LOCALIZATION AND EXTRACTION OF BRAIN ACTIVITY USING GENERALIZED EIGENVALUE DECOMPOSITION

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ABSTRACT

In this paper, a generalized eigenvalue decomposition (GEVD)-based approach is proposed to remove continuous interferences included in MEG observations. The GEVD-based approach can be interpreted as a general framework of pre-whitening that can be combined with various types of signal separation techniques such as principal component analysis (PCA), independent component analysis (ICA) or adaptive beamforming (ABF). An example of extracting movement-related brain activities from single trial data is presented.

Index Terms— MEG, localization, extraction, GEVD

1. INTRODUCTION

It is of great interest to localize and extract stimuli or movement-related brain activities. These target activities are usually buried in various spontaneous activities and the signal-to-noise ratio (SNR) is very low. If the spatial statistics of interference signals such as covariance between the sensors are known in advance, the interference can be effectively removed from the observation by spatial filtering. Such process is termed "pre-whitening," and has been studied in various research fields. In the field of brain imaging, Sekihara *et al.* [1] proposed a combined approach of pre-whitening and adaptive beamformer (ABF). In this paper, a pre-whitening method based on generalized eigenvalue decomposition (GEVD) is examined. The GEVD-based approach was first introduced in the source localization for radar and sonar by Roy *et al.* [2] and was further developed for separation/enhancement of acoustic signals by Doclo *et al.* [3] and Asano *et al.* [4]. In Section 3, a GEVD-based method for the localization and extraction of brain activities is developed and then applied to the magnetoecephalography (MEG) measurements in Section 4.

2. DATA MODEL

Let us denote the observation at MEG sensors as $\mathbf{x}(t) = [x_1(t), \cdots, x_M(t)]^T$, where M indicates the number of sensors. By using the dipole model of the brain electrical activity [5], the observation can be written as

$$\mathbf{x}(t) = \mathbf{A}\mathbf{q}(t) = \sum_{i=1}^{L} \mathbf{a}(\mathbf{r}_i) q(\mathbf{r}_i, t) \tag{1}$$

where $\mathbf{A} = [\mathbf{a}_1, \cdots, \mathbf{a}_L]$ is termed the lead-field matrix. The vector $\mathbf{r}_i = [x_i, y_i, z_i, \Theta]$ is the location vector where $[x_i, y_i, z_i]$ denotes the three-dimensional location of the dipole while $\Theta = \{\theta, \varphi, p\}$ denotes the first and the second tangential and the radial components [6]. The source $q(\mathbf{r}_i, t)$ denotes a single component of the dipole moment corresponding to $\mathbf{r}_i$.

In this paper, it is assumed that the observation consists of the following three components: 1) movement or stimulus-related activities (signals of interest, $q_S(\mathbf{r}_i, t)$) with short duration $\Psi = [T_1, T_2]$; 2) continuous activities throughout the observation (interference, $q_I(\mathbf{r}_j, t)$); and 3) sensor noise ($\mathbf{n}(t)$) [1]. Based on this, the observation $\mathbf{x}(t)$ can be rewritten as

$$\begin{aligned} \mathbf{x}(t) &= \sum_{i=1}^{L_S} \mathbf{a}_S(\mathbf{r}_i) q_S(\mathbf{r}_i, t) + \sum_{j=1}^{L_I} \mathbf{a}_I(\mathbf{r}_j) q_I(\mathbf{r}_j, t) + \mathbf{n}(t) \\ &= \mathbf{x}_S(t) + \mathbf{x}_I(t) + \mathbf{n}(t) \end{aligned} \tag{2}$$

The signal source $q_S(\mathbf{r}_i, t)$ is assumed to be zero for $t \notin \Psi$.

