Multi-Resolution FOCUSS: A Source Imaging Technique Applied to MEG Data

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Summary: A variety of techniques are available for imaging magnetoencephalographic (MEG) data to the corresponding cortical structures. Each performs a functional optimization that includes mathematical and physical restrictions on source activity. Unlike other imaging techniques, MR-FOCUSS (Multi-Resolution FOcal Underdetermined System Solution) utilizes a wavelet statistical operator that allows spatial resolution to be chosen appropriately for focal or extended sources. Control of focal imaging properties is achieved by specifying in an ℓp norm distribution template used to construct the wavelets. In addition, incorporation of a multi-resolution wavelet operator desensitizes the mathematical algorithm to noise, (regularization). Like the FOCUSS imaging technique, an initial estimate of cortical activity is recursively enhanced to obtain the final high resolution imaging results. Studies of model MEG data representing all regions of a realistic cortical model are performed to quantify MR-FOCUSS imaging properties. These modeled data studies included single and multiple dipole sources as well as an extended source model. Thus, MR-FOCUSS is found to be very effective for imaging language processing for pre-surgical planning and provides a high-resolution method to image sequential activation of multiple correlated sources involved in language processing.

Key words: MR-FOCUSS; Magnetoencephalography; MEG; Multiresolution wavelets; Functional imaging; Language mapping.

Introduction

The relationship between MEG sensor amplitudes and amplitudes of the underlying brain electric sources is:

\[ b = b_s + n - Gq_s + n \]  

(1)

The MEG data, \( b \), is a column vector of M sensor amplitudes, which are mixtures of signal, \( b_s \), and noise, \( n \). The sources of the signals and their amplitudes, \( q_s \), are not known. Assuming there are N sources, the column vectors of the M by N forward model gain matrix, \( G \), relate the M sensor array measurements to the N sources in units of magnetic measurement amplitude per unit of source amplitude. For a specific array of sources, components of the gain matrix, \( G \), can be accurately calculated using a multi-sphere head model matched to local variation of the skull curvature (Leahy et al. 1998; van den Broek et al. 1998; Witort and Van Johnson 2002). However, for deep brain sources, it may be necessary to utilize a realistic head model derived from anatomical magnetic resonance imaging (MRI) studies (Mosher et al. 1999). Equation 1 is converted to a spatio-temporal equation by replacing vectors, \( b \) and \( q_s \), with matrices, \( B \) and \( Q_s \), whose columns correspond to successive time points.

Equation 1 is insufficient for determining the source amplitudes, \( q_s \), because only \( b \) is known. As a supplement to Equation 1, two relatively distinct mathematical models of brain activity are utilized. A multiple current dipole model of brain activity (Hämäläinen et al. 1993) is based on the discrete mapping of function to a few small, focal regions of cortex. These active regions are modeled as current dipoles whose locations, orientations and amplitudes must be determined. Alternatively, neuronal activity is treated as a current density continuum that is modeled by a large lattice of dipole sources within the gray matter of the brain (Hämäläinen et al. 1993).

Constraining imaged brain activity to combinations of a few independent compact sites may be inappropriate for studies of complex mental tasks, pathological activity, and sleep (Darvas et al. 2004). For these imaging applications, a continuum model brain electric activity accommodates extended and compact sources that may be simultaneously active. Using either model, brain elec-
tricity activity is estimated by minimizing (maximizing) an imaging metric that includes contributions of individual brain electric sources proportional to their participation in the collective fulfillment of equation 1 as well as other source activity constraints. Ideally, these constraints are derived from prior knowledge of brain activity.

A current density imaging filter is constructed by minimizing the norm of weighted source amplitudes with Equation 1 as a constraint. A prototype current density imaging filter, \( H \) (Bailet et al. 2001; Liu et al. 2002), is applied to MEG data, \( b \), to obtain an estimate of cortical activation, \( q_{\text{estimate}} \):

\[
q_{\text{estimate}} = Hb
\]

\[
H = W^T G^T \left[ G W^T G^T + \Phi(n n^T) \right]^{-1}
\]

\( \Phi(n n^T) \) is a regularization function such as \( \lambda I \) (2)

The matrix, \( W \), is an estimate of source activity that has a covariance matrix, \( WW^T \). The matrix \( G W^T G^T \) is an estimate of the signal covariance matrix. The spatial resolution of imaged activity is good only when \( WW^T \), is an accurate estimate of the source covariance matrix. A popular choice for \( WW^T \) is the identity matrix, \( I \). This is a very poor source covariance estimate for imaging focal source activity.

