RECONSTRUCTING SPATIO-TEMPORAL ACTIVITIES OF NEURAL SOURCES FROM MAGNETOENCEPHALOGRAPHIC DATA USING A VECTOR BEAMFORMER

Kensuke Sekihara[1,2], Srikantan Nagarajan[3], David Poeppel[4], Yasushi Miyashita[1]

[1] *JST Mind Articulation Project, Yushima4-9-2, Bunkyo, Tokyo 113-0034, Japan*
[2] *Tokyo Metropolitan Institute of Technology, Hachioji, Tokyo 191-0065, Japan*
[3] *Bioengineering Department, University of Utah, Salt Lake City, UT 84112-9202*
[4] *Department of Linguistics, University of Maryland, College Park, MD 20472*

ABSTRACT

We have developed a method suitable for reconstructing spatio-temporal activities of neural sources using MEG data. Our method is based on an adaptive beamformer technique. It extends a beamformer originally proposed by Borgiotti and Kaplan to a vector beamformer formulation in which three sets of weight vectors are used to detect the source activity in three orthogonal directions. The weight vectors of this vector-extension of the Borgiotti-Kaplan beamformer are then projected onto the signal subspace of the measurement covariance matrix to obtain a final form of the proposed beamformer's weight vectors. Our numerical experiments demonstrated the effectiveness of the proposed beamformer.

1. INTRODUCTION

Among the various kinds of functional neuroimaging methods, the major advantage of magnetoencephalography (MEG) is its ability to provide fine time resolution in order of milliseconds [1]. Neuromagnetic imaging can thus be used both for visualizing neural activities across different regions as well as for providing information about brain dynamics. For successful use of this technology, efficient algorithms for reconstructing spatio-temporal source activities need to be developed. In this paper, we explore the possibility of applying a class of techniques called adaptive beamforming to spatio-temporal reconstruction of the neural-source activities.

Adaptive-beamforming techniques were originally developed in the fields of array signal processing [2], and has already been applied to the MEG/EEG source-localization problems [3][4][5]. In these applications, however, the reconstruction of source activities at each instant in time was not emphasized; instead, a time-averaged reconstruction of the source activities was obtained. In this paper, we develop a beamformer technique suitable for reconstructing source activities at each instant in time, thus enabling the four-dimensional spatio-temporal reconstruction of the source activities. Our proposed beamformer is based on a vector extension of the Borgiotti-Kaplan beamformer [6], further extending the basic formulation to incorporate the eigenspace projection [7]. The results of our computer simulations demonstrate the superiority of the proposed method over the previously proposed methods.

2. METHOD

2.1. Definitions and problem formulation

Let us define the magnetic field measured by the mth sensor at time t as $b_m(t)$, and a column vector $\boldsymbol{b}(t) = [b_1(t), b_2(t), \ldots, b_M(t)]^T$ as a set of measured data where M is the total number of sensors and the superscript T indicates the matrix transpose. A spatial location (x, y, z) is represented by a three-dimensional vector $\boldsymbol{r}$: $\boldsymbol{r} = (x, y, z)$. The source moment magnitude at $\boldsymbol{r}$ and time t is defined as a three-dimensional vector $\boldsymbol{s}(\boldsymbol{r}, t)$. We define the lead field vector for the jth sensor as $\boldsymbol{l}_j(\boldsymbol{r}) = [l_j^x(\boldsymbol{r}), l_j^y(\boldsymbol{r}), l_j^z(\boldsymbol{r})]$. Here, $l_j^x(\boldsymbol{r})$, $l_j^y(\boldsymbol{r})$, and $l_j^z(\boldsymbol{r})$ are the jth sensor readings caused when a single source exists at $\boldsymbol{r}$ with the unit moment directed in the x, y, and z directions, respectively. This lead field vector $\boldsymbol{l}_j(\boldsymbol{r})$ represents the sensitivity of the jth sensor. We define the lead field matrix, which represents the sensitivity of the whole sensor array, as $\boldsymbol{L}(\boldsymbol{r})$ where its jth row is equal to $\boldsymbol{l}_j(\boldsymbol{r})$.

