Diffusion Magnetic Resonance information as a regularization term for MEG/EEG inverse problem

Brahim Belaoucha, Anne-Charlotte Philippe, Maureen Clerc, Théodore Papadopoulo

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B. Belaoucha, A. Philippe, M. Clerc, T. Papadopoulo
Project Team Athena, INRIA, Sophia Antipolis - Méditerranée, France
Contact: brahim.belaoucha@inria.fr, url: http://www-sop.inria.fr/athena

Several regularization terms are used to constrain the Magnetoencephalography (MEG) and the Electroencephalography (EEG) inverse problem. It has been shown that the brain can be divided into several regions[1] with functional homogeneity inside each one of them. To locate these regions, we use the structural information coming from the diffusion Magnetic Resonance (dMRI) and more specifically, the anatomical connectivity of the distributed sources computed from dMRI. To invistigate the importance of the dMRI in the source reconstruction, we compare the solution based on dMRI-based parcellation to random parcellation.

1 Introduction

MEG/EEG are two non-invasive imaging modalities which provide information on the temporal succession of cognitive processes With imagingmethod the inverse problem is under-constrained because of the big difference between the number of observations (MEG,EEG) and the unknowns, i.e the source intensities. This ill-posed problem has to be constained by prior knowledge on the source space.

Let M be a vector of length m of the MEG/EEG data, G the lead field matrix, and S be the source activation on the cortex.

$$M = GS + \epsilon$$

It is common to use the $L2$ norm as a regularization parameter. The distributed sources minimum-norm (MNE) solutions have over-smoothed magnitude patterns and do not respect specific brain anatomical constrains like sulcus borders, so we further use of the dMRI information as a regularization term.

$$min_S ||M - GS||_2^2 + \lambda ||S||_2^2$$
$$S_\lambda = (G^t G + \lambda I)^{-1} G^t M$$

2 Methods:

1- Parcellation:

Due to the large number N of sources on the cortex, we parcellate the cortex region by region, i.e we use pre-parcellations with big region sizes to segment the whole cortex. In each pre-parcel, which is obtained from **FreeSurfer**, we compute the correlation, C, between the connectivity profiles of the sources obtained from dMRI. The later was obtained using the probabilistic tractography tools within **FSL**. Using *k-means* on the matrix $1 - |C|$, we could cluster the pre-parcel into p regions. p is chosen according to the following condition:

$$p : min_k \frac{\sum_{j=1}^{k} \lambda_j}{\sum_{i=1}^{N} \lambda_i} \geq C_{th}$$

Where λ_i is the i^{th} eigenvalue of $(1 - |C|)$ and C_{th} is a threshold defined by the user. The whole cortex is then divided into P regions.

2- Hard constraint solution (PSS):[3]

In this approach, we assume a constant intensity inside each cortical region. This allows us to reduce the source space from N to P ($P \leq N$). The function to be optimized can be written as:

$$||M - G_P s||_2^2 + \lambda ||s||$$

where $G_P = G \times H_P$ and $S = H_P \times s$.

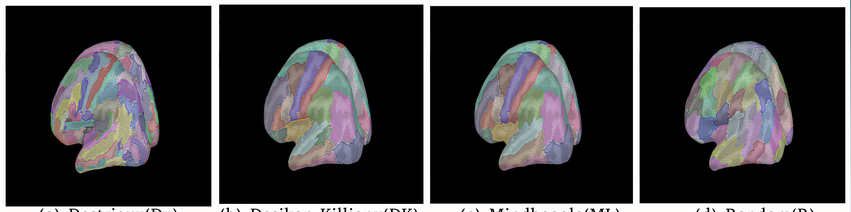
3- Soft constraint solution (PC):[3]

We allow some variation inside each cortical regions p by introducing another term to the objective function that depends on the region size $|p|$.

$$||M - GS||_2^2 + \lambda ||S||_2^2 + \mu ||R_P S||_2^2$$
$$R_P(i,j) = \begin{cases} 1 - \frac{1}{|p|} & \text{if } i = j \\ \frac{-1}{|p|} & \text{if } P(i) \in p \\ 0 & \text{if } P(i) \notin p \end{cases}$$

3 Experiments & Results

We first compare different dMRI parcellations obtained with three different pre-parcellation (Fig.1).



(a) Destrieux(Dx) (b) Desikan-Killiany(DK) (c) Mindboggle(ML) (d) Random(R)

Fig.1: The different pre-clustering approaches used to cluster the cortex

Let's define the similarity, SM, between two clustering results $S_1$and S_2 as:

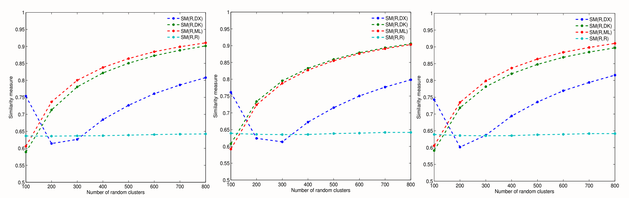
$$SM(S_1, S_2) = max(D(S_1, S_2), D(S_2, S_1)) \text{ where } D(S_1, S_2) = \frac{1}{N} \sum_{i=1}^{n} |S_1(i)| \sum_{j=1}^{m} \frac{|S_1(i) \cap S_2(j)|}{|S_1(i) \cup S_2(j)|}$$

$S(i)$ is a cortex region and n, m are the total number of regions in cortex segmentation S_1 and S_2 respectively. Table.1 shows the resulting number of regions for different threshold values, C_{th}, pre-parcellation, and subjects. The number of regions are relatively similar across subjects for a given threshold value.