Methodologies have been developed for altering the covariance matrix, \( WW^T \), to address current density imaging blur. One method with great potential utilizes corresponding functional MRI (fMRI) results to estimate the source covariance matrix, \( WW^T \) (Dale et al. 2000; Liu et al. 1998). However, the efficacy of this approach is limited because the mathematical relationships between MEG imaged activity and fMRI imaged activity are poorly established (Horwitz and Poeppel 2002). Another approach uses the MEG imaging results of equation 2 to recursively update the estimated source covariance matrix, \( WW^T \). The Focal Underdetermined System Solver (FOCUSS) imaging technique (Gorodnitsky et al. 1995; Gorodnitsky and Rao 1997) uses this recursive update strategy to enhance imaging compact sources. The algorithm was shown to generate a sparse solution in which a few sources, (less than the number of MEG sensors), have nonzero amplitudes (Gorodnitsky et al. 1995). Localization accuracy of FOCUSS is improved when the algorithm is initialized with a source covariance matrix, \( WW^T \), based on prior knowledge of the estimated source activity (Gorodnitsky and Rao 1997; Rao and Kreutz-Delgado 1999). Additional control of focal imaging is obtained by formulating the FOCUSS technique as a constrained minimization of a diversity measure,

\[
E^p(q) = |q|^p,
\]

which is the \( l_p \) norm of \( q \). This imposes a constraint on the statistical distribution of cortical source amplitudes (Rao et al. 2003). The exponent, \( P \), controls focal sparseness of solutions constructed by minimizing \( E^p(q) \). Imaged activity has fewer nonzero source amplitudes when \( P \) is close to 0.

A different recursive imaging strategy utilizes threshold elimination of low amplitude sources from the cortical model combined with increased source grid density in high amplitude regions. Thus, a sequence of cortical models is generated that progressively confines imaged activity to regions of smaller size but increased spatial resolution (Okada et al. 1992; Gavit et al. 2001). Compared to the FOCUSS technique, elimination of low amplitude sources increases the computational efficiency. Also, spatial and temporal constraints are used to minimize noise sensitivity of the algorithm (Gavit et al. 2001). Unfortunately, recursive threshold elimination techniques can become unstable especially when the signal-to-noise ratio is low.

Recursively applied current density imaging techniques incorporate two mathematical features important for high resolution MEG source imaging. First, it is relatively easy to incorporate prior knowledge of brain activation obtained using other MEG imaging techniques or other imaging modalities such as fMRI. Second, they are capable of high-resolution imaging of compact source activity as well as extended regional activation.

We developed the current density imaging technique, MR-FOCUSS to alleviate the noise instability problem associated with recursive algorithms for MEG imaging. In MR-FOCUSS, the dipole grid of cortical sources is transformed into a multiresolution wavelet model of the cortex. In this source basis, the signal content of the data is preferentially imaged using high spatial resolution wavelets while noise is excluded. In contrast, noise is weakly coupled to the lowest resolution wavelet structures, which act as low-pass spatial filters. The small amount of noise incorporated in these wavelets is spread over large regions at very low amplitude. This wavelet source basis is shared with our 2DII imaging technique (Moran and Teply 2000). However, MR-FOCUSS is significantly faster than 2DII because the wavelet subspace basis vectors are calculated once for all MEG data that is imaged and MR-FOCUSS converges in significantly fewer steps than 2DII. Further, MR-FOCUSS enables the focal imaging properties of the algorithm to be selected by specifying the \( l_p \) norm of an imaging metric used to construct the wavelet source template. This method of focal imaging control is similar to the choice of the \( l_p \) norm controlling image sparseness in the FOCUSS algorithm (Rao et al. 2003).