Combinational method for focal brain activation detection using MEG signal

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Abstract: Magnetoencephalography (MEG) is a neuroimaging technique for brain activation detection. However, this technique does not provide a unique solution due to ill-posedness of its inverse solution. Several methods are proposed to improve the MEG inverse solution. Minimum Norm (MN) is a simple method whose solution is distributed and biased toward the superficial sources. In addition, its solution is sensitive to the noise. Several methods are proposed to improve performance of the MN method. In this paper, we propose a method whose solution is less sensitive to the noise and spatially unbiased toward the superficial sources. Control of focal solution properties is achieved by specifying a parameter in the method. Performance of the proposed method is compared to others using simulation studies consisting of single and multiple dipole sources as well as an extended source model. Proposed method has superior performance compared to non-iterative methods. Its performance is similar to the iterative methods but computational load is lower.

1. Description of Purpose (Introduction):

Several methods have been proposed to solve the MEG and EEG inverse problem. Minimum Norm (MN) is a simple method to solve the MEG inverse problem. Solution of MN is spatially extended, biased toward the superficial source locations, and sensitive to the noise [1]. Sensitivity of MN to the noise can be reduced using the regularization technique in the Regularized Minimum Norm (RMN) method [2]. Weighted Minimum Norm (WMN) was proposed to remove bias of the MN solution toward the superficial sources [3]. There are several definitions for the weight matrix in proposed WMN methods in the literature. Low resolution brain electromagnetic tomography (LORETA) is an example of the WMN method which has good localization but its solution is spatially non-focal [4].

Although MN and WMN methods generates spatially extended solutions but their iterative variant can provide focal solutions. Focal underdetermined system solver (FOCUSS) is a recursive WMN method that generates sparse solution. The weight matrix in this method is updated in each iteration according to the previous values of the estimated sources. FOCUSS is sensitive to the noise and needs initial source distribution. In addition, a matrix inversion is required in each iteration of FOCUSS algorithm that causes huge computational load as well as sensitivity to the noise. Although some efforts has been devoted to reduce the computational load of FOCUSS but its computational load is still significant [5].

In this paper, we present a combination method by integrating MN, RMN, and WMN methods. The proposed method is less sensitive to the noise, is un-biased toward the superficial sources, and it can provide focal solutions for focal activation. Control of focal solution properties is achieved by specifying a parameter in the method. Although the proposed method is not an iterative method but it can give focal solutions comparable with the FOCUSS. The computational load of the proposed method is considerably lower than FOCUSS. Performance of the proposed method is compared to others using the simulation studies included single and multiple dipole sources as well as an extended source model. Proposed method has superior performance compared to non-iterative methods. Its performance is similar to the iterative methods but with lower computational load.

2. Method:

MEG forward problem gives the following linear relationship between the dipole sources and the measured magnetic signal in the sensors:

$$b = G.q + n \tag{1}$$

where b is the measured magnetic field in M sensors, q represents N dipole magnitudes, G is the $M \times N$ lead field matrix, and n is the additive noise. MN solution of Eq.(1) in the noise-less condition is represented by $\hat{q} = G^T (GG^T)^{-1}.b = G^+.b$ where G^+ is the pseudo-inverse of G [6]. For removing bias of the MN solution toward the superficial sources, the weighted minimum norm (WMN) method is proposed [4]. This method uses the weight matrix W to give more gain to the deep sources. Its solution is calculated as $\hat{q} = W^{-1}G^T (GW^{-1}G^T)^+ b$. Although the problem of spatial bias of the MN method is reduced by the WMN method, but its solution is still non-focal. Sparse methods like FOCUSS give focal solutions by using iterative methods. However, computational load and instability in the presence of noise are problems of these methods [4].

In this paper, we propose a method which is illustrated in Fig. 1 to get a solution without spatial bias, low sensitivity to the noise, and low computational load with focal solution. In this method, we compute MN and RMN solutions as initial estimation of the next WMN solution. The weight matrix of the WMN method in the both first steps is:

$$W = diag(|\hat{q}|^{\beta_1 \text{ or } \beta_2}) \tag{2}$$

and in the second step, it is defined as:

$$W = diag(|sq_{WMN} + (1-s)q_{RWMN}|^{\alpha}) \tag{3}$$

where $\hat{q}$ is the initial estimation of the source magnitude which is calculated in the previous step (the solution of MN or RMN) and β_1, β_2 and α are the parameters that control sparseness of the solution. The second step in the proposed method is to combine solutions of the WMN from each MN and RMN initializations. We use other parameter, s, as the combination parameter ($0 \le s \le 1$). We should use regularization in presence of noise, but using regularization in the noise-less condition removes spatial details of the solution. Thus, for low signal to noise ratio (SNR), a small value for s should be chosen and vice versa.

