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Comparison of beamformers for EEG source signal reconstruction

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ABSTRACT

Recently, several new beamformers have been introduced for reconstruction and localization of neural sources from EEG and MEG. Although studies have compared the accuracy of beamformers for localization of strong sources in the brain, a comparison of new and conventional beamformers for time-course reconstruction of a desired source has not been previously undertaken. In this study, 8 beamformers were examined with respect to several parameters, including variations in depth, orientation, magnitude, and frequency of the simulated source to determine their (i) effectiveness at time-course reconstruction of the sources, and (ii) stability of their performances with respect to the input changes. The spatial and directional pass-bands of the beamformers were estimated via simulated and real EEG sources to determine spatial resolution. White-noise spatial maps of the beamformers were calculated to show which beamformers have a location bias. Simulated EEG data were produced by projection via forward head modelling of simulated sources onto scalp electrodes, then superimposed on real background EEG. Real EEG was recorded from a patient with essential tremor and deep brain implanted electrodes. Gain – the ratio of SNR of the reconstructed time-course to the input SNR – was the primary measure of performance of the beamformers.

Overall, minimum-variance beamformers had higher Gains and superior spatial resolution to those of the minimum-norm beamformers, although their performance was more sensitive to changes in magnitude, depth, and frequency of the simulated source. White-noise spatial maps showed that several, but not all, beamformers have an undesirable location bias.

1. Introduction

Electroencephalography (EEG) and magnetoencephalography (MEG) are noninvasive tools for functional brain imaging using scalp recording. Compared with other common tools for brain functional imaging such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET), which measure relatively slow changes in blood flow and metabolic activity which are indirect markers of brain electrical activity, EEG and MEG measure brain electrical activity with millisecond temporal resolution. This advantage provides opportunities for studies of highly dynamic and transient neural activity. In recent years, brain source imaging and reconstruction from continuous and single-trial EEG/MEG data have received increased attention aimed at improving the understanding of rapidly changing brain dynamics [1–3] and using this for improved real-time brain monitoring, brain computer interface (BCI), and neurofeedback [4–6]. In contrast, EEG and MEG have poor spatial resolution relative to fMRI and PET. This is, in part, due to EEG and MEG mostly reflecting the electrical activity of the cortical grey matter, with deeper brain activities attenuated and contributing considerably less to the EEG/MEG signals. The beamformer provides a versatile form of spatial filtering,

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suitable for processing data from an array of sensors [7]. Beamformers were originally applied in array signal processing including sonar, radar, and seismic exploration [8]. The basic principle of beamformer design is to allow the neuronal signal of interest to pass through in a certain source location and orientation, called a pass-band, while suppressing noise or unwanted signal in other locations or orientations, called a stop-band [9]. A major limitation of beamformers is that they cannot properly reconstruct two spatially separate but temporally-correlated sources [9–11]; for example, they cancel each other when spatially far from each other or merge when they are spatially placed close to each other [9].

In recent years, new beamformers have been introduced for brain source localization and signal reconstruction from EEG and MEG [7,9,12,13]. The performances of these beamformers have mostly been evaluated in terms of accuracy for source localization of strong electric/magnetic signals, such as epileptogenic spikes [10,14], auditory evoked potentials [7,13,15], and median-nerve evoked potentials [9]. Aside from source localization, the application of beamformers to signal reconstruction of predefined regions of interest (ROI) in the brain is gaining increased attention in neuroimaging laboratories and is a common process in applications of EEG and MEG [16]. Examples of such ROIs are the motor cortex for BCI [17], intracerebral current flow for neurofeedback [16], or any region in the brain found to have consistent changes in activity via functional imaging techniques such as fMRI or PET. However, a comparison of several new and conventional beamformers for time-course reconstruction of a desired source has not been previously undertaken.

Beamformers applied to EEG or MEG fall into two categories: (A) scalar beamformers, which reconstruct the source time-course via a single output, and (B) vector beamformers which, reconstruct the source time-course in 3 orthogonal directions. For scalar beamformers, the orientation of the brain source can be estimated via techniques such as grid search [18,19], whereas vector beamformers do not require orientation of brain sources as they reconstruct the source time-series in 3 orthogonal time-courses. There are two methods for implementation of vector beamformers which are discussed in [20]. In the first method, the vector beamformer is a single beamformer with 3 orthogonal outputs, as applied in [10]. In the second implementation, the vector beamformer is made of 3 scalar beamformers in the 3 orthogonal directions as in [9,21].

In the current study, we investigated the performance of 8 beamformers: (1) minimum-variance (MV) (also known as distortionless minimum-variance [12]), (2) weight-normalized minimum-variance (WNMV) [12] (also known as Borgiotti–Kaplan [7,22]), (3) standardized minimum-variance (SMV) [12], (4) eigenspace extension of the minimum-variance (ESMV) [23], (5) higher-order covariance matrix of minimum-variance (HOC) [9], (6) generalized sidelobe canceller form of quiescent beamformer (GSC) [24], (7) standardized low-resolution electromagnetic tomography (sLORETA) [25], and (8) array-gain constraint minimum-norm with recursively updated Gram matrix (AGMN-RUG) [13]. *Gain*, defined as the ratio of the input signal-to-noise ratio (SNR) to that of reconstructed time-course SNR, was used to quantify the performance of the beamformers in the ROI, with respect to changes in source parameters of depth, orientation, magnitude, and frequency. Spatial and directional pass-bands were provided to show the spatial resolution of the beamformers. White-noise spatial maps of the beamformers were obtained by back-projection of the white noise to the source-space via beamformers to determine which beamformers have a location bias. For the most part, the scalar beamformers were applied to determine the performance of the beamformers with respect to changes in the input parameters and the spatial resolution.

