ABSTRACT

This paper introduces two novel beamforming algorithms, namely the Region Constrained and Multiple Correlated Source Model beamformers, designed to localize and to reconstruct highly correlated brain sources from noisy EEG data. Multiple correlated source simulations have been performed to evaluate the performance of the proposed algorithms, using a realistic 176 × 240 × 256 finite difference head model. Our simulation results show that the Region Constrained-Multiple Correlated Source Model beamformer, obtained by combining the above two beamformers, allows us to localize three perfectly correlated brain sources with very high localization accuracy. Finally, the eigenspace version of this beamformer can be used to reconstruct three correlated brain source signals correctly from simulated noisy EEG data.

Index Terms— Beamformer, beamforming algorithm, EEG, FDM, forward model.

1. INTRODUCTION

Electroencephalography (EEG) inverse source imaging has been widely used to study brain functions and to monitor neural activities [1]. The recorded EEG signals have been used to localize and to reconstruct the brain sources [1], typically represented as electric current dipoles. Numerous inverse solution techniques have been studied in the past [1]. Each of these techniques relies on its own assumptions and constraints to localize the sources. Among them is the beamforming approach that has been explored as a possible way to improve the spatial accuracy of source imaging [2, 3, 4, 5, 6, 7]. A beamformer is essentially a spatial filter that can be applied to any location in the brain. By suppressing the effects of sources at all other places, a beamformer allows us to estimate the source at that particular spatial location from a segment of EEG signals.

There are two major types of beamforming algorithms: 1) scalar beamformers in which the dipole orientation is assumed to be fixed and estimated separately, and 2) vector beamformers that estimate the three dipole components simultaneously. Three major scalar beamformers were proposed in the past, namely the scalar minimum variance beamformer (S-MVB) [8], the scalar weight normalized minimum variance beamformer (S-WNMVB) and the scalar standardized minimum variance beamformer (S-SMVB) [9]. As for the vector beamformers, the most common one is the vector minimum variance beamformer or linearly constrained minimum variance beamformer (LCMV), which was first proposed in [2]. Later, the unit-noise power vector beamformer or vector Borgiotti-Kaplan beamformer (V-BKB) was introduced in [10], where it was shown to perform better than LCMV.

The above five algorithms will be hereafter referred to as the “regular” beamformers. Like other inverse algorithms, these beamformers have their own drawbacks [11] because they are based on the assumption that brain sources are temporally and spatially uncorrelated. In reality this assumption is seldom satisfied, which in turn leads to errors in source localization and reconstruction, especially when there is a large correlation between the sources or background interference.

To improve the performance of the above beamformers, a number of techniques with different additional constraints were developed. These can be classified into two main categories: 1) using additional temporal information of brain sources to further constrain the solution and 2) exploiting the spatial information of brain sources as the constraint. The specific approaches proposed are: 1) eigenspace beamformer [4]; 2) prewhitening beamforming [12]; 3) synthetic aperture magnetoencephalography (SAM) [3]; 4) null constrained beamformer [6]; 5) Backus-Gilbert resolution spread function-constrained and fMRI-guided spatial filter [11]; 6) dynamic imaging of coherent sources (DICS) [5]; 7) dual-core beamformer (DCB) [13].

The motivation of this work arises from the need for a better beamformer for localizing and reconstructing highly cor-
2. NOVEL BEAMFORMING ALGORITHMS

2.1. Multiple correlated source model beamformer (MC-SMB)

Assuming we have $K$ totally correlated sources, so the cross-correlation between any two sources is perfect or $\frac{s_j^T s_k}{s_k^T s_k} = 1$. The simulated EEG signals are computed as

$$\mathbf{m} = g_1 s_1 + \ldots + g_K s_K + \mathbf{n}$$

(1)

$$= \left( \sum_{k=1}^{K} \lambda_k g_k \right) s_o + \mathbf{n}$$

(2)

where $\mathbf{m}$ are the EEG signals, $s_k = \lambda_k s_0$ represents the $k$th source, $g_k = L_k v_k$ is the corresponding gain vector, with $L_k$ and $v_k$ corresponding to the lead field matrix and the source orientation, respectively. Here, $g = \sum_{k=1}^{K} \lambda_k g_k = \left[ L_1, \ldots, L_K \right] \begin{bmatrix} \lambda_1 v_1 \\ \vdots \\ \lambda_k v_k \end{bmatrix} = L \mathbf{v}$ and the additive noise, $\mathbf{n}$, is Gaussian white noise. The composite optimum orientation $\mathbf{v}$ for a scalar beamformer can be found by optimizing the output power or the output SNR of S-MVB, as described in [3]. This beamformer is the generalization of the dual-core beamformers, which has been recently introduced in [13].

2.2. Region constrained (RC) beamformer

For this beamformer the covariance matrix is modified as

$$\mathbf{R}_r = \mathbf{R} + \beta \mathbf{S} + \gamma^2 \mathbf{I}$$

(3)

where $\alpha$ and $\beta$ are the scale factors, $\mathbf{S} = \mathbf{GAG}^T$, $\mathbf{G}$ is the lead field matrix of the constrained region, $\mathbf{A}$ is the weight matrix which can be obtained according to the location of the constrained region (1 for nodes belonging to the region of interest and 0 otherwise), and $\gamma^2$ is the diagonal loading factor. The procedure to modify the covariance matrix is similar to what has been described in [11].