3. GEVD APPROACH

3.1. Generalized Eigenvalue Decomposition

Let us denote the covariance of the observation as

$$\begin{aligned} \mathbf{K} &= E\left[\mathbf{x}(t)\mathbf{x}^T(t)\right], \text{ for } t \notin \Psi \\ \mathbf{R} &= E\left[\mathbf{x}(t)\mathbf{x}^T(t)\right], \text{ for } t \in \Psi \end{aligned} \tag{3}$$

GEVD of $\mathbf{K}$ and $\mathbf{R}$ is defined as

$$\mathbf{R}\mathbf{e}_m = \lambda_m \mathbf{K}\mathbf{e}_m \tag{4}$$

where λ_m and and $\mathbf{e}_m$ denote the eigenvalue and eigenvector, respectively. The eigenvectors of GEVD have the following joint diagonalization property:

$$\mathbf{E}^T\mathbf{K}\mathbf{E} = \mathbf{I} \tag{5}$$
$$\mathbf{E}^T\mathbf{R}\mathbf{E} = \mathbf{\Lambda} \tag{6}$$

where $\mathbf{\Lambda} = \mathrm{diag}[\lambda_1, \ldots, \lambda_M]$ and $\mathbf{E} = [\mathbf{e}_1, \cdots, \mathbf{e}_M]$. Equation (5) indicates the whitening effect of interference in which the variance (power) of interference is reduced to “1”. Equation (4) is equivalent to the following standard eigenvalue decomposition (SEVD):

$$\left(\mathbf{K}^{-T/2}\mathbf{R}\mathbf{K}^{-1/2}\right)\mathbf{f}_m = \lambda_m \mathbf{f}_m \tag{7}$$

The eigenvectors $\mathbf{e}_m$ and $\mathbf{f}_m$ have the following relation [7]:

$$\mathbf{e}_m = \mathbf{K}^{-1/2}\mathbf{f}_m \tag{8}$$

3.2. Localization

The estimation of a spatial spectrum using the GEVD approach was introduced by [2]. When the MUSIC method [8] is used , the spatial spectrum is given by

$$P(\mathbf{r}) = \frac{\mathbf{a}^T(\mathbf{r})\mathbf{a}(\mathbf{r})}{|\mathbf{a}^T(\mathbf{r})\mathbf{E}_N|^2} \tag{9}$$

where $\mathbf{E}_N$ denotes the eigenvectors of GEVD corresponding to the noise subspace as $\mathbf{E}_N = [\mathbf{e}_{L_S+1}, \cdots, \mathbf{e}_M]$. Due to the pre-whitening effect of GEVD, the interferences included in the noise segments ($t \notin \Psi$) are reduced and only the signals of interest are localized.

3.3. Pre-whitening filter

The GEVD-based signal separation/enhancement was proposed by [3, 4]. According to [3], the optimal filter for signal enhancement is given by

$$\mathbf{y}(t) = \mathbf{W}\mathbf{x}(t)$$
$$\mathbf{W} = \mathbf{E}^{-T}\mathbf{G}\mathbf{E}^T \tag{10}$$

$\mathbf{E}^T$, the first term, projects the observation $\mathbf{x}(t)$ into the eigenspace spanned by the eigenvectors $\mathbf{E}$. Also, $\mathbf{E}^T$ reduces the interference by the whitening effect (5). $\mathbf{G} = \mathrm{diag}[\mathrm{g}_1, \cdots, \mathrm{g}_\mathrm{M}]$, the second term, imposes gain on each subspace. In [3], the Wiener filter-based gain was employed. The alternative gain which extracts the signal subspace [4] is defined as

$$\mathbf{g} = [g_1, \cdots, g_M] = [\overbrace{1, \cdots, 1}^{L_S}, 0, \cdots, 0] \tag{11}$$

$\mathbf{E}^{-T}$, the third term, projects the signal processed in the eigenspace back into the observation space. The output $\mathbf{y}(t)$ becomes the estimate of the observation contributed mainly by the signal sources $q_S(\mathbf{r}_i, t)$, i.e., $\mathbf{y}(t) \simeq \mathbf{x}_S(t)$.

