2009 Ninth IEEE International Conference on Bioinformatics and Bioengineering

Beamformer-based Spatiotemporal Imaging of Correlated Brain Activities

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***Abstract*—The past findings have suggested that temporal correlation may relate the communications between the distributed areas. There are some studies in Magnetoencephalography and electroencephalography to analyze the functional connectivity between cortical areas with the oscillations feature of neuronal activity. However, it is also important to observe the functional connectivity through temporal correlation between cortical areas. We proposed a beamformer-based approach which exploits a maximum correlation criterion to maximize the significance level of correlation between brain activities. This criterion leads to a closed-form solution of the dipole orientation. Experiments with simulation data clearly demonstrate the effectiveness, necessity, and accuracy of the proposed method.**

I. Introduction

The past findings have suggested that temporal correlation may relate the communications between the distributed areas. To identify these correlations, millisecond-level of physiological signal measurement is indispensable [1], [2].

Functional magnetic resonance imaging (fMRI) is a very promising approach to investigate the cortico-cortical correlation, but the temporal resolution is insufficient to observe the details of the communications. There are some studies in Magnetoencephalography (MEG) and electroencephalography (EEG) to analyze the functional connectivity between cortical areas with the oscillatory feature of neuronal activity using the analysis tool, dynamic imaging of coherent sources (DICS) [3]. However, there is still no work about investigating the temporal correlation between different cortices. To investigate the temporal correlation between the different cortices, new analysis tools applying on MEG/EEG must be developed.

Nevertheless it is not easy to recover the activity of the cortical region from the recording of MEG/EEG. The so-called inverse problem is a difficult task due to the low signal-to-noise ratio (SNR) and the underlying ill-posed property.

Recently, beamformer is one of the most promising solutions to the inverse problem. [4]. Beamformer performs a spatial filter on recordings of MEG/EEG to filter out the signal at the targeted location, acting as a virtual sensor to measure the signal with a specific orientation. Beamformer can obtain the activities of the targeted location and suppress the influence contributed from other sources by imposing the unit-gain constraint and minimum variance criterion. Given a unit dipole with specified position and orientation, we can calculate a spatial filter from the data covariance matrix and the lead field of the dipole. The neuronal activity of the dipole at the specified position can be obtained by applying this spatial filer on the recordings of MEG/EEG. By repeating the procedure for each position inside the brain, we can obtain the neuronal activities of the whole brain.

There are two kinds of beamformer, vector-type beamformer [5] and scalar-type beamformer [6], [7]. The vector-type beamformer decomposes the dipole orientation into three orthogonal components, each one with a fixed orientation. Every component has its own spatial filter calculated individually. Linearly constrained minimum variance (LCMV) [5] is one of the vector beamformer and it sums the results probed on three directions. There is only one spatial filter used for each specific position in scalar-type beamformer and it determines the direction by maximizing the pseudo Z value. Compared to vector-type beamformer, the major advantage of scalar-type beamformer is that the activity distribution is more focal and higher signal-to-noise ratio [7], [8]. But using vector-type beamformer is more efficient to calculate the spatial filter because all the procedures involved are deterministic.

In the scalar-type beamformer, it is essential to accurately determine the dipole orientation, because it can result in effective spatial filter only when the dipole orientation is accurate [8], [9]. One way to determine the dipole orientation is to use the normal of cortical surface [9]. But the surface reconstruction is very difficult and the reconstruction deviation will decrease the accuracy of dipole orientation. Only when the estimation error is smaller than ten degrees, the spatial filter determined by the cortical surface normal is feasible [9]. Another way to determine the dipole orientation is to maximize the pseudo Z in the synthetic aperture magnetometery (SAM) method [6] by exhaustively evaluating all the possible candidates. Nonlinear optimization method is more efficient, but only can guarantee the suboptimal solution.

