Using Structural Connectivity to Reconstruct Brain Activation and Effective Connectivity

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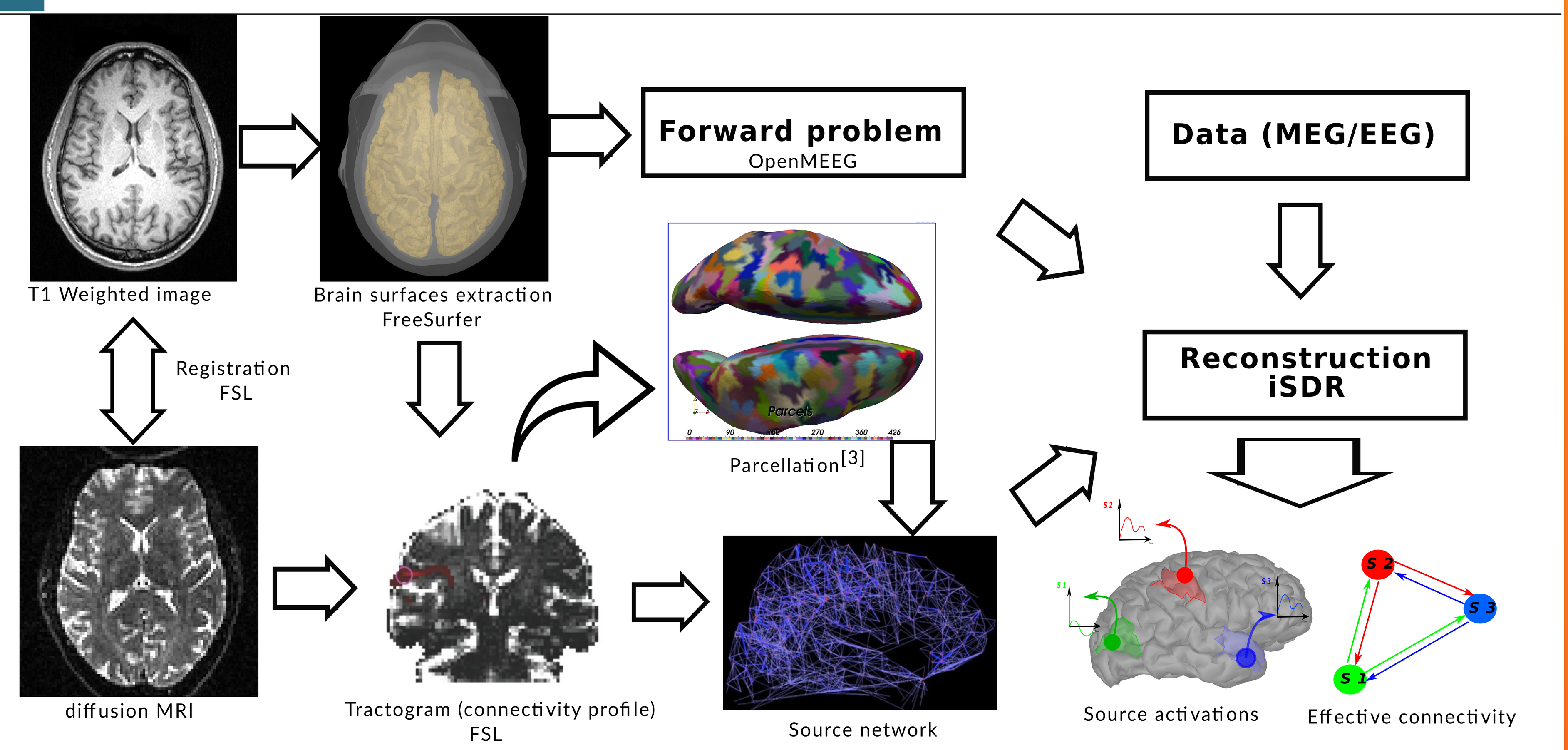
Abstract: Understanding how brain regions interact to perform a specific task is very challenging. EEG and MEG are two non-invasive imaging modalities that allow the measurement of brain activation with high temporal resolution. Several works in EEG/MEG source reconstruction show that estimating brain activation can be improved by considering spatio-temporal constraints but only few of them use structural information to do so. We present a source estimation algorithm that uses brain structural connectivity, obtained from diffusion MRI (dMRI), to constrain the EEG/MEG source reconstruction. Contrarily to most source reconstruction methods which reconstruct activation for each time instant, the proposed method estimates an initial reconstruction for the first time instants and a multivariate auto-regressive model that explains the data in further time instants. This auto-regressive model can be thought as an estimation of the effective connectivity between brain regions.