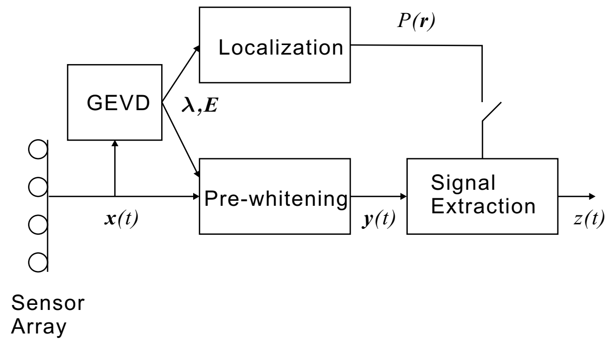

Fig. 1. Block diagram of the proposed GEVD-based localization and signal extraction system.

3.4. Extraction of source signal

Once the pre-whitened observation $\mathbf{y}(t)$ is obtained, various types of signal separation/extraction techniques such as ABF, PCA and ICA can be applied to $\mathbf{y}(t)$ to extract or enhance a certain component from a mixture of L_S signals.

As an example of the supervised signal separation techniques, the minimum variance (MV) ABF is given by

$$z_{MV}(\mathbf{r}, t) = \mathbf{h}^T\mathbf{y}(t) \tag{12}$$
$$\mathbf{h} = \frac{\mathbf{C}^{-1}\mathbf{a}(\mathbf{r})}{\mathbf{a}^T(\mathbf{r})\mathbf{C}^{-1}\mathbf{a}(\mathbf{r})} \tag{13}$$

where $\mathbf{C}$ is the covariance of $\mathbf{y}(t)$ as

$$\mathbf{C} = E\left[\mathbf{y}(t)\mathbf{y}^T(t)\right], \text{ for } t \in \Psi \tag{14}$$

The advantage of the supervised method is that the activity at a certain point $\mathbf{r}$ of the brain can be extracted. The drawback is that a precise model of the electro-magnetic field $\mathbf{a}(\mathbf{r})$ must be provided.

As an example of unsupervised signal separation techniques, the filter for extracting the nth principal component using PCA is given by

$$z_{PCA}(n, t) = \mathbf{d}_n^T\mathbf{y}(t) \tag{15}$$

where $\mathbf{d}_n$ is the nth eigenvector of $\mathbf{C}$. The advantage of the unsupervised method is that no prior knowledge of the brain is required. The drawback is that the estimation of the source location of the extracted signal is difficult.

3.5. Entire system

Figure 1 shows the entire signal processing system. First, GEVD is applied to the MEG observation $\mathbf{x}(t)$ to obtain the eigenvalues and eigenvectors. Using these, pre-whitening filter is constructed and the observation is processed with this filter. The signal of interest $z(t)$ is then extracted from the pre-whitened observation $\mathbf{y}(t)$. When using a supervised extraction method such as ABF, the location of the source of interest can be estimated using GEVD-based localization.

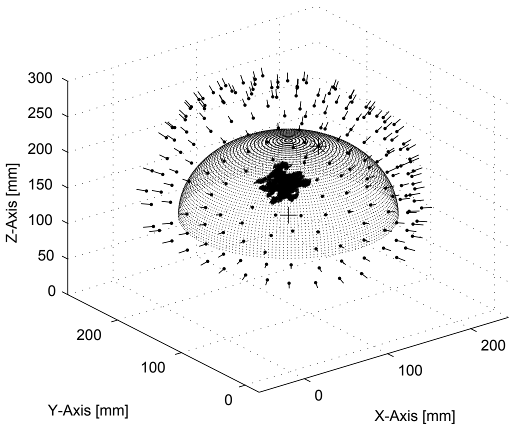

Fig. 2. Location of the MEG sensors and the scanning surface for localization. The dark region on the surface is "ROI" in fMRI measurements.