Recently, a novel spatial filtering technique, called the maximum contrast beamformer (MCB), was proposed by Chen et al [10]. This MCB method has the advantages of good output SNR and focal activity distribution as in scalar beamformers, while the dipole orientation is determined accurately and efficiently in a close-form solution. The method exploits a maximum-contrast criterion that maximizes the ratio of the

978-0-7695-3656-9/09 $25.00 © 2009 IEEE
DOI 10.1109/BIBE.2009.67

reconstructed neuronal activities in the active state to those in the control state and helps to analytically and accurately determine the dipole orientation in a closed-form manner.

In this paper, we propose a beamforming-based imaging method of correlated brain activities, that allows the studies of the temporal interaction between different brain cortices by imaging correlation and reveal the similarity signal pattern. Our method can analytically and accurately determine the dipole orientation in a close-from manner, and determine the spatial filter efficiently for each targeted position. The correlation map can be calculated to reveal cortical regions with significant similarity to the reference position in the brain.

II. Methods

Our method based on the scalar-type beamformer exploits a maximum-correlation criterion that maximizes the significant level of correlation between the reference and each source signal inside the brain.

A. Scalar beamformer

We define a unit dipole with parameter $\theta = \{\mathbf{r}, \mathbf{q}\}$, where $\mathbf{r}$ is the dipole location, $\mathbf{q}$ is the dipole orientation, and $\mathbf{l}_\theta$ is the lead field vector of the unit dipole. The lead field vector is the predicted measurement of N MEG sensors from a unit dipole with orientation $\mathbf{q}$. The lead field vector $\mathbf{l}_\theta$ is calculated by

$$\mathbf{l}_\theta = \mathbf{L_r}\mathbf{q} \ , \tag{1}$$

where $\mathbf{L_r}$ is the lead field matrix of the unit dipole in location $\mathbf{r}$ and can be derived from the forward model.

The MEG recordings $\mathbf{m}(t)$ is decomposed into three components

$$\begin{aligned} \mathbf{m}(t) &= \mathbf{m}_\theta(t) + \mathbf{m}_\delta(t) + \mathbf{n}(t) \\ &= \mathbf{m}_\theta(t) + \mathbf{m}_n(t) \ , \end{aligned} \tag{2}$$

where $\mathbf{m}(t) = \mathbf{l}_\theta \mathbf{s}_\theta(t)$ denotes the magnetic field originated from the source with parameter θ, $\mathbf{m}_\delta(t)$ denotes the magnetic field originated from all other sources, $\mathbf{n}(t)$ is the noise, and $\mathbf{m}_n(t)$ denotes the combination of the noise and the magnetic recordings originated from all other sources.

Scalar MEG beamformer performs spatial filtering on recordings to separate the signals of the location of interest from others. For a dipole source with parameter θ, the output signal of the beamformer $y(t)$ is obtained by

$$y(t) = {\mathbf{w}_\theta}^t \mathbf{m}(t) \tag{3}$$

which approximates the source signal $s_\theta(t)$ of the dipole. To achieve this goal, the spatial filter $\mathbf{w}_\theta$, an $N \times 1$ column vector, can be decided by the unit-gain constraint and the minimum variance criterion. With these constraints, the strength of output signal $y(t)$ can be identical with the source strength $s_\theta(t)$ while suppressing the contribution of the other sources. By the following equation

$$\begin{aligned} y(t) &= {\mathbf{w}_\theta}^t \mathbf{m}(t) \\ &= {\mathbf{w}_\theta}^t \mathbf{m}_\theta(t) + {\mathbf{w}_\theta}^t \mathbf{m}_n(t) \\ &= s_\theta(t) {\mathbf{w}_\theta}^t \mathbf{l}_\theta + {\mathbf{w}_\theta}^t \mathbf{m}_n(t) \\ &= s_\theta(t) + {\mathbf{w}_\theta}^t \mathbf{m}_n(t) \ , \end{aligned} \tag{4}$$