Using these definitions, the relationship between the measured magnetic field and the source moment is expressed as

$$\boldsymbol{b}(t) = \int \boldsymbol{L}(\boldsymbol{r})\boldsymbol{s}(\boldsymbol{r}, t)d\boldsymbol{r}. \quad (1)$$

The problem of the source localization is the problem of obtaining the reasonable estimate of $\boldsymbol{s}(\boldsymbol{r}, t)$ from the array measurement $\boldsymbol{b}(t)$.

2.2. Vector-minimum-variance beamformer

A vector beamformer technique estimates the source moment by applying the following simple linear operation,

$$\hat{\boldsymbol{s}}(\boldsymbol{r},t)=\boldsymbol{W}^T(\boldsymbol{r})\boldsymbol{b}(t). \qquad (2)$$

Here, $\hat{\boldsymbol{s}}(\boldsymbol{r},t)$ is the source moment estimate. The matrix $\boldsymbol{W}$ consists of three column weight vectors,

$$\boldsymbol{W}=[\boldsymbol{w}_x,\boldsymbol{w}_y,\boldsymbol{w}_z], \qquad (3)$$

where the weight vectors, $\boldsymbol{w}_x$, $\boldsymbol{w}_y$, and $\boldsymbol{w}_z$, respectively, detects the x, y, and z components of the source moment $\boldsymbol{s}(\boldsymbol{r},t)$, hence a "vector" beamformer. A minimum-variance beamformer can be extended to this vector form by imposing the following constraints on the weight vectors [3][4],

$$\begin{aligned}
&\boldsymbol{w}_x^T\boldsymbol{l}_x(\boldsymbol{r})=1, \quad \boldsymbol{w}_x^T\boldsymbol{l}_y(\boldsymbol{r})=0, \quad \boldsymbol{w}_x^T\boldsymbol{l}_z(\boldsymbol{r})=0,\\
&\boldsymbol{w}_y^T\boldsymbol{l}_x(\boldsymbol{r})=0, \quad \boldsymbol{w}_y^T\boldsymbol{l}_y(\boldsymbol{r})=1, \quad \boldsymbol{w}_y^T\boldsymbol{l}_z(\boldsymbol{r})=0,\\
&\boldsymbol{w}_z^T\boldsymbol{l}_x(\boldsymbol{r})=0, \quad \boldsymbol{w}_z^T\boldsymbol{l}_y(\boldsymbol{r})=0, \quad \boldsymbol{w}_z^T\boldsymbol{l}_z(\boldsymbol{r})=1. \qquad (4)
\end{aligned}$$

The weight vectors can then be expressed as

$$[\boldsymbol{w}_x^T,\boldsymbol{w}_y^T,\boldsymbol{w}_z^T]=\boldsymbol{R}_b^{-1}\boldsymbol{L}(\boldsymbol{r})[\boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}_b^{-1}\boldsymbol{L}(\boldsymbol{r})]^{-1}[\boldsymbol{f}_x,\boldsymbol{f}_y,\boldsymbol{f}_z], \qquad (5)$$

where $\boldsymbol{f}_x=[1,0,0]^T$ $\boldsymbol{f}_y=[0,1,0]^T$, and $\boldsymbol{f}_z=[0,0,1]^T$.

We encounter two serious difficulties when using this beamformer for spatio-temporal reconstruction of neural activities from actual MEG/EEG data. First, the beamformer output has erroneously large values near the center of the sphere used for the forward calculation. This is because $\|\boldsymbol{L}(\boldsymbol{r})\|$ becomes very small when $\boldsymbol{r}$ approaches the center of the sphere. Second, the output of this beamformer is significantly noisy and its performance is very sensitive to errors in calculating the lead field matrix. In the following section, we propose a beamformer that is free from these two problems.

2.3. Formulation of the proposed beamformer

A two-step procedure is involved in the derivation of the proposed beamformer weight vectors. In the first step, the weight vectors are derived from the following constraints,

$$\begin{aligned}
&\boldsymbol{w}_x^T\boldsymbol{w}_x^T=1, \quad \boldsymbol{w}_x^T\boldsymbol{l}_y(\boldsymbol{r})=0, \quad \boldsymbol{w}_x^T\boldsymbol{l}_z(\boldsymbol{r})=0,\\
&\boldsymbol{w}_y^T\boldsymbol{l}_x(\boldsymbol{r})=0, \quad \boldsymbol{w}_y^T\boldsymbol{w}_y^T=1, \quad \boldsymbol{w}_y^T\boldsymbol{l}_z(\boldsymbol{r})=0,\\
&\boldsymbol{w}_z^T\boldsymbol{l}_x(\boldsymbol{r})=0, \quad \boldsymbol{w}_z^T\boldsymbol{l}_y(\boldsymbol{r})=0, \quad \boldsymbol{w}_z^T\boldsymbol{w}_z^T=1. \qquad (6)
\end{aligned}$$

