Combined EEG/MEG source analysis using calibrated finite element head models

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Abstract

We propose a new method for a combined MEG/EEG source analysis. We optimize the tissue conductivities of a realistically shaped four-compartment finite-element head volume conductor based on measured somatosensory evoked potentials (SEP) and fields (SEF). Our proposed method uses the source parameters from the MEG dipole fit as a constraint for the conductivity estimation based on the EEG. The method was implemented with an iteration scheme to take into account the insensitivity of MEG to radial source orientations, resulting in more accurate conductivity estimation using the EEG data. Our simulation studies showed that the method was able to simultaneously estimate both for the brain and skull conductivities as well as the parameters of the underlying source in somatosensory cortex. The application to measured SEP and SEF data indicated a skull-brain conductivity ratio of 1:25, which, in agreement with recent studies, is significantly lower than the commonly used ratio of 1:80. The individually optimized volume conductor model can be subsequently used for the analysis of clinical or cognitive data acquired from the same subject.

Keywords
Combined EEG/MEG; source analysis; realistic four-compartment head modeling; in vivo conductivity estimation; finite element method; somatosensory evoked potentials and fields

1 Introduction

For accurate reconstruction of the underlying neural sources from combined EEG and MEG data, one needs a realistic forward model which requires accurate representation of tissue geometries as well as estimation of the tissue conductivities [1]. The extraction of the geometrical information from magnetic resonance imaging (MRI) data and the use of the finite element method (FEM) for the numerical computations has led to a flexible and an accurate EEG and MEG forward modeling approach [1-6]. This paper presents a new method for an estimation of individual tissue conductivity parameters that uses somatosensory evoked potential (SEP) and field (SEF) data. The resulting calibrated four-compartment FE head model can be used in the analysis of subsequently acquired clinical or cognitive EEG/MEG data from the same subject. Our approach was inspired by three-compartment boundary element head model EEG/MEG calibration procedures [7,8]. The method should further stabilize the EEG data based low resolution conductivity estimation (LRCE) approach proposed in [1].

2 Materials and Methods

2.1 FEM volume conductor and source space

We used a bi-modal T1-/PD-weighted MRI data approach for the segmentation of the four head tissue compartments skin, skull, cerebrospinal fluid (CSF) and brain [1]. From the segmented dataset, a tetrahedral FE model with 165K nodes and about 1 million elements and a cortical surface source space mesh with 2 mm resolution was generated using the CURRY software (http://www.neuro.com). The resulting four-compartment FE model is shown in Fig.1.

For the representation of dipole current sources we used the Venant FE approach based on comparison of the performance of three different approaches (subtraction, Venant, partial integration) which suggested that for sufficiently regular meshes it yields suitable

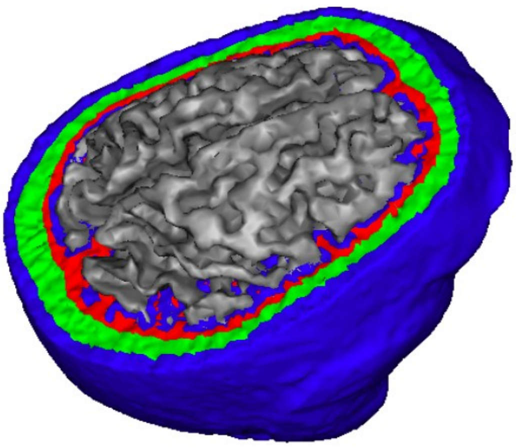

Figure 1 Four compartment FE model composed of scalp, skull, CSF, and brain. Also shown is the cortical source surface.

accuracy over all realistic source locations [2]. In addition, this approach is computationally very efficient when employed in combination with the FE transfer matrix approach [6]. Because of the limited regularity of the potential function [5], we contented ourselves with linear FE basis functions. EEG and MEG transfer matrices were computed using an algebraic-multigrid-preconditioned conjugate gradient solver [2,6].