the source signal $s_\theta(t)$ can be obtained by applying unit-gain costrain, ${\mathbf{w}_\theta}^t \mathbf{l}_\theta = 1$. We still have to reduce the leakage from all other sources, ${\mathbf{w}_\theta}^t \mathbf{m}_n(t)$. This is equivalent to minimize the variance of $y(t)$. Therefore, the optimal spatial filter $\hat{\mathbf{w}}_\theta$ can be calculated by

$$\begin{aligned} \hat{\mathbf{w}}_\theta = \arg\min_{\mathbf{w}_\theta} E\{|y(t) - E\{y(t)\}|^2\} + \alpha \|\mathbf{w}_\theta\|^2 \\ subject \quad to \quad {\mathbf{w}_\theta}^t \mathbf{l}_\theta = 1 \ , \end{aligned} \tag{5}$$

where E represents the expectation value and α represents the parameter of Tikhonov regularization. Here α is a parameter to restrict the norm of $\hat{\mathbf{w}}_\theta$, corresponding to the shape of beamformer spatial filter. Substituting (4) into (5), we can solve the equation by Lagrange multipliers and obtain the optimal solution of $\hat{\mathbf{w}}_\theta$:

$$\begin{aligned} \hat{\mathbf{w}}_\theta &= \arg\min_{\mathbf{w}_\theta} {\mathbf{w}_\theta}^t (\mathbf{C} + \alpha \mathbf{I}) \mathbf{w}_\theta \quad subject \quad to \quad {\mathbf{w}_\theta}^t \mathbf{l}_\theta = 1 \\ &= \frac{(\mathbf{C} + \alpha \mathbf{I})^{-1} \mathbf{l}_\theta}{{\mathbf{l}_\theta}^t (\mathbf{C} + \alpha \mathbf{I})^{-1} \mathbf{l}_\theta} \ , \end{aligned} \tag{6}$$

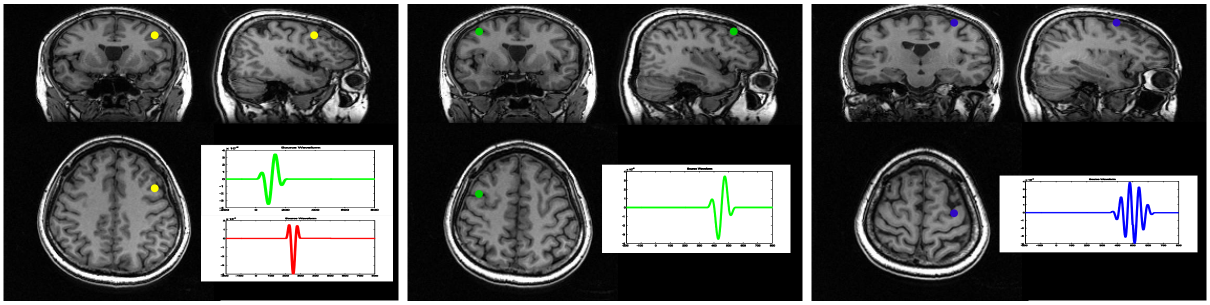
where $\mathbf{C}$ is the $N \times N$ covariance matrix of the MEG recordings $m(t)$ and $\mathbf{I}$ is the $N \times N$ identity matrix.

B. Imaging of the brain activities correlated to the reference signal

For each dipole source in location $\mathbf{r}$ with fixed orientation $\mathbf{q}$, we can use (6) to obtain the spatial filter, and further compute the dipole activity by using (3). Once we apply the procedure mentioned above individually to each position of head region, we can obtain the activities of the whole brain.