The resulting weight vectors are expressed as

$$\boldsymbol{w}_\mu=\frac{\boldsymbol{R}_b^{-1}\boldsymbol{L}(\boldsymbol{r})[\boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}_b^{-1}\boldsymbol{L}(\boldsymbol{r})]^{-1}\boldsymbol{f}_\mu}{\sqrt{\boldsymbol{f}_\mu^T\boldsymbol{\Omega}\boldsymbol{f}_\mu}}, \qquad (7)$$

where $\mu=x,y$, or z, and

$$\boldsymbol{\Omega}=[\boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}_b^{-1}\boldsymbol{L}(\boldsymbol{r})]^{-1} \cdot \boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}_b^{-2}\boldsymbol{L}(\boldsymbol{r})[\boldsymbol{L}^T(\boldsymbol{r})\boldsymbol{R}_b^{-1}\boldsymbol{L}(\boldsymbol{r})]^{-1}.$$

We define $\boldsymbol{e}_j$ as a eigenvector corresponding to a signal-level eigenvalue of $\boldsymbol{R}_b$, and a matrix $\boldsymbol{E}_S$ as the matrix whose columns consist of the signal-level eigenvectors such that $\boldsymbol{E}_S=[\boldsymbol{e}_1,\ldots,\boldsymbol{e}_P]$. In the second step, the final weight vector for the proposed beamformer, $\bar{\boldsymbol{w}}_\mu$, is derived by projecting the weight vector $\boldsymbol{w}_\mu$ onto the signal subspace of the measurement covariance matrix,

$$\bar{\boldsymbol{w}}_\mu=\boldsymbol{E}_S\boldsymbol{E}_S^T\boldsymbol{w}_\mu. \qquad (8)$$

The projection onto the signal subspace using the above equation, however, cannot preserve the null constraints imposed on the orthogonal components in (6) [8]. Nevertheless, the proposed beamformer obtained using Eqs. (7 – (8) can detect the three components of the source moment even though the null constraints are not preserved, as shown below.

Let us assume that a single source exists at $\boldsymbol{r}$. Then, the magnetic field $\boldsymbol{b}(t)$ is expressed as $\boldsymbol{b}(t)=[\eta_x\boldsymbol{l}_x(\boldsymbol{r})+\eta_x\boldsymbol{l}_y(\boldsymbol{r})+\eta_z\boldsymbol{l}_z(\boldsymbol{r})]s(t)$, where $[\eta_x,\eta_y,\eta_z]$ expresses the orientation of this source, and $s(t)$ is its moment time course. Then, the estimated x component of the source moment, $\hat{s}_x(t)$, is obtained using

$$\hat{s}_x(t)=\bar{\boldsymbol{w}}_x^T\boldsymbol{b}(t)=\boldsymbol{w}_x^T\boldsymbol{E}_S\boldsymbol{E}_S^T (\eta_x\boldsymbol{l}_x(\boldsymbol{r})+\eta_x\boldsymbol{l}_y(\boldsymbol{r})+\eta_z\boldsymbol{l}_z(\boldsymbol{r}))s(t). \qquad (9)$$

Because the vector $(\eta_x\boldsymbol{l}_x(\boldsymbol{r})+\eta_x\boldsymbol{l}_y(\boldsymbol{r})+\eta_z\boldsymbol{l}_z(\boldsymbol{r}))$ is in the signal subspace, the relationship,

$$\boldsymbol{E}_S\boldsymbol{E}_S^T(\eta_x\boldsymbol{l}_x(\boldsymbol{r})+\eta_x\boldsymbol{l}_y(\boldsymbol{r})+\eta_z\boldsymbol{l}_z(\boldsymbol{r})) =(\eta_x\boldsymbol{l}_x(\boldsymbol{r})+\eta_x\boldsymbol{l}_y(\boldsymbol{r})+\eta_z\boldsymbol{l}_z(\boldsymbol{r})), \qquad (10)$$

holds, and, thus, we finally get

$$\hat{s}_x(t)=\boldsymbol{w}_x^T(\eta_x\boldsymbol{l}_x(\boldsymbol{r})+\eta_x\boldsymbol{l}_y(\boldsymbol{r})+\eta_z\boldsymbol{l}_z(\boldsymbol{r}))s(t) \propto \eta_x s(t). \qquad (11)$$