Algorithm 1: The iterative framework for the MCSM beamformer

1: $L_0 = \text{NULL}$
2: for $k = 1$ to NSOURCE do
3: Compute the normalized output power of SMVB, $P_{out} = \lambda_{max} \left( \mathbf{G}^T \mathbf{G}, \mathbf{G}^T \mathbf{R}^{-1} \mathbf{G} \right)$, for every node inside the region of interest where $\mathbf{G} = [L_k, L_0]$, $L_k$ is the lead field matrix of the current node, and $\lambda_{max}$ is the maximum generalized eigenvalue.
4: Find the global maximum of the resulting tomographic map.
5: Update $L_0$: $L_0 = [L_0, L_k]$, where $L_k$ is the lead field matrix for the global maximum location.
6: end for

3. RESULTS

In this study, we simulate 3 brain sources to imitate the physiological distribution of spontaneous brain activity. The first two sources at 12 Hz are located in the frontal cortex and in intraparietal sulcus. The third source, also at 12 Hz, is located in the sensorimotor hand area. The coherence between these 3 sources is 1, so they are perfectly correlated, and amplitudes of the three sources are $3 \mu A, 5 \mu A$ and $1 \mu A$, respectively. To make the simulation more realistic, Gaussian white noise is added with $SNR = 4$ dB.

Figure 1, 2 and 3 show the output of S-MVB, SAM and LCMV. We can see clearly that the tomographic maps of these related brain sources. Here, we propose the multiple correlated source model and region constrained beamforming algorithms, which our simulation results show are promising in solving the highly correlated source problem.

The proposed beamforming algorithms are described in the next section. In the results section, the performance of the new algorithms are evaluated in more realistic conditions with 3 perfectly correlated brain sources and additive Gaussian white noise. The studies are carried out using a $176 \times 240 \times 256$ head model with a resolution of $1 \text{mm} \times 1 \text{mm} \times 1 \text{mm}$ and 6 tissues, constructed from an anatomical MR image using the FMRIB Software Library (FSL). We have developed the Finite Difference Neuroelectromagnetic Head Modeling Software (FNS) to collect all the required forward solutions for an 128-electrode array.

In the following sections, lower case Greek letters represent scalars, lower bold case Roman letters represent column vectors, and upper bold case Greek or Roman letters represent matrices.
Fig. 4: The output tomographic maps of MCSMB

Fig. 5: The output tomographic maps of RC-MCSMB

According to Algorithm 1 in section 2.1, each correlated brain source needs to be identified separately using a recursive framework. Assuming the number of brain sources (NSOURCE) is known in advance, we break the whole process into NSOURCE steps. The tomographic map obtained from the $k^{th}$ step is used to detect the $k^{th}$ source, which is located at the global maximum in the map. In our simulation study, we have 3 simulated sources, thus 3 steps are required. The output tomographic maps obtained from these steps are given in Figure 4. By using MCSMB we can localize all 3 simulated brain sources with localization errors of 10.6 mm, 5.1 mm and 24 mm, respectively. As we can see, the output map of the third source is spread out because its power is much smaller than that of the first and second sources. The localization error of the third source is still large (24 mm). To reduce this localization error, we combine the RC and MCSM beamformers to form the Region Constrained-Multiple Correlated Source Model Beamformer (RC-MCSMB). Here, we assume the activated regions are known, given by spheres centered at the simulated source locations with a radius of 30 mm. The steps described in Algorithm 1 are followed, with the covariance matrix $R$ replaced by $R + \lambda G_iG_i^T$, where $G_i$ is the lead field matrix of the activation region, and the regularized parameter is given by $\lambda = \frac{2\sigma_{\max}(R)}{\sigma_{\max}(GG^T)}$. Using RC-MCSMB we can identify the three brain sources with corresponding localization errors of 4.6 mm, 1.7 mm and 1.4 mm. The activated regions are shown in Figure 5.

In the source reconstruction study, we assume the locations of 3 brain sources are known. Once the EEG signals have been generated, we then use them to reconstruct the brain sources at their original locations. Figure 6 and 7 show the 3 reconstructed sources for the different beamformers studied. It can be seen very clearly that reconstructed sources of S-MVB, SAM and LCMV are very noisy and distorted, and their amplitudes are much smaller than those of the original sources. The output of MCSMB is similar to the
original sources, however, they are still noisy. If we apply the eigenspace projection to MCSMB, then the reconstructed signals of this new beamformer are improved. However, the amplitudes of the reconstructed sources are reduced by about 20%.

4. CONCLUSIONS

The region constrained beamformer is proposed which allows us to incorporate the knowledge of brain source regions into the beamformer design. The multiple correlated source model beamformer is also introduced. This beamformer can identify 3 perfectly correlated sources in the multiple source study. Most importantly, the combination of the region constrained and multiple correlated source model beamformers can identify 3 perfectly correlated brain sources with very high localization accuracy and reconstruction quality. This finding is significant as no beamformer has been able to identify more than 2 correlated sources with high localization accuracy in the past.

5. REFERENCES