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Modified Beamspace Method for the Spatial Filtering of Magnetoencephalographic Data

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INTRODUCTION

Magnetoencephalography (MEG) and electroencephalography (EEG) are noninvasive measurement tools that provide high temporal resolution on the units of milliseconds to investigate neuronal activity in the brain. MEG and EEG measure the magnetic fields and the scalp electrical potentials produced by the current sources, respectively. MEG systems utilize gradiometer and/or magnetometer connected to superconducting quantum interference devices (SQUIDs) as sensors, while EEG systems are metal electrodes connected to differential amplifiers. It is well-known that the main advantage of MEG over EEG is its invulnerability to the distortions caused by various layers of cerebrum such as skull, scalp, muscle, and cerebrospinal fluid (Baillet, Mosher, & Leahy, 2001; Hamalainen, Hari, Ilomoniemi, Knuutila, & Lounasmaa, 1993). Estimating the neuronal source parameters mainly as source locations and magnitudes has been a great interest of researchers, with the aim of imaging the brain with a fine temporal resolution. The techniques for the extraction of these parameters are known as inverse methods. Various inverse methods, such as least-square estimation (Baillet et al., 2001), vector beamformers (Sekihara, Nagarajan, Poeppel, Marantz, & Miyashita, 2001), Multiple Signal Classification (MUSIC) (Mosher, Lewis, & Leahy, 1992), minimum norm solutions (Hauk, 2004), maximum likelihood-based solutions have been proposed in literature. Even in a noiseless environment, there is not a unique solution for the source parameters, which makes the problem ill-posed. Hence, all inverse methods depend on some assumptions about the sources, and when these assumptions are not appropriate in the unknown sources, satisfactory results may not be obtained.

Most information contained in MEG measurements reflects signals originated from the cortex because of the relatively short distances between the cortex and the magnetometers/gradiometers in the MEG system. Nevertheless, there have been some attempts to detect the sources arising from deep areas of the brain, such as brainstem (Parkkonen & Mäkelä, 2002), thalamus (Tesche, 1998), hippocampus (Tesche & Karhu, 2000), and cerebellum (Tesche & Karhu, 1997). However, the success of these attempts was limited.

Before using any inverse method, preprocessing of data may dramatically increase the overall performance in terms of both accuracy and computational efficiency. Preprocessing methods are realized for different goals, including artifact removal, dimension reduction, and noise removal. Among these methods signal space projection (SSP) (Tesche, Uusitalo, Ilmoniemi, Huotilainen, Kajola, & Salonen, 1995; Uusitalo & Ilmoniemi, 1997) relies on removing contributions from undesired sources by exploiting their spatial structures. Because of the assumed orthogonality of source and artifact spaces, the interesting part is also mostly modified while suppressing the undesired part. Popular and efficient signal processing methods such as independent component analysis (James & Gibson, 2003; Vigario, Sarela, Jousmaki, Hamalainen, & Oja, 2000) and adaptive filtering (Ahmar & Simon, 2005; Constantin, Richard, Lengelle, & Soufflet, 2005) have also been employed to cope with similar problems. These techniques mostly suffer from assumptions of strong uncorrelatedness or independency. Gross and Ioannides (1999) defined, evaluated and compared various linear transformation techniques, including the beamspace approach. The beamspace method relies on projecting data by maximizing the power with an orthogonal transformation matrix that spans the space of the leadfield obtained by forward modeling computations. This preprocessing technique has recently been shown to increase the performance of main source localization algorithms (Rodriguez, Baryshnikov, Van Veen, & Wakai, 2006). Signal space separation (SSS), provided first by Taulu and Kajola (2005), is also a novel technique designed principally for removing interferences from MEG measurements. Since there is no charge on the sensor array volume, Laplace's equation becomes satisfied for magnetic scalar potential. Utilizing this fundamental law of physics, the SSS method decomposes the recorded magnetic field into two parts using vector spherical harmonic basis functions: one for the signals coming from the inside the sensor array volume, and the other coming from the outside it. The method can effectively remove the external interferences without imposing unrealistic assumptions by estimating the coefficients in the least-linear square sense.