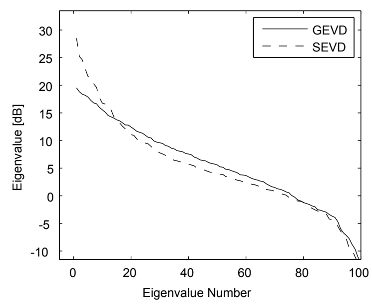

Fig. 3. Eigenvalue distribution of $\mathbf{R}$. The eigenvalues with higher orders ($m > 100$) are omitted.

4. EXPERIMENTS

4.1. Conditions

The observation was obtained using 208-channel MEG sensors. Brain activities during the movements of a hand of a subject (the game of 'paper, stone and scissors') were measured. Figure 2 shows the locations of sensors and the scanning surface for localization (hemisphere with a diameter of 105 mm). In this figure, the region of interest (ROI), which is the active brain region for fMRI measurements when the same movement of hand is conducted, is also depicted.

4.2. Results

Figure 3 shows the eigenvalue distribution of $\mathbf{R}$. By comparing the eigenvalues of GEVD and SEVD, it can be seen that the eigenvalues with lower orders (up to around 10) were reduced for the case of GEVD. Since the eigenvalue distribution reflects the spatial power distribution of sources, this can be interpreted to mean that the powers of the interferences $q_I(\mathbf{r}_i, t)$ are larger than that of the target signals $q_S(\mathbf{r}_i, t)$ and that the lower order eigenvalues of SEVD mainly contain the

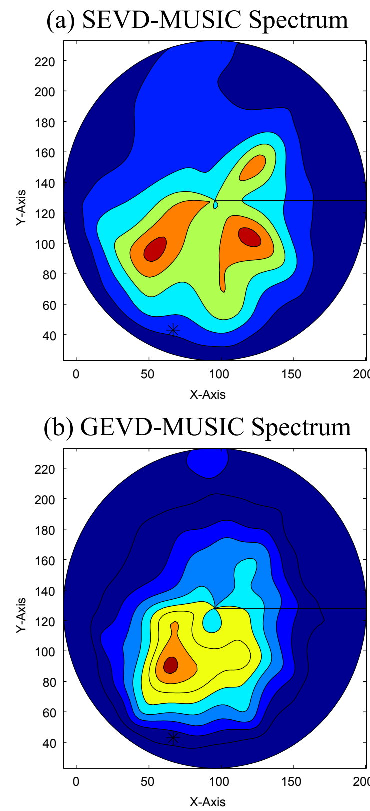

Fig. 4. Spatial spectrum obtained using the MUSIC method.

power of interferences. This power of interferences was reduced by the whitening effect of GEVD.

Figure 4 shows the spatial spectrum obtained by using the MUSIC method. For the sake of comparison, eigenvectors of SEVD and GEVD were used to calculate (9). When SEVD was employed, three regions on the surface were highlighted. For the case of GEVD, on the other hand, two of them vanished and a single region remained. This is also due to the whitening effect.

Figure 5 shows one of the sensor observation, $x_m(t)$, and the GEVD filter output, $y_m(t)$. The sensor $m = 160$, which is empirically known to show a high correlation with hand movement, was chosen. Figure 5(a) shows the sensor observation $x_m(t)$ for a single trial, while (b) shows the observation averaged over 30 trials $\overline{x_m(t)}$. The onset of the target signal is shown by the vertical dotted line in (a). From this, movement-related brain activity can be seen in the averaged observation. In (c), which shows the GEVD filter output $y_m(t)$, it can be seen that the signals in the period [1,1500] ($t \notin \Psi$) were reduced by the whitening effect. However, the signal for $t \in \Psi$ ([1501,2000]) is still somewhat noisy compared with that of (b). By averaging $y_m(t)$ over multiple trials, the movement-related activity was considered to be extracted more clearly, as shown in (d).