2.2 Tissue Conductivity Estimation

Our approach to low-resolution tissue conductivity estimation is presented as Algorithm 1. We focus here on the estimation of the conductivity of skull (σ_{skull}) and that of the brain (σ_{brain}).

2.3 Reference data for simulation

For the verification of Alg.1 we used data from 63 EEG electrodes and from a 275 axial gradiometer MEG (plus 29 reference sensors for noise reduction). A single quasi-tangential dipole source was simulated in the left somatosensory SI cortex located at (196.3, 162.2, 170.2) mm, oriented along the y axis, and with the amplitude of 10 nAm. In the simulation, conductivities of 0.33, 0.0135, 1.79, 0.365 S/m were assumed for the skin, skull, CSF, and brain, respectively.
In contrast to other studies using three-compartment head modeling [7,8], we thus included the important CSF compartment [9,10]. Gaussian noise was added to the simulated EEG and MEG data at signal-to-noise (SNR) ratios of 40, 25, and 20 dB [1].

3 Results

3.1 Verification using simulation

We used the following set of conductivities for the

$$\begin{aligned}
X &= \{s_{left},\ \sigma_{brain},\ \sigma_{skull}\} \\
\sigma_{brain} &\in \{0.12,\ 0.332,\ 0.48\ S/m\} \\
\sigma_{skull} &\in \{0.0042,\ 0.0055,\ 0.0083,\ 0.0095,\ 0.0111, \\
&\qquad 0.0123,\ 0.0133,\ 0.0144,\ 0.0166,\ 0.0221,\ 0.0415\} \\
\sigma_{scalp} &= 0.33, \\
\sigma_{CSF} &= 1.79\ S/m
\end{aligned}$$

Algorithm 1 Iterative combined MEG/EEG approach for tissue conductivity estimation

step 0: Define discrete sets of conductivity values for brain and skull tissue (e.g., different measured values from the literature)

do while *variance-to-data-not-well-explained*

- **step 1**: MEG dipole fit. Result: Single SEF source at location $\overline{x}$ with orientation $\overline{o}_1$ and magnitude m_1.
- **step 2**: Keeping location and moment $(m_1 \cdot \overline{o}_1)$ constant, perform LRCE fit (Lew et al., HBM, 2009) for brain and skull conductivity. Result: σ_{brain_1} and σ_{skull_1}.
- **step 3**: Keeping only the dipole location $\overline{x}$ fixed and using the optimized volume conductor with conductivities. σ_{brain_1} and σ_{skull_1}, compute $\overline{o}_2$ and m_2 by means of a linear least square fit to the EEG data. Result: $\overline{o}_2$ and m_2 (step 3 is necessary since $\overline{o}_1$ and m_1 might be spurious in the case that the source is not optimally quasi-tangential.
- **step 4**: Fix $\overline{x}$ and $\overline{o}_2$ and perform linear least square fit to the MEG data. Result: m_3.
- **step 5**: Keeping $\overline{x}$ and moment $\overline{o}_2 * m_3$ constant, perform EEG LRCE fit for brain and skull conductivity. Result: σ_{brain_2} and σ_{skull_2}.

end

step 6: Given σ_{brain_2} and σ_{skull_2}, compute $\overline{o}_3, m_4$ using a normalized linear least square fit to both EEG and MEG data (Fuchs et al., Electroenc.Clin.Neurophysiol., 1998)

Final result for estimated parameters: $\overline{x}, \overline{o}_3, m_4, \sigma_{brain_2}$ and σ_{skull_2}.

Table 1: Results for brain and skull tissue conductivity estimation from the simulated combined EEG/MEG data for the different noise levels (magnitude error in %, orientation error in degree, explained variances of EEG (varEEG) and MEG (varMEG) in %).

