

# New Methods in EEG Source Localization based on EEG and Post-Mortem Pathology Data



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## Introduction

A central task in neuroscience is to determine the location of electrical activity from neural origin inside the brain. Electrical signals can be recorded at a high resolution in time but low resolution in space, thus making it difficult to locate its sources unambiguously.

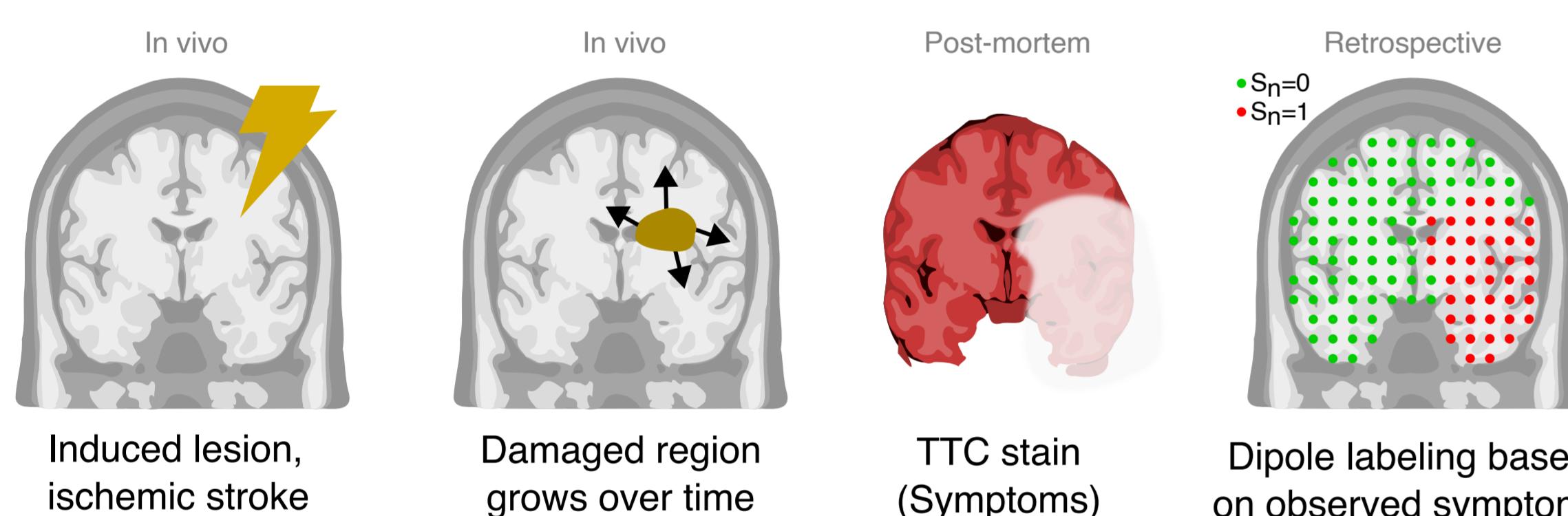
The electrical source localization methods can be enhanced by considering data from additional imaging modalities. We propose a simple model using binarized pathology data to enhance electrical source imaging from EEG recordings.



## Motivation

This project is based on the goal is to study the temporal evolution of the acute ischemic stroke in the middle cerebral artery. In the experiments with animal models, electrophysiological recordings can be obtained while ischemic stroke is induced.

Post-mortem, the subject's brain is stained with triphenyltetrazolium (TTC) to identify tissues damaged by hypoxia; this pathology data is referred to as **symptoms**.



## Model

The forward model of EEG and distributed electrical dipoles over a grid inside the brain can be written as a matrix equation [2]:

$$\mathbf{Y} = \mathbf{GJ} + \varepsilon \quad (1)$$

with  $\mathbf{Y} \in \mathbb{R}^{M \times T}$  EEG data,  $\mathbf{J} \in \mathbb{R}^{N \times T}$  magnitudes of dipoles,  $\varepsilon \in \mathbb{R}^{N \times T}$  noise, and  $\mathbf{G} \in \mathbb{R}^{M \times N}$  encodes the mixture of neural electric dipoles.

Pathology information is used to construct a label for each dipole in the grid,  $S \in \{0, 1\}^{N \times 1}$ , so that  $S_n = 1$  if the  $n$ -th dipole is located on a region where symptoms were observed.

Brain is also divided into  $K$  arbitrary regions. An indicator matrix,  $L \in \{0, 1\}^{N \times K}$ , is constructed so that  $L_{n,k} = 1$  if the  $n$ -th dipole is in the  $k$ -th region.