We can also obtain $\hat{s}_y(t)=\bar{\boldsymbol{w}}_y^T\boldsymbol{b}(t)\propto\eta_y s(t)$ and $\hat{s}_z(t)=\bar{\boldsymbol{w}}_z^T\boldsymbol{b}(t)\propto\eta_z s(t)$ in exactly the same manner. Thus, the eigenspace-projection beamformer in Eq. (8) can detect the three components of the source moment, even though the null constraints are not preserved. This beamformer improves the output SNR without sacrificing the spatial resolution. Our numerical experiments will show that the eigenspace projection is almost essential to obtain the source-activity reconstruction at each instant in time.

2.4. Extension to a prewhitened eigenspace-projection beamformer

In real-life situations, MEG data usually contains interference arising from background brain activities. Often, such activities overlap the signal activities of interest, and make the interpretation of source-estimation results difficult. Such interference is known to cause spatially non-white noise in neuromagnetic measurements, and if the information on the noise covariance matrix is available, the influence of the interference can be significantly reduced by using the spatial prewhitening technique [9].

The extension from the eigenspace projection beamformer to a prewhitened eigenspace projection beamformer is straightforward. Let us define the noise covariance matrix as $\boldsymbol{R}_n$. Let us also denote $\widetilde{\lambda}_j$ and $\widetilde{\boldsymbol{e}}_j$, respectively, as an eigenvalue and a corresponding eigenvector obtained by solving the generalized eigenvalue problem,

$$\boldsymbol{R}_b \widetilde{\boldsymbol{e}}_j = \widetilde{\lambda}_j \boldsymbol{R}_n \widetilde{\boldsymbol{e}}_j, \tag{12}$$

The signal subspace projector $\widetilde{\boldsymbol{E}}_S \widetilde{\boldsymbol{E}}_S^T$ can then be obtained using the matrix $\widetilde{\boldsymbol{E}}_S = [\widetilde{\boldsymbol{e}}_1, \widetilde{\boldsymbol{e}}_2, \ldots, \widetilde{\boldsymbol{e}}_{P'}]$. The prewhitened eigenspace beamformer weight can be obtained using

$$\widetilde{\boldsymbol{w}}_x = \widetilde{\boldsymbol{E}}_S \widetilde{\boldsymbol{E}}_S^T \boldsymbol{w}_x,\ \widetilde{\boldsymbol{w}}_y = \widetilde{\boldsymbol{E}}_S \widetilde{\boldsymbol{E}}_S^T \boldsymbol{w}_y, \text{ and } \widetilde{\boldsymbol{w}}_z = \widetilde{\boldsymbol{E}}_S \widetilde{\boldsymbol{E}}_S^T \boldsymbol{w}_z. \tag{13}$$

3. NUMERICAL EXPERIMENTS

We conducted numerical experiments to show the effectiveness of the proposed beamformer. A coil alignment of the 37-channel Magnes™ biomagnetic measurement system (Biomagnetic Technologies Inc., San Diego) was used for these simulations. Three sources were assumed to exist on a plane. Here, the first and second sources were the sources of interest, and the third source was considered background interference. The coordinate system and the source-sensor configuration are depicted in Fig. 1. The source moment time-course of the three sources are also shown in this figure.

The results of the spatio-temporal reconstruction obtained using the previously-proposed vector minimum-variance beamformer in Eq. (5) are shown in Fig. 2. Here, to avoid the artifacts caused by the variation of $\|\boldsymbol{L}(\boldsymbol{r})\|$, the normalized lead field is used [4]. Contour maps in the left-hand side indicate the distributions of the source-moment magnitude $|\hat{s}(t)|$ on the source-existing plane at the three time instants of 220, 268, and 300 ms. The estimated time courses at the pixels nearest to the three source locations are shown in the right-hand side. These results show that the spatio-temporal reconstruction obtained using the weight vectors from Eq. (5) was significantly noisy.