Throughout this paper, plain italics indicate scalars, lower-case boldface italics indicate vectors, and upper-case boldface italics indicate matrices. Subscript b refers to assumed location or orientation of the source and subscript d refers to actual location or orientation of the source. The Frobenius norm was used to obtain the norm of the matrices and vectors.

2. Beamformer algorithms

The reconstructed source time-series $\hat{s}(t, \boldsymbol{r}_b, \boldsymbol{q}_b)$ from the EEG for a scalar beamformer is

$$\hat{s}(t, \boldsymbol{r}_b, \boldsymbol{q}_b) = \boldsymbol{w}^T(\boldsymbol{r}_b, \boldsymbol{q}_b)\boldsymbol{b}(t), \tag{1}$$

where $\boldsymbol{r}_b = [r_{bx}, r_{by}, r_{bz}]^T$ (mm) and $\boldsymbol{q}_b = [q_{bx}, q_{by}, q_{bz}]^T$ are the assumed source location and orientation respectively for calculation of the beamformer weight vector, $\| \boldsymbol{q}_b \| = 1$, $\boldsymbol{w}(\boldsymbol{r}_b, \boldsymbol{q}_b)$ is the weight vector for the scalar beamformer, and $\boldsymbol{b}(t) = [b_1(t), b_2(t), \ldots, b_M(t)]^T$ is the measured EEG data on M electrodes at time t. Each beamformer has its own formulation of $\boldsymbol{w}(\boldsymbol{r}_b, \boldsymbol{q}_b)$.

For a vector beamformer the reconstructed time-course can be written as

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

In the above implementation, the vector beamformer is a single beamformer with 3 orthogonal outputs, as shown in [10]. A second implementation is shown in [9]:

$$\hat{\boldsymbol{s}}_\mu(t, \boldsymbol{r}_b) = \boldsymbol{w}_\mu^T(\boldsymbol{r}_b)\boldsymbol{b}(t), \quad \mu = x, y, z. \tag{3}$$

Similar to [20], we call the first implementation a 3-D vector beamformer and the second implementation a 3-scalar vector beamformer.

Spatial filters can also be divided into two main families: minimum-variance and minimum-norm based spatial filters. In this study the MV, WNMV, SMV, HOC and ESMV beamformers belong to the minimum-variance family of spatial filters whereas GSC, sLORETA, and AGMN-RUG beamformers belong to the minimum-norm family of spatial filters. The minimum-variance spatial filters seek an adaptive solution for the minimization of the reconstructed source power. For the scalar beamformers, and without the loss of generality, this can be expressed as

$$\boldsymbol{w}(\boldsymbol{r}_b, \boldsymbol{q}_b) = arg\,\min_{\boldsymbol{w}(\boldsymbol{r}_b, \boldsymbol{q}_b)}(\boldsymbol{w}^T(\boldsymbol{r}_b, \boldsymbol{q}_b)\boldsymbol{C}\boldsymbol{w}(\boldsymbol{r}_b, \boldsymbol{q}_b)) \tag{4}$$

subject to

$$\begin{aligned} &\boldsymbol{w}^T(\boldsymbol{r}_b, \boldsymbol{q}_b)\boldsymbol{l}(\boldsymbol{r}_b, \boldsymbol{q}_b) = 1 \quad \text{for MV, ESMV, and HOC,} \\ &\boldsymbol{w}^T(\boldsymbol{r}_b, \boldsymbol{q}_b)\boldsymbol{w}(\boldsymbol{r}_b, \boldsymbol{q}_b) = 1 \quad \text{for WNMV,} \\ &\boldsymbol{w}^T(\boldsymbol{r}_b, \boldsymbol{q}_b)\boldsymbol{l}(\boldsymbol{r}_b, \boldsymbol{q}_b) = (\boldsymbol{l}^T(\boldsymbol{r}_b, \boldsymbol{q}_b)\boldsymbol{C}^{-1}\boldsymbol{l}(\boldsymbol{r}_b, \boldsymbol{q}_b))^{1/2} \quad \text{for SMV,} \end{aligned} \tag{5}$$

and

$$\boldsymbol{l}(\boldsymbol{r}_b, \boldsymbol{q}_b) = \boldsymbol{L}(\boldsymbol{r}_b)\boldsymbol{q}_b. \tag{6}$$

$\boldsymbol{L}(\boldsymbol{r}_b) = [\boldsymbol{l}_x(\boldsymbol{r}_b), \boldsymbol{l}_y(\boldsymbol{r}_b), \boldsymbol{l}_z(\boldsymbol{r}_b)]$ mm is $M \times 3$ lead-field matrix which gives the sensitivities of M EEG sensors for an assumed source location at $\boldsymbol{r}_b$ and $\boldsymbol{C}$ is the covariance matrix of EEG channels

$$\boldsymbol{C} = \langle \boldsymbol{b}(t)\boldsymbol{b}^T(t) \rangle, \tag{7}$$

where $\langle \ldots \rangle$ is the ensemble average. Since the minimum-variance beamformers require the inverse of the covariance matrix $\boldsymbol{C}^{-1}$, a problem may arise when the $\boldsymbol{C}$ is not full rank. Brookes et al. [26] have suggested using a long window (i.e., as long as possible) of sensor data for calculation of $\boldsymbol{C}$, which helps $\boldsymbol{C}$ retain its full rank and obtain a better spatial resolution. However, using a long window of sensor data increases the risk of including the artefacts which happen frequently during recordings. Alternatively, when the use of a long window is not possible or the input SNR is high then $\boldsymbol{C}$ will not be a full rank matrix and the regularized inverse is suggested $(\boldsymbol{C} + \gamma \boldsymbol{I})^{-1}$ instead of $\boldsymbol{C}^{-1}$, where $\boldsymbol{I}$ is the unitary matrix,