1 Main ideas

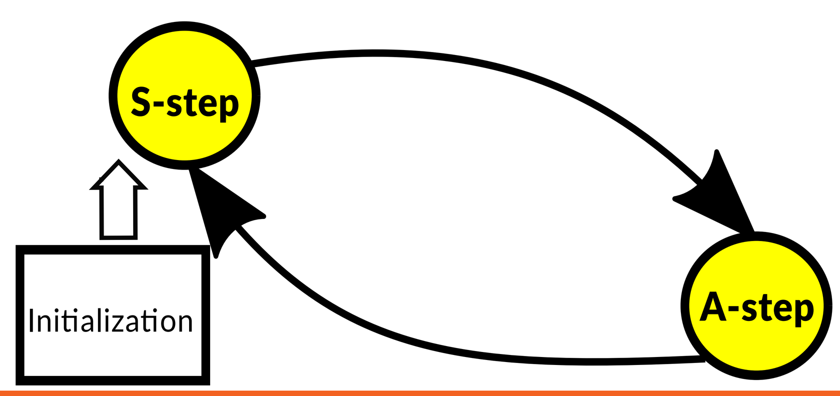
- Reduce the source space using dMRI (parcellation).
- Search for a spatio-temporal model of sources given by:
  - Initial sources values.
  - AR coupling coefficients between parcels.
- The above model must explain observed values for a given time window.

2 Processing pipeline



3 iterative Source and Dynamics Reconstruction (iSDR)

- Source model: $\mathbf{J}_t = \sum_{i=1}^{p} \mathbf{A}_i \mathbf{J}_{t-i} + \varepsilon_t$.
  $\mathbf{J}_t$ and $\varepsilon_\mathbf{t}$ are sources and noise at time t. Matrices $\mathbf{A}_i$, $i \in [1, p]$ contain non-zero elements only for neighbor sources or sources connected through white matter.
- Minimization of: $U(\mathbf{J}) = \frac{1}{2} \|\mathbf{M}_v - \mathbf{G}_d \mathbf{J}_v\|_2^2 + \lambda \|\mathbf{J}\|_{21}$, where:
  - $\mathbf{M}_v = \mathrm{vec}(\mathbf{M})$, $\mathbf{M} \in \mathbb{R}^{N_c \times (T-p)}$, represents the measurements between $p+1$ and T.
  - $\mathbf{J}_v = \mathrm{vec}(\mathbf{J})$, $\mathbf{J} \in \mathbb{R}^{N_s \times (T-1)}$ contains the sources' activity between the first time sample and $T-1$.
  - $\mathbf{G}_d \in \mathbb{R}^{N_c(T-p) \times N_s(T-1)}$ is a spatio-temporal lead-field matrix, depending on the leadfield $\mathbf{G}$ and matrices $\mathbf{A}_i$.
- Sparsity of $\mathbf{J}$ ($\|\mathbf{J}\|_{21}$) induces sparsity on $\mathbf{A}_i$.
- Find $\mathbf{J}_t$, $i \in [1, p]$ (S-Step) and $\mathbf{A}_i$, $i \in [1, p]$ (A-Step) using an extension of the MxNE algorithm [1].