In this article, we propose a novel preprocessing method in the spherical harmonics domain to decompose the MEG signal into specific parts, whose sources arise from user-prescribed concentric spherical regions. A particular case of this approach is presented to separate the data into parts corresponding to deep and superficial regions of the brain, without using inverse solutions. Throughout this article, plain italics denote scalars, lower case boldface symbols denote vectors, uppercase boldface symbols denote matrices, superscripts T and H stand for transpose and Hermitian transpose, and $\|.\|$, $tr(.)$, * indicate Euclidean norm, and trace and complex conjugate operations, respectively.

BACKGROUND

Our algorithm to decompose the signal into deep and superficial regions is highly dependent on the SSS and beamspace methods, which were briefly introduced in the previous section. In this section, we supply the necessary definitions to support the algorithm development.

The mapping from current sources to the magnetic fields in a noiseless environment can be described as:

$$b_k(t) = \int_{\Omega} \mathbf{h}_k(\mathbf{r'}) \cdot \mathbf{j}(\mathbf{r'})\, d\Omega \qquad (1)$$

where Ω is the whole source space, $\mathbf{r'}$ stands for the source locations, and $\mathbf{h}_k$ is the leadfield mapping of the current sources $\mathbf{j}$ to the magnetic field measurements at the k^{th} sensor, denoted as $b_k(t)$. The SSS method decomposes an M channel MEG signal:

$$\mathbf{b} = [b_1(t), b_2(t), \ldots, b_M(t)]^T =$$

$$\sum_{l=0}^{\infty}\sum_{m=-l}^{l} \alpha_{lm}\mathbf{x_{lm}} + \sum_{l=0}^{\infty}\sum_{m=-l}^{l} \beta_{lm}\mathbf{y_{lm}} = \mathbf{b}_{in} + \mathbf{b}_{out} \qquad (2)$$

into two components, where inner component $\mathbf{b}_{in}$ corresponds to source locations $\|\mathbf{r'}\| < R$, and the outer component $\mathbf{b}_{out}$ corresponds to $\|\mathbf{r'}\| > R$, and R is the radius of the sensor array. Based on the quasistatic approximation of Maxwell's equations, this separation is achieved using two different sums of vector spherical harmonic functions $\mathbf{x}_{\mathrm{lm}}$ and $\mathbf{y}_{\mathrm{lm}}$ (Taulu & Kajola, 2005). Spherical harmonic functions are orthonormal eigenfunctions of the Laplacian operator on the spherical surface, which makes them naturally useful tools for MEG signal processing, and hence has been suggested in literature for different purposes. For instance, Popov (2002) proposed a continuation of MEG data around the surface of the sensor array using a spherical harmonics expansion. They were also commonly utilized for the computation and approximation of the MEG forward problem (Jerbi, Mosher, Baillet, & Leahy, 2002; Nolte, Fieseler, & Curio, 2001; Nolte, 2003).

Equation 2 may be rewritten in an algebraic form as:

$$\mathbf{b} = \mathbf{S}\omega \qquad (3)$$

where the $(M \times p)$ dimensional basis functions matrix $\mathbf{S} = [\mathbf{S}_{in}\ \mathbf{S}_{out}]$ comprises inner and outer basis functions:

$$\mathbf{S}_{in} = [\mathbf{x}_{1,-1}, \mathbf{x}_{1,1}, \mathbf{x}_{2,-2}, \ldots, \mathbf{x}_{L_{in},L_{in}}] \qquad (4)$$

$$\mathbf{S}_{out} = [\mathbf{y}_{1,-1}, \mathbf{y}_{1,1}, \mathbf{y}_{2,-2}, \ldots, \mathbf{y}_{L_{out},L_{out}}]$$

and the $(p \times 1)$ coefficient vector $\boldsymbol{\omega} = [\boldsymbol{\alpha}\ \boldsymbol{\beta}]^T$ contains the SSS coefficients for inner and outer parts:

$$\boldsymbol{\alpha} = [\alpha_{1,-1}, \alpha_{1,1}, \alpha_{2,-2}, \ldots, \alpha_{L_{in}, L_{in}}]$$

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