

EEG source localisation and cortical mapping

Mathematics of electrical imaging: modeling, theory and implementation, Toulouse

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This research was undertaken when I was a member of the FACTAS team at the Inria Centre at Université Côte d'Azur and the Analysis team of IMB. This work was done jointly with Paul Asensio, Jean-Michel Badier, Juliette Leblond and Jean-Paul Marmorat.

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- Typically it is assumed that the head is a nested layered conductor with distinct layers (brain, skull, scalp) having different but constant electric conductivities.
- Using EEG data, a Cauchy data completion problem (recovery of the electric potential and normal currents) can be solved on the outer surfaces of the scalp, skull and cortex (inverse cortical mapping problem).

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- The hope is that this will improve numerical accuracy and provide context in the analysis of the recovery results.

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 - ▶ the Newton potential maps the (distributional) divergence of the members of space continuously.
 - ▶ the space is uniformly smooth.
- We will present a method for solving the inverse problems of source localisation and cortical mapping simultaneously with the source modelled as vector measures supported on the white matter fibres.

Definitions and preliminaries

- Let $\gamma : [0, l] \rightarrow \mathbb{R}^3$ be a Lipschitz mapping and let $S := \gamma([0, l])$. If γ is such that

$$\mathcal{H}_1(\gamma([a, b])) = b - a, \quad \forall [a, b] \subset [0, l],$$

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- Hence for each white matter fibre we can define a collection of vector measure $\mathbf{R}_{h\gamma} = h(\gamma(t))\gamma' \mathcal{H}_1$, with $\gamma(t)$ being an arclength parametrisation of the white matter fibre and $h \in L^1(\gamma' \mathcal{H}_1)$.

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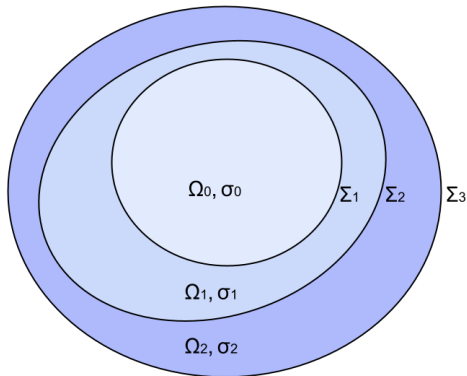
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- In the source localisation we aim to recover $h(\gamma(t))$.

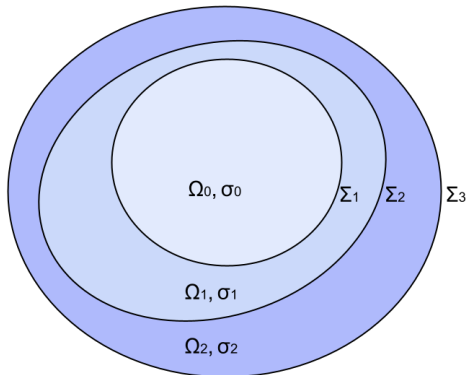
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- For each Σ_i , σ_i^- and σ_i^+ are σ inside and outside Σ_i , respectively, ϕ^- and ϕ^+ are the non-tangential limits of ϕ approaching from inside and outside, respectively.

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- Regularity of solutions to elliptic PDEs imply that ϕ satisfies the following transmission conditions on each Σ_i , $i = 1, 2, 3$

$$\begin{aligned}\phi^- &= \phi^+ \\ \sigma^- \partial_\nu \phi^- &= \sigma^+ \partial_\nu \phi^+.\end{aligned}$$

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- Using a result of Gezelowitz, Sarvas showed that ϕ associated with μ_0 , at $x \in \mathbb{R}^3 \setminus \text{supp}(\mu_0)$ are:

$$\sigma(x)\phi(x) = \frac{1}{4\pi} \int_0^l \frac{(x - \gamma(t))}{|x - \gamma(t)|^3} \cdot h(\gamma(t))\gamma'(t) dt$$

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where \mathcal{H}_2^i is the 2-dimensional Hausdorff measure on Σ_i , ν is the unit outer normal on Σ_i .

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- It can be shown that all divergence-vector measure $\mathbf{R}_{h\gamma}$ are silent, that is all vector measures such that,

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- A concrete example are all vector measures $\mathbf{R}_{h\gamma}$ with $h = 1$ and $\gamma(0) = \gamma(l)$.
- The existence of silent sources implies non-uniqueness of solutions to the inverse source localisation problem hence it is ill-posed.

Inverse problems

Problem 1

Given EEG data f and parameters $\alpha, \beta, \lambda, \lambda_i > 0, i = 1, 2, 3$, find

$$(\mu_0, \phi_1, \phi_2, \phi_3) = \underset{(\mu_0, \phi_1, \phi_2, \phi_3)}{\operatorname{arg\,inf}} \mathcal{T}_{f, \lambda}(\mu_0, \phi_1, \phi_2, \phi_3),$$

where

$$\begin{aligned} \mathcal{T}_{f, \lambda} := & \alpha \|\mathcal{F}_1(\mu_0, \phi_1, \phi_2, \phi_3) - f\|^2 + \beta \|\mathcal{F}_2(\mu_0, \phi_1, \phi_2, \phi_3)\|^2 \\ & + \lambda \mathfrak{R}\left(\|\mu_0\|_{[\mathcal{M}(\Sigma_0)]^3}\right) + \sum_{i=1}^3 \lambda_i \|\phi_i\|_{L^2(\Sigma_i)}^2. \end{aligned}$$