Subject	Random			Destrieux			Desikan-kiliany			Mindboggle		
	60%	70%	80%	60%	70%	80%	60%	70%	80%	60%	70%	80%
1	217	323	355	308	431	503	150	194	270	132	195	227
2	199	300	362	297	400	544	144	198	250	128	186	244
3	215	306	368	295	415	537	149	196	246	145	189	214
4	215	306	369	304	432	533	146	199	241	126	185	237

Table.1: The final number of cortex regions vs C_{th} value and pre-parcellation.

Fig.2 shows the SM values between the random cortex segmenation (with similar number of parcels) and the 3 atlases shown in Fig.1. These values are smaller than thoseobtained between atlases (Fig.2 table).



Subject 1 Subject 2 Subject 3

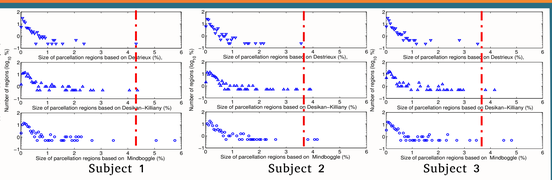
Subject Id	SM(DX,DK)	SM(DX,ML)	SM(DK,ML)
1	0.77	0.79	0.76
2	0.78	0.76	0.75
3	0.80	0.78	0.73
4	0.79	0.80	0.79
5	0.76	0.78	0.76
6	0.71	0.82	0.83

SM

Fig.2: SM values between the different parcellations of different subjects.

On the other hand, the SM between random cortex parcellations of the same number of regions is much smaller than the SM between the resulting parcellation that are based on the atlases.

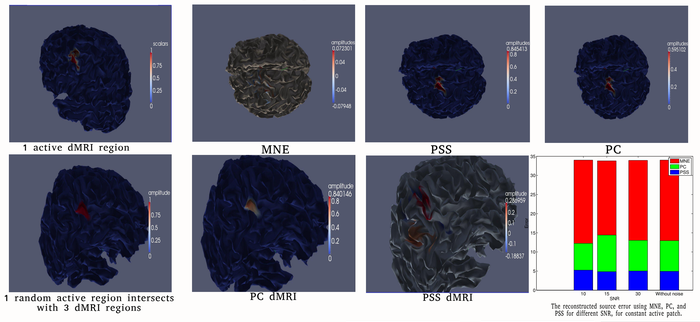
Because ML and DK give bigger regions than the DX, we decided to use the later for source reconstruction.



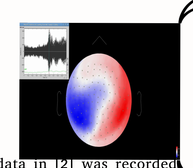
Subject 1 Subject 2 Subject 3

3.1 Synthetic data

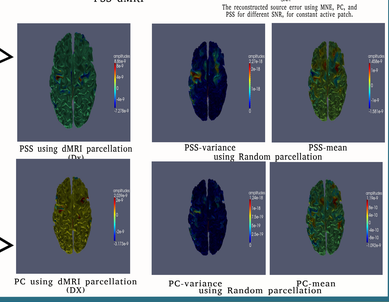
In the first line we activate one dMRI patch, and in the second a random region that intersects with three dMRI regions



3.2 Real data [2]



The MEG data in [2] was recorded from visual stimulus. We computed the mean of the trials to reduce the noise and use it to reconstruct the sources intensities for the different approaches.



4 Conclusion

PSS and to a smaller extent PC improve over MNE and are more robust to noise. Variance is higher around the activated patch for PSS than PC, when random clustering is used. PSS works well for small patchs when the activity is constant over the patch. The random clustering was not geometrically constrained like the dMRI parcellation. The effect of these atlas boundaries should be invistigated. Cortex parcellations based on the geometrical pre-parcellation (DX, DL, and ML) and k-means are more similar to each other than random parcellations. Future work will be looking in using a mixed norm for the reduced source space.

References

[1] Grova, et al. Evaluation of EEG localization methods using realistic simulations of interictal spikes. NeuroImage, 29(3):734, 2006. [2] Henson,et al. A Parametric Empirical Bayesian Framework for the EEG/MEG Inverse Problem: Generative Models for Multi-Subject and Multi-Modal Integration. Frontiers in human neuroscience, 5, 2011. [3] Philippe, et al. Cortex parcellation via diffusion data as prior knowledge for the meg inverse problem. In International Symposium on Biomedical Imaging, 2013.