Title

Comparing Finite Difference Forward Models Using Free Energy based on Multiple Sparse Priors

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Introduction

Due to the ill-posed nature of the EEG source localization problem, the spatial resolution of the reconstructed activity is limited to several centimeters (Baillet, 2001). Advanced forward modeling of the head can contribute to improve the spatial resolution (Hallez, 2007). The boundary element method or BEM is commonly used due to its computation speed. More advanced volume modeling methods, such as finite difference methods or FDM, are computationally more intensive but allow estimating sources inside gray matter (Vanrumste, 2000). FDM also allows to incorporate tissue anisotropy and skull inhomogeneities (Hallez, 2008).

Variational Bayesian approaches are getting more popular to solve the reconstruction problem (Friston, 2008 and Wipf, 2010). They allow incorporating several types of prior information in order to get a unique source distribution. Parametric empirical bayes or PEB implemented into the SPM software package allows also to compare different models, incorporating different prior information, based on their free energy (Henson, 2009). However, using PEB in SPM only BEM forward models can be compared. Based on the fact the uncertainty on the anatomy can be incorporated within the free energy (Lopez, 2012), this work extended the PEB framework to FDM models.

Methods

Simplif.	Model		Tissue	Segmentation	Conductivity (S/m)
-	Reference		Compact	CT	$\sigma_{iso} = 0.0064$
			Spongy	CT	$\sigma_{iso} = 0.02865$
			Air cavities	CT	$\sigma_{iso} = 0.0$
SKULL	1		Compact	CT	$\sigma_{iso} = 0.0064$
			Spongy	eroded compact	$\sigma_{iso} = 0.02865$
			Air cavities	CT	$\sigma_{iso} = 0.0$
	2		Compact + Spongy	CT	$\sigma_{aniso} \begin{cases} \sigma_{rad} = 0.0105 \\ \sigma_{tang} = 0.0191 \end{cases}$
			Air cavities	CT	$\sigma_{iso} = 0.0$
	3		Compact + Spongy	CT	$\sigma_{iso} = 0.02$
			Air cavities	CT	$\sigma_{iso} = 0.0$
AIR CAVITIES	4		Compact + Air cavities	CT	$\sigma_{iso} = 0.0064$
			Spongy	CT	$\sigma_{iso} = 0.02865$
	5		Compact	CT	$\sigma_{iso} = 0.0064$
			Spongy + Air cavities	CT	$\sigma_{iso} = 0.02865$
SKULL AND AIR	6		Compact	CT	$\sigma_{iso} = 0.0064$
			Spongy	eroded compact	$\sigma_{iso} = 0.02865$
	7		Compact + Spongy + Air cavities	CT	$\sigma_{iso} = 0.02$

Figure 2: Summary of the different skull models that were analysed. The first 3 models differed in the way compact and spongy bone were modeled based on CT images. Differences in air cavity modeling were expressed in M4 and M5. M6 and M7 were further simplifications of air cavity and skull modeling. M2 was different because in this model the skull was modeled homogeneously with anisotropic conductivities. For some models the spongy bone was modeled as an erosion of compact bone, this is expressed as the eroded compact notification in the segmentation column

A reference FDM model (see Figure 1) incorporating 7 different tissue types served as our ground truth to simulate 27 channels of scalp EEG data in 3 conditions: 1 noiseless condition and 2 noisy with a SNR of 5 dB and 1 dB channel noise. Based on 8528 FDM grid points we simulated 124 gray matter sources of 10 Hz oscillating dipole activity sampled at 256 Hz during 1 s to generate 124 different EEG time serie for every condition.

7 Different FDM head models were compared after reconstruction (see Figure 2). The sources were reconstructed with the multiple sparse prior inversion technique implemented in SPM (Friston, 2008). To speed up the calculation time, the orientations of the 8528 dipoles distributed in gray matter were calculated before reconstruction using the approach proposed in Phillips, 2002.

Finally, the performance of the different models was evaluated comparing both the percentage of simulated sources with localization error, and the free energies.