3. Simulation Results:

In this section, performance of the proposed method is compared to other conventional methods. The simulated magnetic field is generated using current dipoles. Computational load of the proposed and other methods are compared using simulation results. Moran and his colleagues developed "MEG-Tools" software to implement and demonstrate the MEG inverse solution [7]. We utilize this software to perform our simulations in this section. We use the head model extracted from the anatomical Magnetic Resonance Images (MRI) of a human subject's head. The MRI consists 316 coronal slices contains 256×256 pixels and voxel size is 0.9375×0.9375×0.9375 mm^3.

Arrangement of the MEG sensors is the same as the MEG imaging device from 4D Neuroimaging (San Diego, CA, USA) and contains 148 gradient sensors. In order to co-register coordinates of the MEG sensors with the anatomical MRI data, about 3,000 digitization points are marked on the subject's scalp. The scalp is laser scanned to accurately mark these points. The Cartesian coordinates of these points along with the locations and directions of the MEG sensors are expressed in a common coordinate system. On the other hand, anatomical data from MRI are used to distinguish different head segments and to find scalp surface for co-registering the digitization points on it. The lead matrix is obtained from symmetric spherical head model whose brain tissues radii (including gray matter, white matter, skull, and head skin) are taken from the anatomical MRI data.

We use "localization error" to compare performance of the methods. The localization error is defined as the distance between the dipoles with maximum moments in the simulated and estimated source spaces. After criteria definition, performance of the proposed method with other methods is compared using multiple simulation studies. In the first simulation, a single active simulated source is considered as shown in Fig. 2. The reconstructed source from some conventional methods and the proposed method in noiseless condition are shown in Fig. 3. As shown in Fig. 3, MN and LORETA have smooth spatial solutions, but FOCUSS and our combination method give focal solutions at the correct location.

In the second series of simulation, we compare performance of the proposed method with other methods to reconstruct deep and superficial sources. We considered 15 different locations for a single active dipole shown in Fig. 4 and compare the errors of different methods in reconstruction. This simulation is performed for both noisy and noiseless conditions. Additive Gaussian noise is added to the measured signal. The localization error is illustrated in Fig. 5. Computational load of the proposed is compared with other method. The computational load of the proposed method is less than FOCUSS and similar to MN, WMN, and LORETA. With this low computational load, the proposed method shows excellent performance in reconstructing focal or extended sources and deep or superficial sources in different SNR conditions.

4. Conclusion

There are several methods in the literature for solving the inverse problem of MEG. The MN method is taken as a benchmark in all cases. Solution of MN is spatially extended, biased toward the superficial source locations, and sensitive to the noise. Its sensitivity to the noise can be reduced using regularization techniques, e.g. Regularized Minimum Norm (RMN) method. By using Weighted Minimum Norm (WMN), the bias of the MN solution toward the superficial sources can be reduced. However, the RMN and WMN methods generate non-focal solutions. The iterative FOCUSS algorithm provides a focal solution but it is sensitive to the noise and its computational load is high. In this paper, we proposed a three-step weighted method to provide a focal solution with low computational load in the presence of noise. Extensive simulation studies showed appropriate performance of the proposed method for both focal and extended sources in different SNR conditions. Low computational load of the proposed method was shown with respect to the iterative methods like FOCUSS.