Figure 6 shows the final output of the system $z(t)$. Fig-

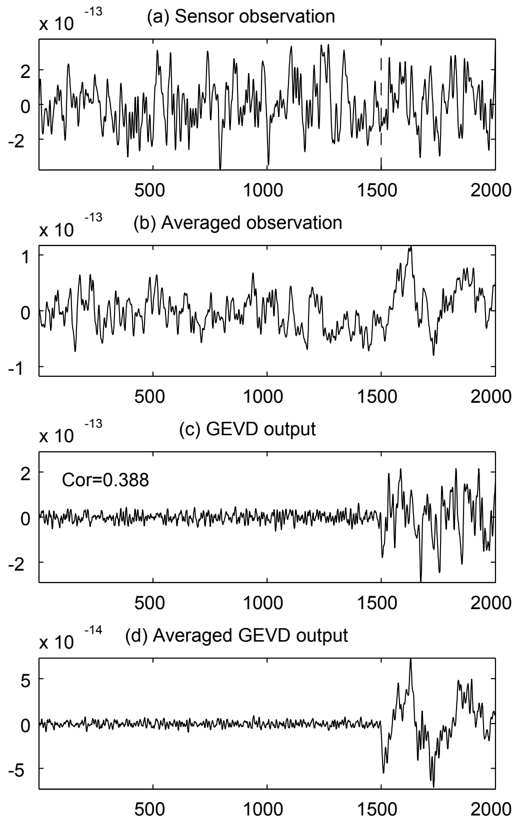

Fig. 5. Observed and estimated sensor signals. (a) Observed sensor signal $x_m(t)$; (b) averaged sensor signal $\overline{x_m(t)}$; (c) the output of the GEVD filter $y_m(t)$; (d) the averaged output of the GEVD filter $\overline{y_m(t)}$.

ure 6(a) shows the case for MV-ABF while (b) shows the case for PCA. For MV-ABF, the focal point $\mathbf{r}$ is chosen so that the spatial spectrum $P(\mathbf{r})$ is the largest. In this particular example, both MV-ABF and PCA yielded waveforms similar to that of the averaged GEVD output $\overline{y_m(t)}$ shown in Fig.5(d).

5. DISCUSSION AND CONCLUSION

In this paper, a method of pre-whitening of MEG observation using GEVD is proposed. From (10) and (8), it is obvious that the pre-whitening filter "$\mathbf{\Pi}_S$" proposed in [1] is a special form of the GEVD approach with the gain $\mathbf{g} = [\lambda_1, \cdots, \lambda_L, 0, \cdots, 0]$. In this sense, the proposed method is a generalization of pre-whitening in which an arbitrary gain function $\mathbf{g}$ can be used. GEVD-based localization and extraction of the brain activity was applied to the MEG observation and it was shown that the movement-related brain activity could be extracted from single trial data. The next step of this study is to apply the proposed approach to the automatic classification of brain activities.

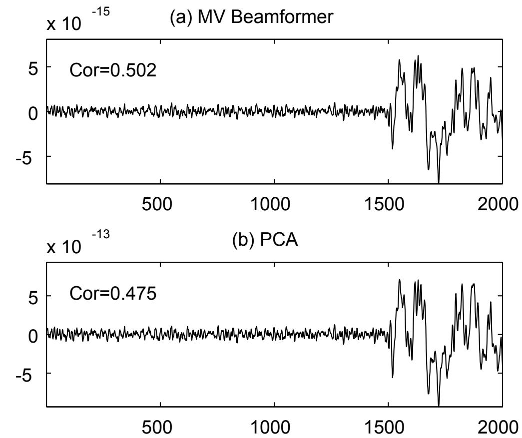

Fig. 6. The extracted brain signal $z(t)$. (a) the output of the MV beamformer $z_{MV}(\mathbf{r}, t)$; (b) that of PCA $z_{PCA}(1, t)$. The value "Cor" indicates the correlation coefficient with $\overline{y_m(t)}$ (Fig.5(d)).

6. ACKNOWLEDGMENT

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