Although there are many origins of activities in brain, we aim to focus on correlated brain activities. In other words, what we want to reveal is only some specific brain activities. Through the spatial filter calculated by the conventional methods, we may obtain strong non-targeted activities in the filtered outputs. Therefore, we propose a method to reveal the imaging of the brain activities correlated to the targeted signal. In contrast to the original beamforming methods which provide statistical maps to reveal the regions having significant neuronal activities, we calculated the correlation between the source signal and the targeted one:

$$\begin{aligned} R_\theta &= \frac{E\{|{\mathbf{w}_\theta}^t \mathbf{m}(t) \mathbf{a}(t)|\}}{E\{|{\mathbf{w}_\theta}^t \mathbf{m}(t)|^2\}^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \\ &= \frac{\{{\mathbf{w}_\theta}^t E\{|\mathbf{m}(t)\mathbf{a}(t)|^2\} \mathbf{w}_\theta\}^{\frac{1}{2}}}{\{{\mathbf{w}_\theta}^t \mathbf{C}_m \mathbf{w}_\theta\}^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \\ &= \frac{\{{\mathbf{w}_\theta}^t \mathbf{C}_{am} {\mathbf{C}_{am}}^t \mathbf{w}_\theta\}^{\frac{1}{2}}}{\{{\mathbf{w}_\theta}^t \mathbf{C}_m \mathbf{w}_\theta\}^{\frac{1}{2}} E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \ , \end{aligned} \tag{7}$$



(a) (b) (c)

Fig. 1. Dipole sources of simulation data contain (a) the first two sources at yellow location with different temporal activities (in red and green), (b) another source at green location with the same temporal activities as the green one at (a), and (c) the last source at the blue location with the temporal activities in blue.

where $\mathbf{a}(t)$ is the targeted signal given by users. The value of R_θ indicates the significant level of similarity between the dipole activity with parameter θ and the targeted signal.

The solution of $\hat{\mathbf{w}}_\theta$ is derived with parameter $\theta = \{\mathbf{r}, \mathbf{q}\}$. To obtain the activities of the whole brain, the proposed method scans through the whole brain by setting the position parameter $\mathbf{r}$ to each position within the brain area. But the orientation parameter $\mathbf{q}$ is difficult to determine. Instead of the exhaustive search, we propose a closed-form solution to determine the dipole orientation. By substituting (1) to (6), we obtain:

$$\begin{aligned}\hat{\mathbf{w}}_\theta &= \frac{(\mathbf{C}+\alpha\mathbf{I})^{-1}\mathbf{L}_\mathbf{r}\mathbf{q}}{\mathbf{q}^t\mathbf{L}_\mathbf{r}^t(\mathbf{C}+\alpha\mathbf{I})^{-1}\mathbf{L}_\mathbf{r}\mathbf{q}} \\ &= \frac{\mathbf{A}_\mathbf{r}\mathbf{q}}{\mathbf{q}^t\mathbf{B}_\mathbf{r}\mathbf{q}} \ , \end{aligned} \tag{8}$$

where $\mathbf{A}_\mathbf{r} = (\mathbf{C}+\alpha\mathbf{I})^{-1}\mathbf{L}_\mathbf{r}$ and $\mathbf{B}_\mathbf{r} = \mathbf{L}_\mathbf{r}^t\mathbf{A}_\mathbf{r}$ depend only on the parameter position $\mathbf{r}$. We determine the optimal dipole orientation $\hat{\mathbf{q}}$ which can maximize the correlation between the source signal s_θ and the targeted signal:

$$\begin{aligned}\hat{\mathbf{q}} &= \arg\max_{\mathbf{q}} \left(\frac{(\mathbf{w}_\theta{}^t\mathbf{C}_{am}\mathbf{C}_{am}{}^t\mathbf{w}_\theta)^{\frac{1}{2}}}{(\mathbf{w}_\theta{}^t\mathbf{C}_m\mathbf{w}_\theta)^{\frac{1}{2}}E\{|\mathbf{a}(t)|^2\}^{\frac{1}{2}}} \right)^2 \\ &= \arg\max_{\mathbf{q}} \frac{\mathbf{q}^t\mathbf{A}_\mathbf{r}^t\mathbf{C}_{am}\mathbf{C}_{am}{}^t\mathbf{A}_\mathbf{r}\mathbf{q}}{\mathbf{q}^t\mathbf{A}_\mathbf{r}^t\mathbf{C}_m\mathbf{A}_{\mathbf{r}_\mathbf{q}}\mathbf{q}} \\ &= \arg\max_{\mathbf{q}} \frac{\mathbf{q}^t\mathbf{P}_\mathbf{r}\mathbf{q}}{\mathbf{q}^t\mathbf{Q}_\mathbf{r}\mathbf{q}} \ , \end{aligned} \tag{9}$$

where $\mathbf{C}_{am}$ is the $N \times 1$ cross-covariance matrix between the targeted signal $a(t)$ and the MEG recordings $m(t)$, $\mathbf{C}_m$ is the $N \times N$ covariance matrix of the MEG recordings $m(t)$, and $\mathbf{P}_\mathbf{r} = \mathbf{A}_\mathbf{r}{}^t\mathbf{C}_{am}\mathbf{C}_{am}{}^t\mathbf{A}_\mathbf{r}$ and $\mathbf{Q}_\mathbf{r} = \mathbf{A}_\mathbf{r}{}^t\mathbf{C}_m\mathbf{A}_\mathbf{r}$ are both 3×3 matrices. The solution of (9) is the eigenvector corresponding to the maximum eigenvalue of the matrix $\mathbf{Q}_\mathbf{r}^{-1}\mathbf{P}_\mathbf{r}$.

III. Experiments

We performed experiments to verify the proposed method described in Section II and to evaluate the location accuracy of correlated sources. The magnetic signals were simulated according to the 204 planar gradiometers of a whole-head neuromagnetometer (Vectorview system, Neuromag Ltd., Finland).

Four dipole sources with temporal profiles of sinusoidal were located in three position inside the brain, as shown in Figure 1. Strengths of the red, green, and blue profiles are all 40 nAm. The profile in the green position is as the red profile at yellow position with 350 ms delay. The orientation of each of the four dipoles was arbitrarily set on the plane tangential to the head sphere. We used (2) to compute the simulated MEG signals induced from the four dipole sources, as well as additive background noises from 3000 random dipoles with the standard deviation of 25 nAm.

We applied independent component analysis on the simulated measurements to extract components (Figure 2) and manually selected four components C1, C2, C3, and C4. Then we calculated and imaged the correlation distribution between each of the selected component and brain activities by (7) as shown in Figure 3. The correlation map of the estimated source is focal and significant, and the source localization error is 0 mm for all chosen components.

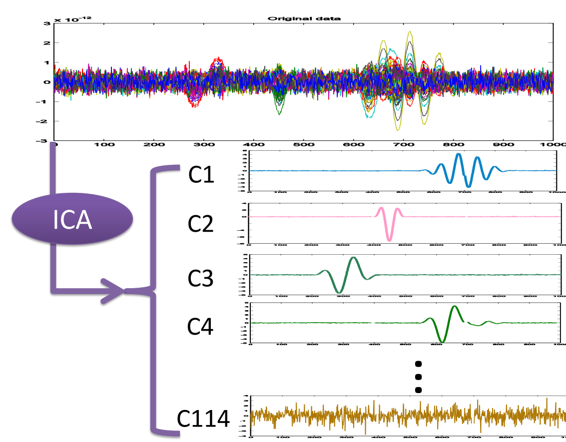
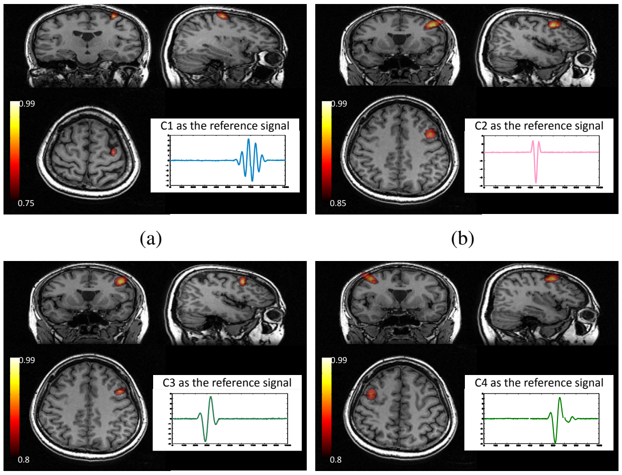