MEG 40dB noise, localization error = 2.2 mm								
EEG	$\sigma_{\mathbf{brain_2}}$	$\sigma_{\mathbf{skull_2}}$	$\overline{o}_3$	ori err (deg)	m_4	mag err (%)	varEEG	varMEG
40dB	0.332	0.0166	(-0.1 1.0 -0.1)	8	9.1	9	98.1	98.5
25dB	0.332	0.0166	(-0.1 1.0 -0.1)	8	9.2	8	95.4	98.5
20dB	0.332	0.0166	(-0.2 1.0 -0.1)	10	9.1	9	89.0	98.5

MEG 25dB noise, localization error = 1.7 mm								
EEG	$\sigma_{\mathbf{brain_2}}$	$\sigma_{\mathbf{skull_2}}$	$\overline{o}_3$	ori err (deg)	m_4	mag err (%)	varEEG	varMEG
40dB	0.332	0.0166	(-0.1 1.0 0.0)	6	9.0	10	99.0	93.7
25dB	0.332	0.0166	(-0.1 1.0 0.1)	6	9.3	7	94.5	93.8
20dB	0.332	0.0166	(-0.1 1.0 0.0)	7	9.2	8	89.5	93.7

MEG 20dB noise, localization error = 4.6 mm								
EEG	$\sigma_{\mathbf{brain_2}}$	$\sigma_{\mathbf{skull_2}}$	$\overline{o}_3$	ori err (deg)	m_4	mag err (%)	varEEG	varMEG
40dB	0.332	0.0133	(-0.3 1.0 0.0)	16	11.2	12	97.4	90.3
25dB	0.332	0.0144	(-0.3 1.0 0.1)	16	11.3	13	93.2	90.4
20dB	0.48	0.0221	(-0.2 1.0 0.0)	10	10.0	0	87.2	90.2

Table 2: Statistical results for 10 EEG/MEG datasets with SNR of 20dB (magnitude error in %, orientation error in degree, explained variance in %).

#	σ_{br_2}	σ_{sk_2}	o_3	ori err (deg)	m_4	mag err (%)	varEEG	varMEG
1	0.48	0.0221	(-0.2 1.0 0.0)	10	10.0	0	87.2	90.2
2	0.332	0.0166	(-0.2 1.0 0.0)	14	12.2	22	87.8	89.4
3	0.332	0.0144	(-0.3 1.0 0.0)	15	11.4	14	89.5	90.5
4	0.332	0.0144	(-0.1 1.0 0.1)	8	10.7	7	82.6	90.6
5	0.332	0.0123	(-0.2 1.0 0.0)	11	10.3	3	86.5	90.1
6	0.332	0.0123	(-0.3 1.0 0.0)	16	10.1	1	89.3	89.1
7	0.332	0.0166	(-0.3 1.0 0.0)	15	11.0	10	90.5	90.6
8	0.48	0.0221	(-0.2 1.0 -0.1)	16	10.5	5	89.9	89.0
9	0.332	0.0166	(-0.2 1.0 0.1)	11	11.2	12	86.6	90.2
10	0.332	0.0166	(-0.3 0.9 -0.1)	19	10.8	8	91.0	90.3
mean	**0.36**	**0.0164**	(-0.2 1.0 0.0)	**14**	10.8	**8**	**88.1**	**90.0**
std	0.06	0.0034	(0.1 0.0 0.1)	3	0.7	1	2.5	0.6

verification of Alg.1 (X indicates the set of free parameters).

The conductivities for brain and skull used in the forward simulation were not part of the set to avoid an “inverse crime”. Using a single iteration (further iterations did not significantly change the results), our procedure resulted in the estimated parameters shown in Table 1. Table 2 shows a statistical result for 10 different 20 dB SNR scenarios for EEG and MEG. Despite of the high noise level, the mean of the estimated conductivities (σ_{brain} = 0.36 S/m, σ_{skull} = 0.0164 S/m) is in an approximate agreement with the reference conductivities (σ_{brain}=0.365 S/m, σ_{skull} = 0.0135 S/m). The average (±standard deviation) of the localization results was (196.5±0.7, 161.9±3.8, 170.4±0.9) mm, the mean thus has a localization error of 0.4 mm. For the high noise level of 20 dB, we achieve an average 14 degree orientation error and 8% magnitude error and explained variances of about 90% for both EEG and MEG.