3 Experiments and results

- Evaluation on real dataset described in Wakeman et al [2].
- Simultaneous recording of MEG/EEG data during a face recognition task where a subject is shown famous, unknown or scrambled faces.
- Dataset contains dMRI and T1 images.
- Acquired data can be explained by our model with few regions as soon as $p > 1$ (Fig. 1).
- Reconstructions using EEG and MEG show a clear negative peak at the FG around 200ms for $p > 1$ which matches literature (Fig. 2).
- Non-null coefficient in the final A can be considered as the effective connectivity used during the task (Fig. 3).

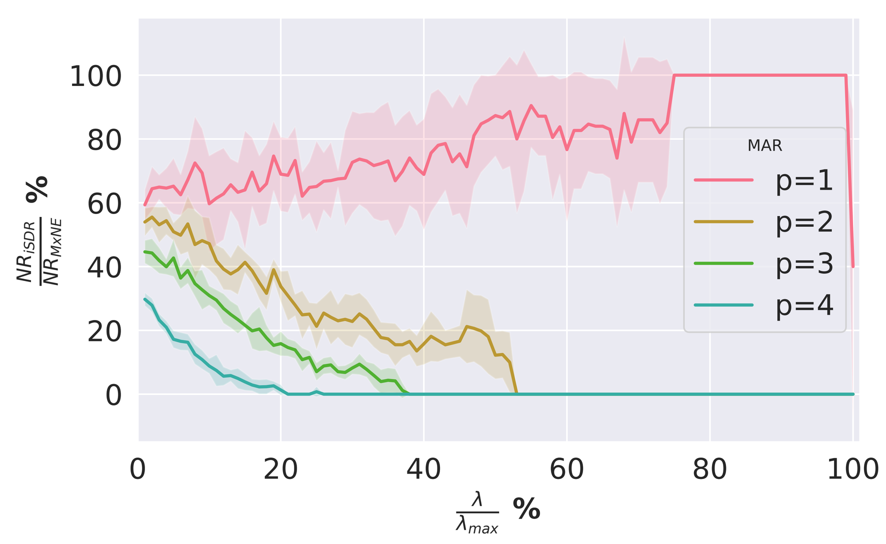


Fig 1 : Mean and standard deviation of the relative number of active regions discovered by our method for different MAR orders, compared to MxNE. The horizontal axis refers to the relative value of the regularization parameter, while the vertical axis refers to the ratio of the number of regions recovered by the two methods.

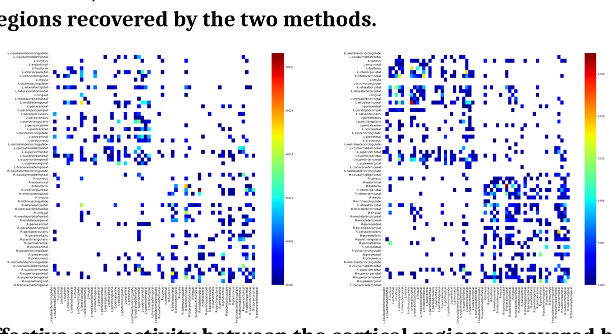


Fig 3 : Effective connectivity between the cortical regions recovered by iSDR with p=4 from EEG (left) and MEG (right) data, computed as the weighted average of absolute MAR weights, over subjects and A_i's.