Fig. 2. The simulated data was decomposed by ICA into 114 components.

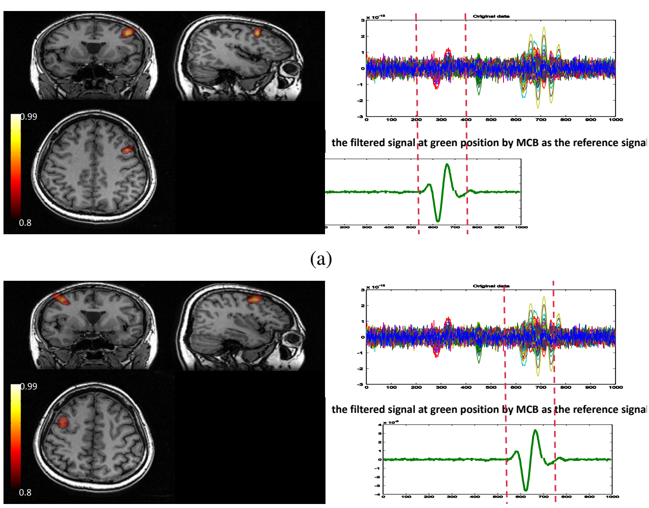
We applied MCB on the simulated recordings to calculate



(a) (b) (c) (d)

Fig. 3. The correlation map calculated with the reference signal (a) C1, (b) C2, (c) C3, and (d) C4.

the F-statistic maps which reveal cortical regions with significant difference of activities between the active and control states. Then we chose the filtered signal at the highest F value position from 350 to 550 ms interval as the reference signal. Then we calculated the correlation map between the reference signal and brain activities at different time interval. Figure 4(a) shows the corelation map from 0 to 200 ms, and Figure 4(b) shows the map from 350 to 550 ms. It is obviously that both maps match the dipole locations at the corresponding time interval.

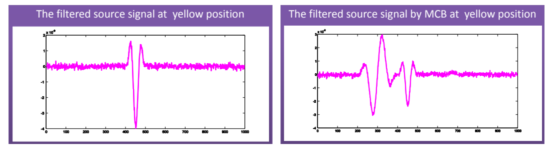


(a) (b)

Fig. 4. The correlation maps calculated with the reference signal filtered by MCB at different time intervals within (a) [0, 200] ms and (b) [350, 550] ms.

IV. Discussion and Conclusions

The result in Figure 5(a) is the reconstructed signal at the highest correlation position when we used C2 as the reference signal. The filtered signal is similar to reference signal even there are two source signals at the position. When we used the conventional source localization technique, we can reconstruct the signal containing two sources. The Figure 5(b) is the result calculated by MCB. The reconstructed signal is not similar to what we focus on, that is why we need to develop the proposed method to reveal the correlated level according to a specified reference. The reference can be a component decomposed by ICA, a cortical activities inside the brain, or the peripheral signal such as EMG measurement.



(a) (b)

Fig. 5. (a) The filtered signal at the yellow position obtained by our method (b) The filtered signal in the yellow position obtained by MCB.

In this work, we have proposed a beamformer-based imaging approach to map the correlated brain activities. The maximum correlation criterion helps to estimate a spatial filter efficiently that can maximize the significance level of correlation between brain activities.

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