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with some initial guess for $k = 0$ by solving the problems

$$\begin{aligned} \boldsymbol{\mu}_0^{\{k+1\}} &= \arg \inf_{\boldsymbol{\mu}_0} \mathcal{T}_{f,\lambda}(\boldsymbol{\mu}_0, \phi_1^{\{k\}}, \phi_2^{\{k\}}, \phi_3^{\{k\}}) \\ (\phi_1^{\{k+1\}}, \phi_2^{\{k+1\}}, \phi_3^{\{k+1\}}) &= \arg \inf_{(\phi_1, \phi_2, \phi_3)} \mathcal{T}_{f,\lambda}(\boldsymbol{\mu}_0^{\{k\}}, \phi_1, \phi_2, \phi_3). \end{aligned}$$

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- This is a minimising sequence for which $\mathcal{T}_{f,\lambda}(\mu_0^{\{k\}}, \phi_1^{\{k\}}, \phi_2^{\{k\}}, \phi_3^{\{k\}})$ converges at least linearly because of the uniform smoothness.

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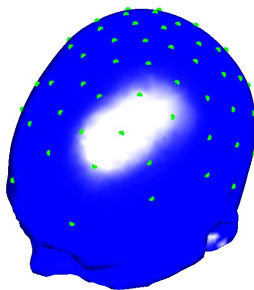
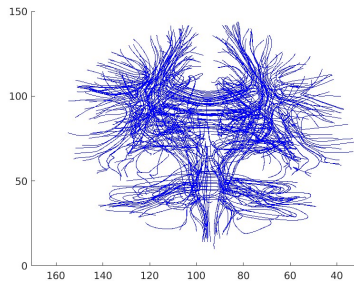
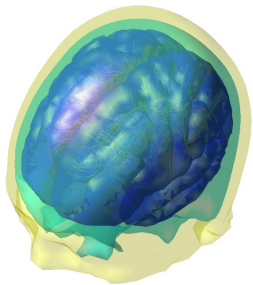
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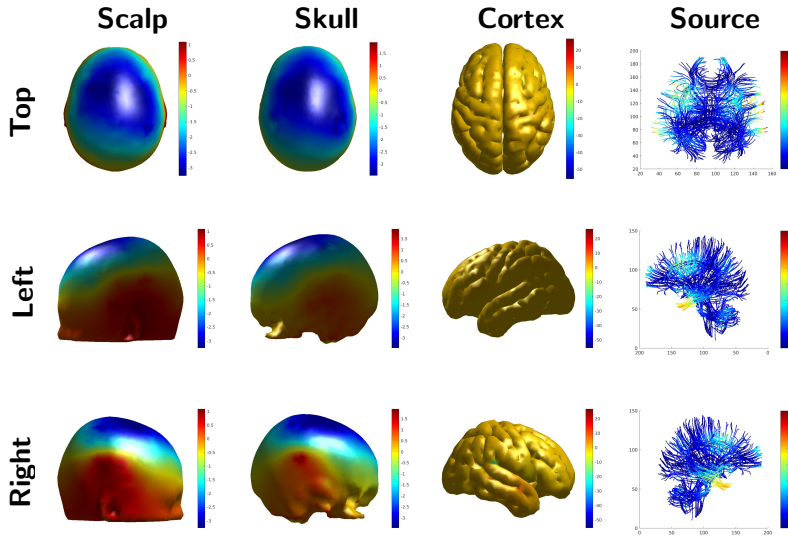


Figure: Source recovery with real auditory EEG data for the N100 response.

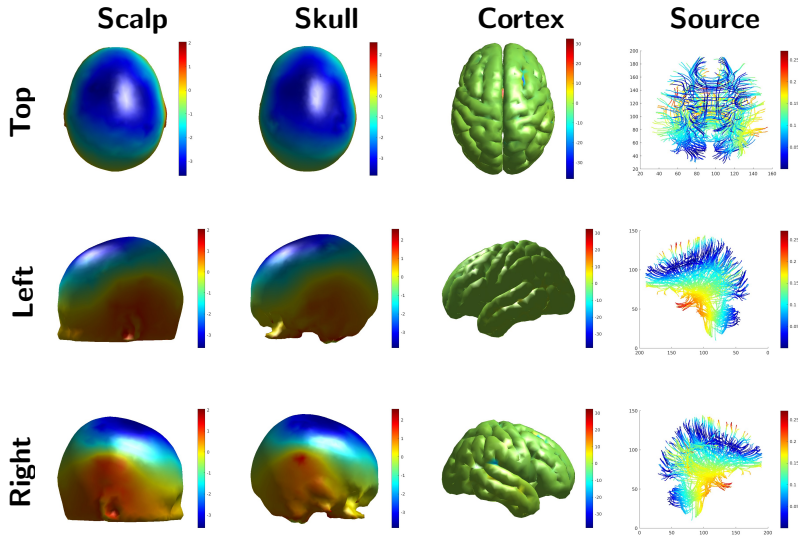


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- We provided the mathematical requirements for such a source model.
- There is a need to improve the computational efficiency.
- Of particular interest is to study if it is possible to change the regularisation parameters at each step of the alternating minimisation algorithm in order to get a norm-minimising equivalent solution in the end.

Thank you :)