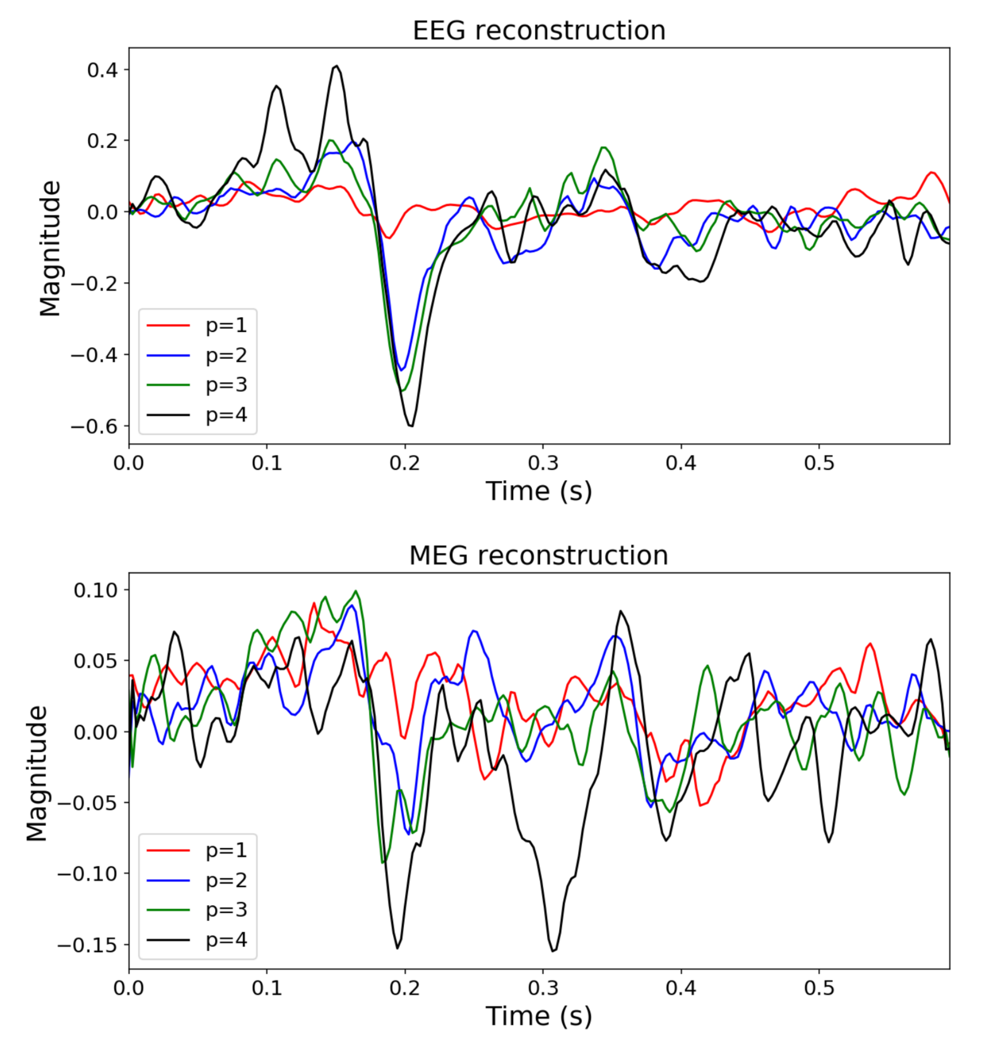


Fig. 2: The group median activation using iSDR in the right FG computed over the eleven subjects using (a) EEG and (b) MEG data with differentMAR orders.

4 Contributions and Conclusion

- Brain activation and effective connectivity reconstruction method using an extension of the MxNE solver.
- Sources are constrained to follow a MAR model of order p.
- Such a model can fit real M/EEG measurements with relatively few activated regions as soon as $p > 1$.
- Recovered activated regions coherent with the task used to acquire the dataset.

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References: [1] Gramfort, A. (2012), *'Mixed-norm estimates for the M/EEG inverse problem using accelerated gradient methods'*, Physics in Medicine and Biology vol 57, no. 7.
[2] Wakeman, D. G, (2015), *'A multi-subject, multi-modal human neuroimaging dataset'*, Scientific Data 2.
[3] Belaoucha, B. (2016), *'Cortical surface parcellation via dMRI using mutual nearest neighbor condition'*, IEEE 13th International Symposium on Biomedical Imaging (ISBI).

iSDR code is available at `https://github.com/BBELAOUCHA/iSDR_p`