5. Reference

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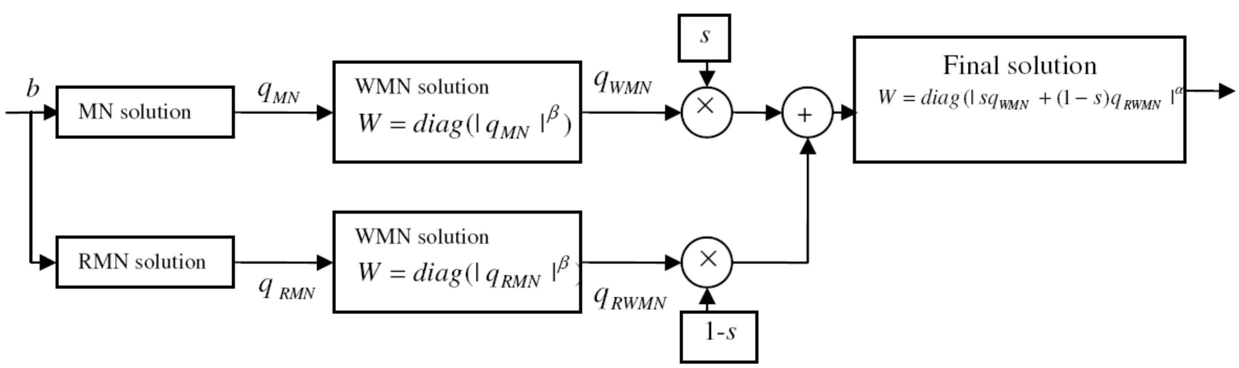

Fig. 1. Illustration of the block diagram of the proposed combination method.

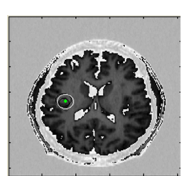

Fig. 2. Illustration of the location of the simulated single active dipole which is used in first simulation.

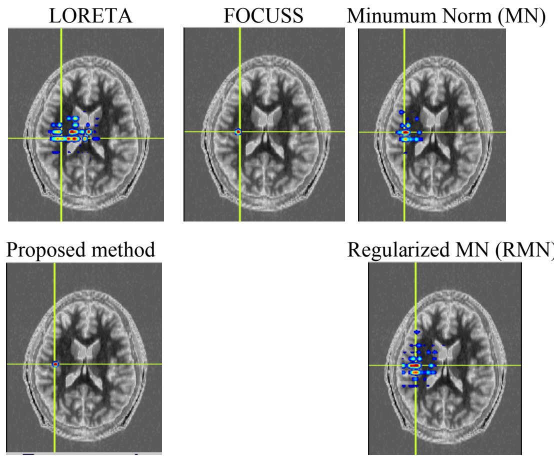

Fig. 3. Reconstruction of the single dipole shown in figure 2 using different methods. For the proposed method, s=0.5, α=4, and $\beta_1 = \beta_2 = 2$ are used.

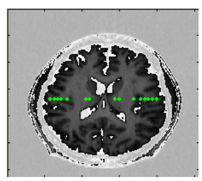

Fig. 4. Illustration of 15 different locations of the active dipoles simulated for evaluating the performance of the proposed method and other methods to reconstruct deep and superficial sources.

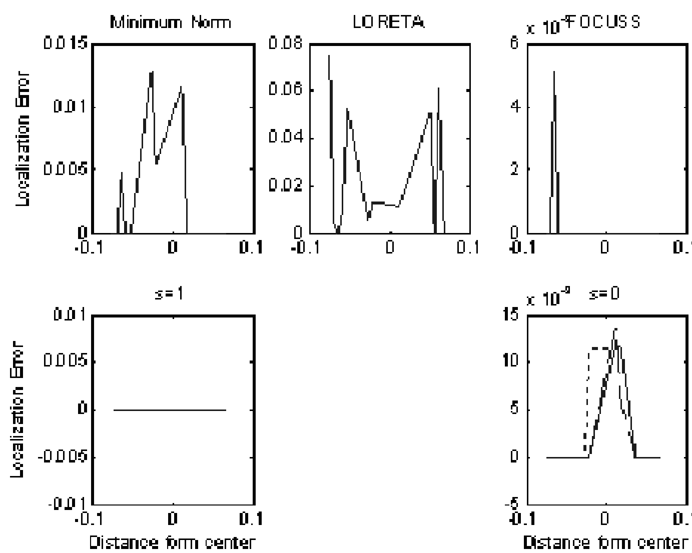

Fig. 5. Localization errors for deep and superficial sources in the noiseless condition. Negative and positive values of the x axis represent dipoles in the left and right hemispheres, respectively. Top row shows the sparseness errors of the MN, LORETA, and FOCUSS methods. Bottom row shows the sparseness errors of the proposed method. Solid, dash, and doted lines represent solutions of the proposed method with ($\beta_1 = \beta_2 = 2$, α=2), ($\beta_1 = \beta_2 = 4$, α=2), and ($\beta_1 = \beta_2 = 8$, α=8), respectively.