Thus  $\mathbf{J}$  is fragmented in space, based on the pathology data and anatomical region, using the respective variables  $\mathbf{U} \in \mathbb{R}^{K \times T}$ ,  $\mathbf{N} \in \mathbb{R}^{N \times T}$ .

$$\mathbf{Y} = \mathbf{GJ} + \varepsilon \quad (2)$$

$$\mathbf{J} = L_S \mathbf{U} + \mathbf{N} \quad (3)$$

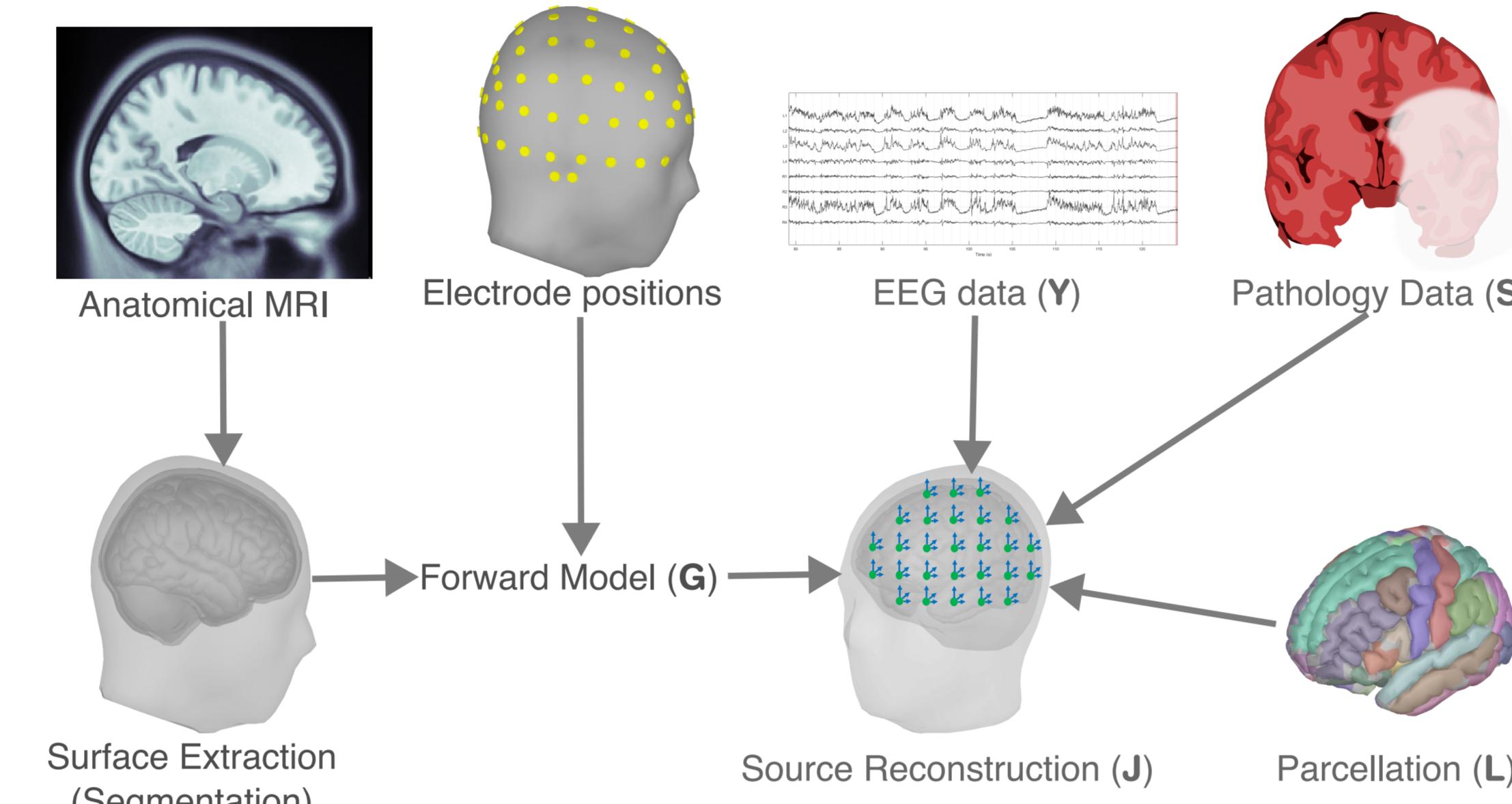
where  $L_S = \text{diag}(S) L$ . These vector are assumed to follow Gaussian distributions independent of time:  $\varepsilon \sim \mathcal{N}(0, \sigma^2 \mathbf{I})$ ,  $\mathbf{N} \sim \mathcal{N}(0, \gamma_0^2 \mathbf{I})$ ,  $\mathbf{U} \sim \mathcal{N}(0, \gamma_1^2 \mathbf{I})$ , with  $\gamma_0^2 \ll \gamma_1^2$ . The Maximum A Posteriori estimator is constructed for  $\mathbf{J}$  as