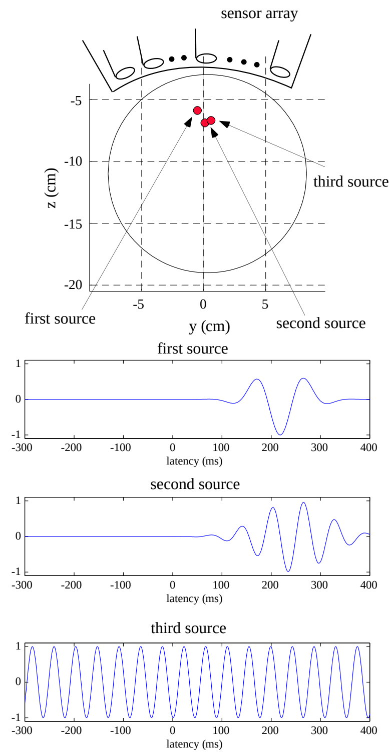

Figure 1: Source-sensor configuration and source time courses assumed in the numerical experiments

The results of the application of the proposed beamformer to the same computer-generated data set are shown in Fig. 3. These results show that this beamformer technique not only improves the SNR considerably but also improves the spatial resolution. We also applied the prewhitened eigenspace-projection beamformer of Eq. (13) to test its effectiveness in removing the influence of the background activity. The noise covariance matrix was calculated using the computer-generated data in the prestimulus time window from -300 ms to 0 ms. The results are shown in Fig. 4. These results clearly show that the influence of the third source was removed, and demonstrate the effectiveness of the proposed prewhitened beamformer.

4. REFERENCES

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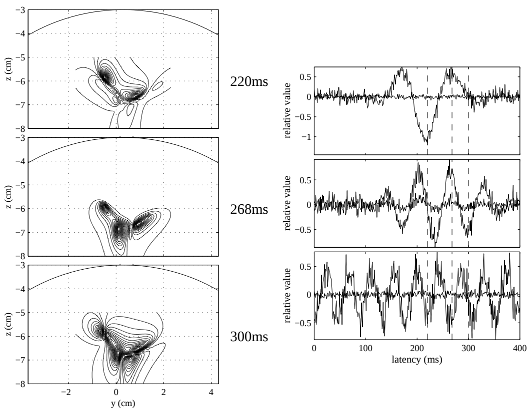

Figure 2: Results of the source reconstruction experiments for previously-proposed vector minimum-variance beamformer.

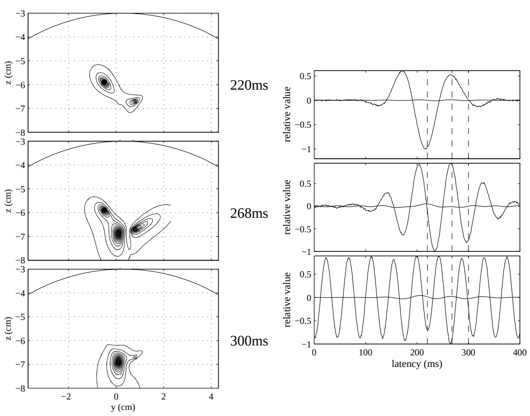

Figure 3: Results of the source reconstruction experiments for proposed vector beamformer technique.

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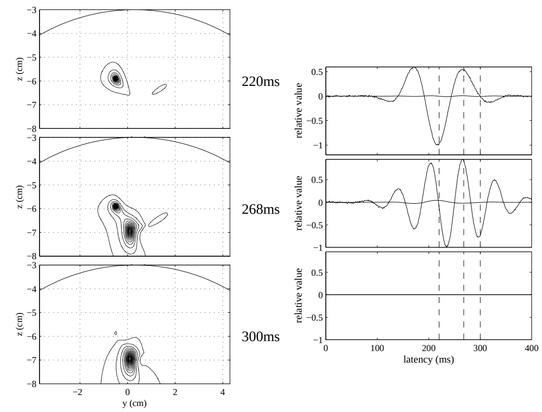

Figure 4: Results of the source reconstruction experiments for proposed prewhitened beamformer technique.

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