Using diffusion MRI information in the Maximum Entropy on Mean framework to solve MEG/EEG inverse problem

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Magnetoencephalography (MEG) and Electroencephalography (EEG) inverse problem is well-known to require regularization to avoid ill-posedness. Usually, regularization is based on mathematical criteria (minum norm, ...). Physiologically, the brain is organized in functional parcels and imposing a certain homogeneity of the activity within these parcels was proven to be an efficient way to analyze the MEG/EEG data [1][6]. The parcels information can be computed from diffusion Magnetic Resonances Imaging (dMRI) by grouping together source positions shared the same connectivity profile (computed as tractograms from diffusion images). In this work, three parcel-based inverse problem approaches have been tested. The first two approaches are based on minimum norm with added regularization terms to account for the parcel information. They differ by the use of a hard/soft constraint in the way they impose that the activity is constant within each parcel [4]. The third approach is based on the Maximum Entropy on Mean (MEM) framework [2]. The dMRI-base and random cortex parcellation, we test also the use of Multivariate Source Pre-localization (MSP) [5] in the source reconstruction.

1 Methods

Let the magnetic field, b, be the measured by the MEG sensors during a large number of repetitions of a given task, and m be the sample statistics of the mean value of the instantaneous magnetic field on the sensors with additive noise ϵ , and G is the leadfield matrix.

$$m = E[b] \qquad\qquad m = GE[R] + \epsilon$$

The source space of size N is parcelized into K regions. R is the multidimentional continuous random variable that describes the intensities of the distributed sources. We denote by $d\mu$ the reference probability distribution and can be computed as:

$$d\mu(r) = \sum_S \prod_{k=1}^{K} d\mu(r_k|S_k)\pi(S_k)$$

where $\pi(S_k)$ is the probability that the patch k is active or not, and S is the set of state variable .

1/ MEM framework:[2]

R has the following probability law: $dp(r) = f(r)d\mu(r)$

The $\mu - entropy$ is defined as:

$$S_\mu(dp) = -\int log\frac{dp}{d\mu}dp$$

The source intensities are obtained by minimizing the following functional:

$$L(p, \lambda, \lambda_0) = -S_\mu(dp) + \lambda^t(m - Gr) + \lambda_0(1 - \int dp(r))$$

The solution is:

$$dp(r) = exp(\lambda^t Gr - F^*(G^t\lambda))d\mu(r)$$

$$F^*(\zeta) = log \int exp(\zeta^t r)d\mu(r)$$

Assuming K uncorrelated cortical regions, the reference probability distribution and the source intensity in every patch P_l can be computed as:

$$d\mu(r) = \sum_S \prod_{k=1}^{K} \pi(S_k)d\mu(r_k|S_k)$$

$$r_{i,l} = \sum_S \tilde{\pi}(S) \bigtriangledown_i F^*_{S_l}(\xi)_{|\xi=G^t\lambda^t} \qquad\qquad i \in P_l, l = 1, .., K$$

where:

$$\tilde{\pi}(S) = \frac{\prod_{k=1}^{K}\pi(S)F^*_{S_k}(A^t\lambda_k)}{\sum_S\prod_{k=1}^{K}\pi(S)F^*_{S_k}(A^t\lambda_k)} \qquad F^*_{S_k}(\xi_k) = log\int exp(\xi_k^t r_k)d\mu(r_k|S_k)$$

We used the $CMEM$ implementation [5].

2/ Hard constraint (PSS):[4]

In this approach we assume a constant amplitude in each cortical region, which allows us to reduce the source space from N to K ($K \leq N$). The intensities is obtained by minimizing the following:

$$U(r) = ||m - G_k r_K||_2^2 + \lambda||r_K||_2^2$$

G_k is the reduced leadfield matrix.

3/ Soft constraint (PC):[4]

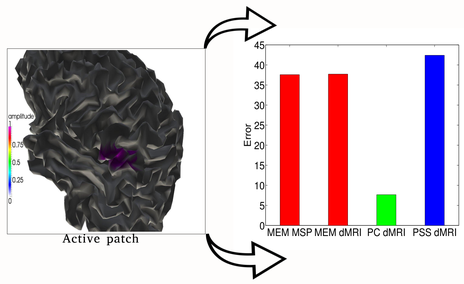
Some variation in each patch is allowed by introducing the Laplacian regularization inside each patch. The solution is obtained by minimizing the following:

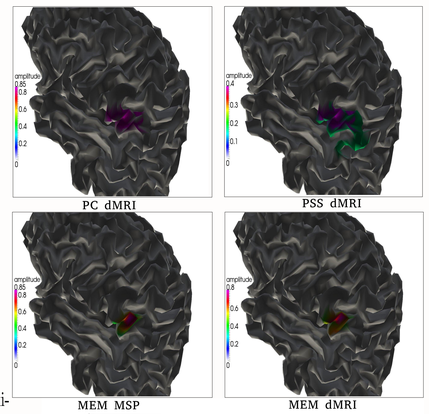
$$U(r) = ||m - Gr||_2^2 + \lambda||r||_2^2 + \mu||Wr||_2^2$$

$$W(i,j) = \begin{cases} 1 - \frac{1}{|p|} & \text{if } i = j \\ \frac{-1}{|p|} & \text{if } r(i) \in p \\ 0 & \text{if } r(i) \notin p \end{cases}$$

2 Results

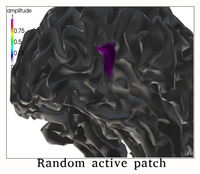
2.1 Synthetic data

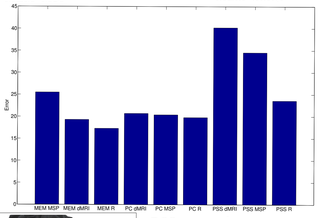


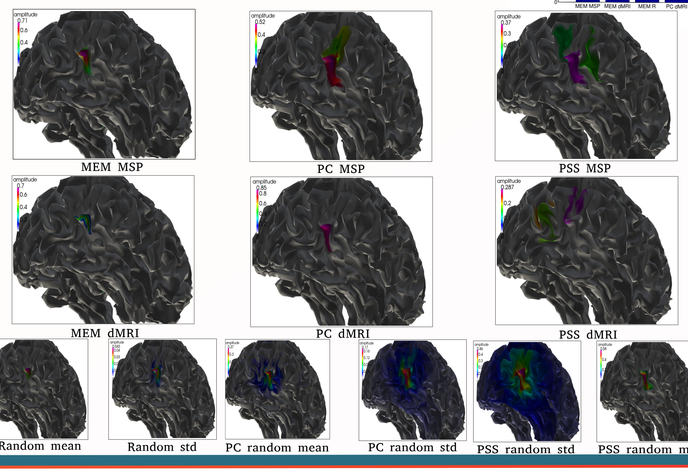


In all the results, we neglected the sources that are less than 40% of the maximum intensity. The error was computed as follows:

$$Error(r_{orig}, r_{method}) = \sum_{i=1}^{N} |r_{orig}(i) - r_{method}(i)|$$







PSS tends to activate neighbor regions, this yields to high variance when using random parcellation. MEM solution is more focal and less affected by noise.

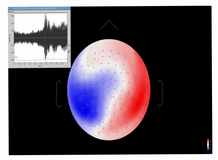
Execution Time
PSS: 0.5s
MEM: 19.4s
PS: 20min
Random: 100 parcellation

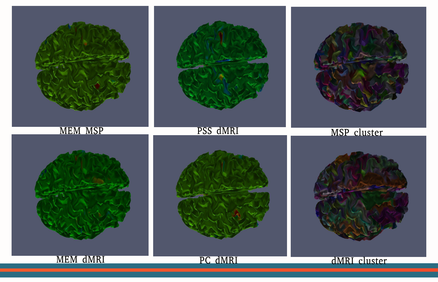
Similarly to [6], 100 random parcellation were generated with fixed region size. It uses the connected vertices to grow the regions till it reach a fixed size. There was no constraint in the contrary to the dMRI parcellation which was obtained via Destrieux atlas.

(See poster P3-036)

2.2 Real data

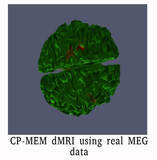
In this part of the work, the three reconstruction algorithms were used to find the activation map on the cortex from a real MEG data[3].The data [3] includes also the T1 and DWI information. The MEG/EEG was recorded from a visual stimulus (3 class pictures). The average trials for one subject and one class (famous face) was used.



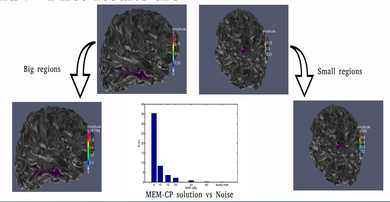


3 Conclusion

MEM solution was enhanced by using the dMRI parcellation. PC is quite insensitive to parcellation but is very computationally intensive. Contrary to MEM and PC, PSS while being very fast is quite sensitive to the choice of parcellation. Interestingly, the best results are obtained by averaging solutions over multiple random clustering (at the cost of computational time), which might be interesting if no dMRI information is available. This is maybe due to the constrained dMRI pre-parcellation. A post clustering of the boundaries on the dMRI parcellation can be done to reduce the effect of the geometrical constraint. Future work will look at generalizing these results to EEG. Another direction is to use the reduced leadfield in the MEM framework (CP-MEM) by using G_K and r_K instead of G and r. First results are:



CP-MEM dMRI using real MEG data



References

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