$$\hat{\mathbf{J}} = [\gamma_0 \mathbf{I} + L_S (L_S^T L_S)^{-1}] \mathbf{M} \mathbf{G}^T \mathbf{Y}, \quad (4)$$

$$\mathbf{M} = [\mathbf{G} (\gamma_0 \mathbf{I} + L_S (L_S^T L_S)^{-1}) \mathbf{G}^T + \sigma^2 \mathbf{I}]^{-1}. \quad (5)$$

## Implementation

Computations were carried out using Matlab 2021b. Surfaces (head, inner and outer skull, brain cortex) were extracted using the CAT 12 toolbox, and the forward model was computed using the OpenMEG toolbox, included within the Brainstorm toolbox [4].



## Evaluation metrics

Synthetic data protocol: one dipole is selected randomly, the known magnitude is set to  $\mathbf{J}_n(t) = \sin(2\pi t)$  at 15 Hz.

We tested 1,000 trials over different levels of noise against some classical methods: Tikhonov regularization and sLORETA [3].

Parameters were selected via Generalized Cross-Validation [1]. Brain cortex was parcellated using the Desikan-Killiani anatomical atlas.

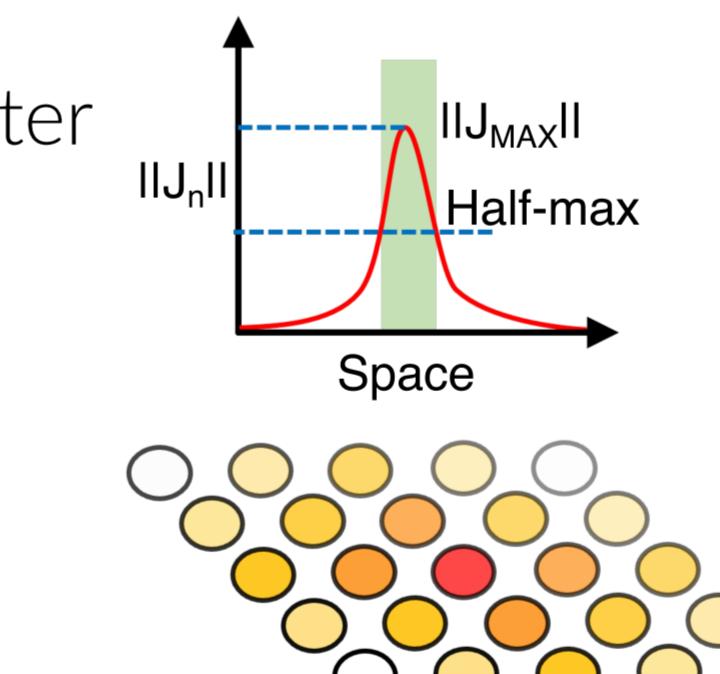
Performance was measured with the following metrics:

**Localization Error.** Source location is estimated as the center of mass of reconstructed  $\mathbf{J}$ ,

$$\text{pos}_{\text{source}} = \frac{\sum_{n=1}^N \|\hat{\mathbf{J}}_n\| \text{pos}_n}{\sum_{n=1}^N \|\hat{\mathbf{J}}_n\|}.$$

**Half-Max Size.** Measurement of dispersion,

$$\text{HMS} = \text{vol} \left\{ n; \|\hat{\mathbf{J}}_n\| > \frac{1}{2} \|\hat{\mathbf{J}}_{\text{MAX}}\| \right\}.$$



## Results

Missing due to a synchronization error with Google Drive.

## Future work

We proposed a fast method to incorporate binary pathology data, obtained post-mortem, to enhance source localization based on EEG.

For this work we assumed that the damaged region is constant over time. However, this method can be easily extended to consider a time-changing damaged region. Extensions of this method with other types of data as prior is being investigated.

## References

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- [2] H. Hallez, B. Vanrumste, R. Grech, J. Muscat, W. De Clercq, A. Vergult, Y. D'Asseler, K. P. Camilleri, S. G. Fabri, S. Van Huffel, et al. Review on solving the forward problem in EEG source analysis. *Journal of Neuroengineering and Rehabilitation*, 4(1):1–29, 2007.
- [3] M. A. Jatoi, N. Kamel, A. S. Malik, I. Faye, and T. Begum. A survey of methods used for source localization using eeg signals. *Biomedical Signal Processing and Control*, 11:42–52, 2014.
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