$$\mathbf{W}_{mn}=(\mathbf{L}\mathbf{R}_{mn}\mathbf{L}^T+\lambda^2\mathbf{C})^{-1}\mathbf{L}\mathbf{R}_{mn},\ \ \hat{\mathbf{s}}=\mathbf{W}_{mn}{}^T\mathbf{b} \tag{1}$$

$\mathbf{R}_{mn}$ is weighting matrix, $\mathbf{C}$ is noise covariance matrix, λ^2 is regularization parameter and $\hat{\mathbf{s}}$ is reconstructed source. While from spatial filter, weight matrix $\mathbf{W}_{sp}$ is derived as

$$\mathbf{W}_{sp}=\mathbf{R}_{sp}{}^{-1}\mathbf{L}(\mathbf{L}^T\mathbf{R}_{sp}{}^{-1}\mathbf{L})^{-1},\ \ \hat{\mathbf{s}}=\mathbf{W}_{sp}{}^T\mathbf{b} \tag{2}$$

$\mathbf{R}_{sp}$ is the spatial covariant matrix of the measurement.

The output of the ith sensor at time t is denoted as $b_t(i)$, the vector $\boldsymbol{b}(i)=[b_1(i), b_2(i), \cdots, b_T(i)]$ expresses the whole time courses (from 1 to T) of the ith sensor output, and $\mathbf{b}$ is

$$\mathbf{b}=\begin{bmatrix}\boldsymbol{b}(1) & \boldsymbol{b}(2) & \cdots & \boldsymbol{b}(i) & \cdots & \boldsymbol{b}(I)\end{bmatrix}^{\mathrm{T}}, \tag{3}$$

where I is the number of sensors. The weight matrix $\mathbf{W}_{pa}$ of the proposed approach is then obtained,

$$\mathbf{W}_{pa}=\mathbf{R}_{pa}{}^{-1}\mathbf{L}(\mathbf{L}^T\mathbf{R}_{pa}{}^{-1}\mathbf{L})^{-1},\ \ \hat{\mathbf{s}}=\mathbf{W}_{pa}{}^T\mathbf{b}\,. \tag{4}$$

$$\mathbf{R}_{pa}=\begin{bmatrix}R_{1,1} & R_{1,2} & \cdots & R_{1,I}\\ R_{2,1} & R_{2,2} & \cdots & R_{2,I}\\ \vdots & \vdots & \ddots & \vdots\\ R_{I,1} & R_{I,2} & \cdots & R_{I,I}\end{bmatrix},\ R_{i,j}=\frac{\boldsymbol{b}(i)\bullet\boldsymbol{b}(j)}{\|\boldsymbol{b}(i)\|_2\cdot\|\boldsymbol{b}(j)\|_2} \tag{5}$$

$\mathbf{R}_{pa}$ is the correlation gram matrix, $\bullet$ is the inner product, $\|\ \|_2$ is the standard L2-norm. $R_{i,j}$ reveals the similarity degree between the ith and the jth sensor measurements.

III. Simulations and Results

The system configuration for the simulations used 151 axial gradiometers on CTF MEG machine. An overlapping spheres model was applied for the forward calculation of the magnetic fields. Gaussian white noise with SNR values (15, 10, 5, 3 dB) was added to MEG sensors to model and represent the range of instrumentation noise. Three extended patch sources were selected on the cortical surface, and three time series *x(t)*, *y(t)* and *z(t)*, according to the following autoregressive model were assigned as activity time series to the patches 1, 2 and 3, respectively.

$$\begin{aligned} x(t) &= 0.6x(t-1) + 0.65y(t-2) \\ y(t) &= 0.5y(t-1) - 0.3y(t-2) - 0.3z(t-4) \\ z(t) &= 0.8z(t-1) - 0.7z(t-2) \end{aligned} \tag{6}$$

The connectivity information of sources revealed by the Granger in network form, shown in Fig. 1, was considered as the underlying source connectivity. The arrow reveals the connectivity direction, source 3 caused 2, and 2 caused 1. The width of each line represents the connectivity magnitude, which means the connectivity strength of source 2 to 1, i.e. 0.4070 is stronger than that of 3 to 2, i.e. 0.1634.

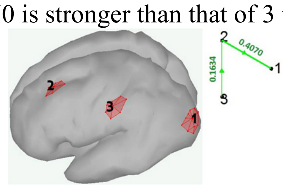

Fig. 1. The underlying source connectivity network.

Three source time series were estimated using inverse techniques, then, the Granger was applied to the estimated source series. Table I shows the reconstructed connectivity network, where "$i \rightarrow j$" represents the connectivity direction from the source i to j. As shown, the underlying connectivity network can be revealed by all three inverse techniques, however, the reconstructed connectivity magnitudes from the proposed approach are in closer agreement with the underlying truth than those from linear estimation or spatial filter.

TABLE I
THE RECONSTRUCTED CONNECTIVITY NETWORK

SNR (dB)	Direction	Connectivity Magnitude		
		Linear Estimation	Spatial Filter	Proposed Method
15	2→1	0.4041	0.3808	0.4015
	3→1	0	0	0
	3→2	0.1530	0.1527	0.1562
10	2→1	0.4102	0.3844	0.4053
	3→1	0	0	0
	3→2	0.1484	0.1529	0.1568
5	2→1	0.4186	0.4121	0.4088
	3→1	0	0	0
	3→2	0.1445	0.1428	0.1572
3	2→1	0.4222	0.4148	0.4087
	3→1	0	0	0
	3→2	0.1427	0.1420	0.1567

In order to examine trends of the resultant connectivity as SNR decreases, The reconstruction error was defined as the L2 norm of the difference between the reconstructed and underlying connectivity. As shown in Table II, for the linear estimation, there is an increase in reconstruction error as SNR decreases. This reflects the direct pattern of noise effect on the source connectivity network reconstruction of linear estimation. At high SNRs (15 and 10 dB) the results of linear estimation are better than those of spatial filter, while at low SNRs (5 and 3 dB) the linear estimation shows worse results than the spatial filter. For the spatial filter, the results at low SNRs are better than those at high SNRs, which shows a somewhat reversed pattern compared to linear estimation. We should point out that the noise cannot influence the source connectivity network reconstruction directly when using the spatial filter. The proposed approach has lower error than linear estimation and spatial filter for all SNRs, also, the error fluctuates within a narrow range. This leads to the fact that the proposed approach can contribute robust abilities to the connectivity reconstruction.

TABLE II
THE ERROR OF RECONSTRUCTED CONNECTIVITY NETWORK

SNR (dB)	L2-Norm Error (10^{-4})		
	Linear Estimation	Spatial Filter	Proposed Method
15	1.17	8.01	0.82
10	2.35	6.21	0.46
5	4.92	4.50	0.42
3	6.57	5.19	0.48

IV. Conclusion

This article described inverse techniques to reconstruct source connectivity network from MEG data, and compared the effectiveness of linear estimation, spatial filtering and proposed approach, on the metrics of the connectivity magnitude and error. We confirmed that the noise effect for linear estimation is direct, while the effect for spatial filter is indirect, moreover, linear estimation is advantageous for connectivity reconstruction of high quality MEG data, while, the benefit for the case of spatial filter is the low SNR environment. This article also proposed a inverse technique to improve the MEG source connectivity network reconstruction. The results indicated that the proposed approach prevents the inclusion of spurious connectivity, enhances the reconstruction accuracy, decreases the error fluctuation, therefore, represents profiles of the original source connectivity network precisely.

V. References

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