Precise Estimation of Correlated Bio-Electromagnetic Activities in Deep Source Space

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Abstract — In this paper, an improved Wiener inverse technique for precisely estimating the correlated bio-electromagnetic activities in the deep source space was proposed. A novel weighting matrix building method obtained from the relationship between the electromagnetic flux densities and the dipole sources was presented, so as to enhance the property representation for the correlated deep sources. The results confirmed that the proposed technique provides more detailed information for the source estimation, improves the result accuracy and is physically more reasonable than the conventional Wiener inverse techniques.

I. Introduction

Magnetoencephalography (MEG) is a common non-invasive human brain mapping technique used to estimate the bio-electromagnetic activities occurring in the source space. The main goal of bio-electromagnetic inverse computation is to accurately localize the activities at a fine time series resolution, and to provide functional information about source dynamics. To solve such a electromagnetic inverse problem, various approaches for estimating spatio-temporal activities have been proposed. Among such approaches, a class of techniques called Wiener inverse filter have been widely used recently. Generally, the Wiener technique requires a weighting matrix to represent the metric associated with the knowledge about locations or relationships of sources. However, this knowledge cannot be determined *a priori* by electromagnetic nondestructive methods, the conventional Wieners have usually assumed that all source activities are completely uncorrelated, which means that relationships between neighboring sources are ignored. When using the inverse techniques, the estimated amplitude for a source at the deep locations is always weaker than actual. Furthermore, the deeper a activity lies and the more it is surrounded by anisotropic sources, the more complex the source relationships influence on the inverse resolution. Therefore, an appropriate relationship should be taken into account when building the weighting matrix to improve the quality of the source estimation. Toward this object, the geometrical information, such as, the Euclidean distance and the three-dimensional geodesic distance of the adjacent sources were used to make the artificial relationship. Indeed, the weighting matrix should be designed in order to reflect the desired property of the sources, in other words, when estimating the temporarily correlated source activities, we should plan this property with respect to the correlation [1]-[4].

This paper proposed an improved Wiener inverse technique with a suggested weighting matrix obtained from the relationship between electromagnetic flux densities and dipole sources so as to reflect the correlation property of sources. The simulation results demonstrated that the proposed approach can estimate the correlated deep sources more precisely than the conventional Wiener inverse techniques.

II. Methods

MEG source reconstruction is an ill-posed inverse problem of the form $\mathbf{b} = \mathbf{L}\mathbf{s}$, where $\mathbf{b}$ is a vector of the MEG sensor measurement, $\mathbf{s}$ is a vector of the unknown source and $\mathbf{L}$ is the leadfield matrix. The expression for inverse operator $\mathbf{W}$ according to Wiener filtering technique is

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

where $\mathbf{R}$ is the weighting matrix and $\mathbf{C}$ is the noise covariance matrix, $\hat{\mathbf{s}}$ is the reconstructed source [5]. In the conventional Wieners, the relationships between the neighboring sources are assumed to be ignored, which means that the weighting matrix is a diagonal matrix. If source can be expected at any location in the source equally, this diagonal matrix become identity matrix. Also, the leadfield weightings can be imposed to each diagonal entry of $\mathbf{R}$ [6], then the weighting matrix is expressed as,

$$\mathbf{R} = \begin{bmatrix} \|\boldsymbol{l}(1)\|_2^2 & 0 & \cdots & 0 \\ 0 & \|\boldsymbol{l}(2)\|_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \|\boldsymbol{l}(J)\|_2^2 \end{bmatrix}, \tag{2}$$

where J is the number of sources, $\|\mathbf{x}\|_2$ is the standard L2-norm of a vector $\mathbf{x}$, $\boldsymbol{l}$ will be explained hereunder.

The output of the ith sensor is denoted as $l_i(j)$ when a single unit-magnitude source exists at the jth volume element of the source space, therefore, $l_i(j)$ indicates the sensitivity of the ith sensor to a source located at the jth volume element. The vector $\boldsymbol{l}(j) = [l_1(j), l_2(j), \cdots, l_I(j)]^T$ expresses the sensitivity of the whole sensor array for the jth source, here I is the number of sensors, and this sensitivity information can be revealed by using the leadfield matrix

$$\mathbf{L} = [\boldsymbol{l}(1) \quad \boldsymbol{l}(2) \quad \cdots \quad \boldsymbol{l}(j) \quad \cdots \quad \boldsymbol{l}(J)]. \tag{3}$$