Results

The results are presented in Figure 3. The effect of the different noise conditions from noiseless to SNR = 5 dB and 1 dB was expressed as an increase in percentage error and a decrease in free energy. The lower the free energy, the worse the data is explained by a certain model. This agrees with our expectation when adding more channel noise.

Homogeneous models of the skull, (M2, M3 and M7) did not have a good performance. It can be noted that M2 (with anisotropy) had better performance than M3 and M7. The effect of differences in air cavity modeling were much less expressed in this study comparing M1 - M4 - M5 and M6. This also agrees with our expectations because no electrodes were directly capturing the EEG above the considered air cavities. The models with eroded spongy bone M1 and M6 performed worse in comparison with the reference model and M5 respectively. Based on Figures 2 and 3, M4 is modeled the closest to the reference model. It is also preferred over M5 because the conductivity of compact is closer to air than spongy bone.

Conclusions

In this work is shown that the PEB framework can be used to compare more complex FDM models which enables more advanced studies exploiting the possibilities of FDM into SPM, for example performing a Bayesian average over FDM models (Lopez, 2012).

We can conclude that the model evidences and error rates are equal indicators of model performance. This means the model evidence can be used as an indicator of forward model performance without knowledge of the underlying neural source activity.

The results show the opportunities of FDM modeling over BEM to include heterogeneous compartments and anisotropy in the skull.

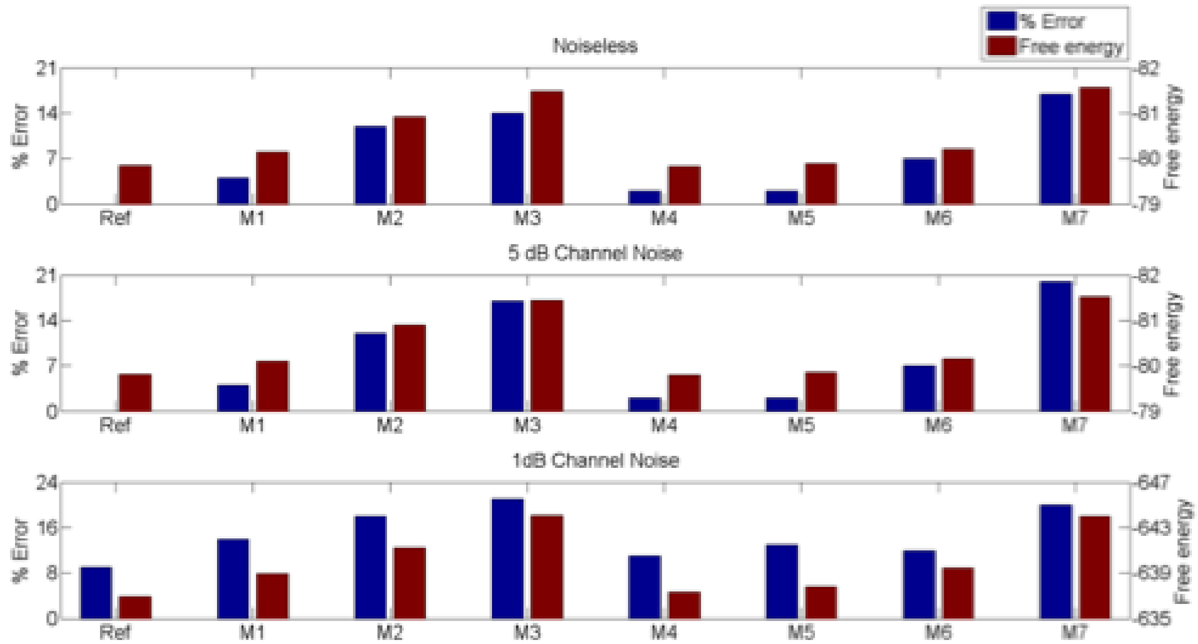

Figure 3: An overview of the % Error and Free energy values for each model. On the left y-axis, we show the percentage of sources that were not perfectly reconstructed. The right y-axis is reversed and contains the Free energy values. The reconstruction results are shown from top to bottom for the 3 simulation conditions

References (max. 10)

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