3.2 Application to SEP/SEF data

We acquired SEP/SEF responses to right index finger tactile stimulation using a protocol as described in [1]. The averaged datasets had SNRs of 24dB (SEP) and 30dB (SEF) and we focus on the evaluation of the first tactile component at 35 ms after stimulus onset. Based on the literature, the following set of conductivities were used:

$$\begin{aligned}
X &= \{s_{somato},\ \sigma_{brain},\ \sigma_{skull}\} \\
\sigma_{scalp} &= 0.33\ S/m,\ \sigma_{CSF} = 1.79\ S/m \\
\sigma_{brain} &\in \{0.12,\ 0.332,\ 0.48,\ 0.57\ S/m\} \\
\sigma_{skull} &\in \{0.0024, 0.0028, 0.0033, 0.0042, 0.0046, 0.0055, \\
&\qquad 0.0079, 0.0133, 0.0144, 0.0221, 0.0332, 0.0415, 0.0664\}
\end{aligned}$$

For the MEG dipole fit, we used a simulated annealing optimization in combination with a truncated singular value decomposition [11] and literature conductivities (σ_{scalp}=0.33, σ_{skull}=0.0164, , σ_{CSF}=1.79, σ_{brain}=0.36 S/m) for the volume conductor. The

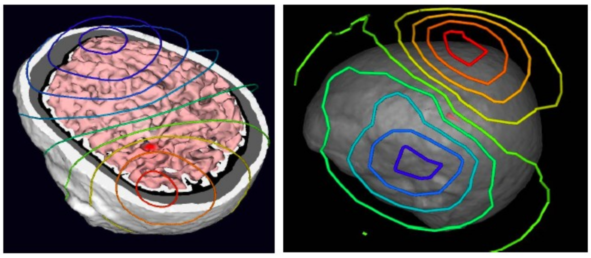

Figure 2 The reconstructed source in somatosensory SI cortex together with the measured SEP (left) and SEF (right) data at the peak amplitude of the first tactile component.

proposed Alg.1 resulted in $\sigma_{skull} = 0.0133$ S/m and $\sigma_{brain} = 0.332$ S/m, corresponding to σ_{skull}: σ_{brain} = 1:25, in agreement with [12]. The source was located in the primary somatosensory SI cortex with an orientation right-frontal to left-occipital (see Figure 2) and a magnitude of 14 nAm. The explained variances of SEP and SEF data were 96.1% and 93%, respectively.

4. Discussion

We developed a procedure for a combined analysis of EEG and MEG data using a calibration procedure where individual conductivity parameters of a realistic four-compartment FE head volume conductor model are adjusted so that the model predictions optimally match both measured SEP and SEF data evoked by tactile stimulation. We studied the feasibility of the method using a simulation. The application to experimental SEP/SEF data indicated σ_{skull}: σ_{brain} = 1:25, which is in agreement with [12] and much lower than the commonly used ratio of 1:80. The volume conductor model with accurate geometry and optimized conductivity parameters can be subsequently used for combined analysis of clinical or cognitive EEG and MEG data acquired from the same subject. However, since the conductivity and thickness of the skull are intimately linked parameters in any volume conductor model, it is important to pay attention to accurate geometry specification when the conductivity estimates obtained from the somatosensory data are employed in modeling of signals originating from other brain regions.

5. Acknowledgement

This research was supported by the DFG projects WO1425/1-1 and JU445/5-1 and by the NIH grants 2-P41-RR12553-07 (NCRR), P41-RR14075 (NCRR), 1R01EB009048-01 (NIBIB), and 5R01EB006385-03 (NIBIB).

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