Physically, close similar $\boldsymbol{l}$s should have larger relationship, and their mutual effects should be taken into account when building the weighting matrix. In this paper, the source relationship is defined as the similarity degree of the sensitivities of the whole sensor array for the neighboring sources, the weighting matrix is expressed as,

$$\mathbf{R} = \begin{bmatrix} R_{1,1} & R_{1,2} & \cdots & R_{1,J} \\ R_{2,1} & R_{2,2} & \cdots & R_{2,J} \\ \vdots & \vdots & \ddots & \vdots \\ R_{J,1} & R_{J,2} & \cdots & R_{J,J} \end{bmatrix}$$

$$R_{i,j} = \frac{\boldsymbol{l}(i) \bullet \boldsymbol{l}(j)}{\|\boldsymbol{l}(i)\|_2 \cdot \|\boldsymbol{l}(j)\|_2}\ , \quad (4)$$

where $\bullet$ stands for the inner product. The $R_{i,j}$ reveals the MEG measurement similarity between the ith and the jth activity sources.

III. Simulations and Results

To evaluate the performance of inverse techniques to estimate sources, we need to know the exact underlying mechanisms inside of a real human brain. Since this information is hard to verify by in vivo experiments, we resorted to a simulation with known source configurations. The system configuration for the simulations used 151 axial gradiometers on CTF MEG machine, and to utilize anatomical information, interface between white and grey matter was extracted from MRI T1 images of an MNI standard brain and tessellated to build the source space. An overlapping spheres model was applied for the forward calculation of the electromagnetic field. Gaussian white noise with the SNR value 10 dB was generated and added to the simulated magnetic recordings. two point sources indicated by small black dots in Fig. 1 were selected within insula in order to represent the locations of the deep source space. Three correlated time series *x(t)*, *y(t)* and *z(t)*, according to the following autoregressive model (5) were generated, and *x(t)* and *y(t)* were assigned to the two point sources, respectively. The correlation degree of the source series *x(t)* and *y(t)* revealed by the Granger connectivity analysis is 0.4904.

$$\begin{aligned} x(t) &= 0.6x(t-1) + 0.65y(t-2) \\ y(t) &= 0.5y(t-1) - 0.3y(t-2) - 0.3z(t-4) \\ z(t) &= 0.8z(t-1) - 0.7z(t-2) \end{aligned} \quad (5)$$

The estimation results as shown in Fig.1 are the magnitude average of the estimated source time series by using different Wiener methods. As can be seen, the left activity source is well localized by all three methods, nevertheless, the proposed Wiener distribution is less extended than those from the two conventional Wieners. For the right activity source, the conventional Wieners produce several ambiguous and spurious activity sources at a considerable distance from the truth, hence the location of the second activity is not found successfully, however, the proposed Wiener seems to be very effective because a focused source is obtained and the true activity is well localized. From the comparison, we can evidently observe that the proposed Wiener technique can precisely estimate the correlated activities in the deep source space.

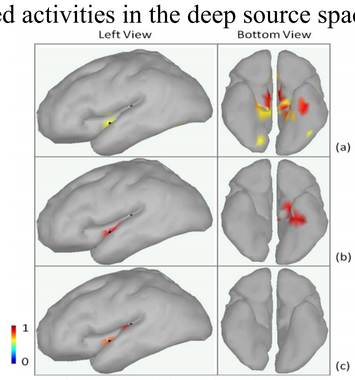

Fig. 1. Estimation results obtained by using the different Wiener methods. Original locations are indicated by small black dots. (a) The conventional Wiener with identity weighting matrix. (b) The conventional Wiener with weighting matrix $\mathbf{R}_s$. (c) The proposed Wiener with weighting matrix $\mathbf{R}_c$.

IV. Conclusion

The Wiener inverse technique proposed in this paper employs the suggested correlation weighting matrix to enhance the representation for profiles of correlated bio-electromagnetic activities located in the deep source space. Based on simulations carried out, we confirmed that the proposed Wiener effectively enlarges the property of the deep sources, provides more detailed information for the source localization, and then improve the final estimation, therefore is physically more reasonable. In this study, the use of the correlation to build the weighting matrix is just an ideal starting point. In fact, revealing the relationship of sources is an active topic in the research community, many methods have been proposed, such as, correlation, synchrony, coherence, Granger causality, etc. Therefore, reasonable use of more sophisticated relationship analysis methods is required for a more efficient and broad application of the proposed Wiener inverse technique in estimating the correlated deep activity sources.

V. References

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