Imaging Brain Activity

and application to Brain-Computer Interfaces

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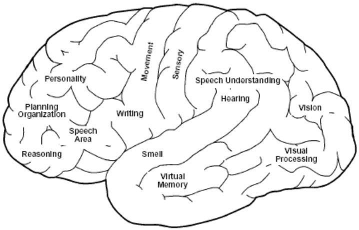
Imaging in Paris Seminar

Introduction

Functional Areas of the Brain



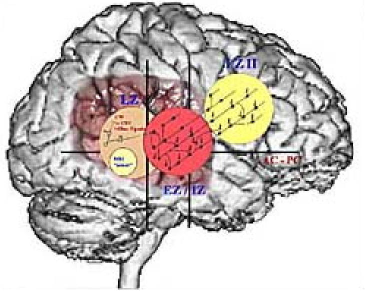
- schematic organization
- variability of cortical foldings
- subject-dependent localization of activity

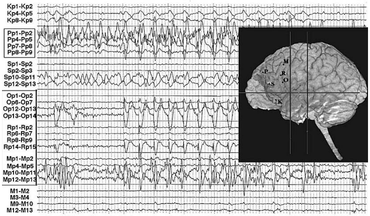
Brain activity can be localized:

- invasively: brain stimulation, depth electrodes
- non-invasively: neuroimaging

Introduction

Example: neuroimaging for presurgical evaluation of epilepsy



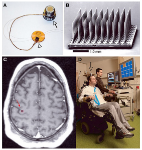


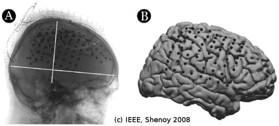
Epileptogenic regions must be localized precisely

- intracerebral recordings
- non-invasive recordings

Functional regions also to be localized precisely for surgical planning

Acquisition devices

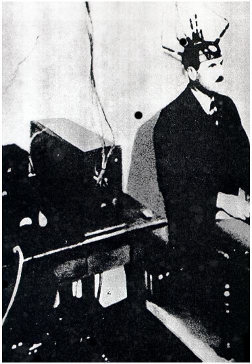




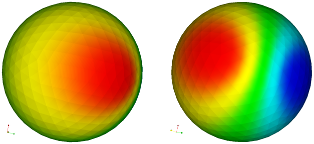
Device	Neurophysiological measure
Microelectrode Arrays action potentials (single neurons)	electric potential $\rightarrow$ spikes
Intracerebral electrodes post-synaptic + action potentials (10^2 neurons)	electric potential$\rightarrow$ LFP and spikes
Electrocorticography post-synaptic activity (10^3 neurons)	electric potential
Electro (Magneto)encephalography post-synaptic activity (10^4 neurons)	electric potential / magnetic field
functional MRI brain metabolic activity	O_2 consumption in 3D
functional Near-Infrared Spectroscopy brain metabolic activity	O_2 consumption of region between optodes

Non-invasive recordings: electric potential

1924: Hans Berger measures electrical potential variations on the scalp.

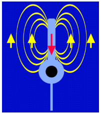


- birth of **Electro-Encephalography (EEG)**
- several types of oscillations detected (alpha 10 Hz, beta 15 Hz)
- origin of the signal unclear at the time
- scalp topographies ressemble dipolar field patterns

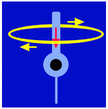


Noninvasive recordings: from electric to magnetic field

A dipole generates both
an **electric** and a **magnetic** field



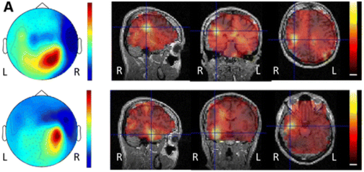
electric field



magnetic field

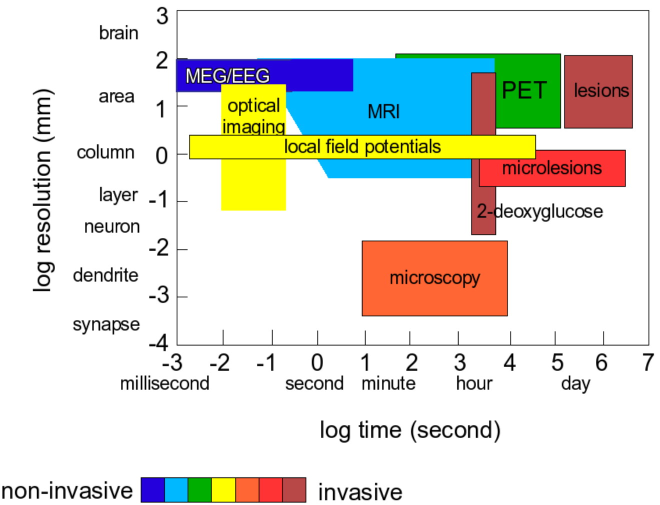
- 1963: Magnetocardiography,
- 1972: **Magneto-Encephalography (MEG)**
  D. Cohen, MIT, measures alpha waves, 40 years after EEG
  Superconductive QUantum Interference Device
  Magnetic shielding

Advantage of MEG over EEG: spatially more focal



[Badier, Bartolomei et al, Brain Topography 2015]

Comparison between modalities



To achieve this resolution with EEG or MEG requires...

[Baillet Mosher Leahy IEEE Sig Proc Mag 2001]

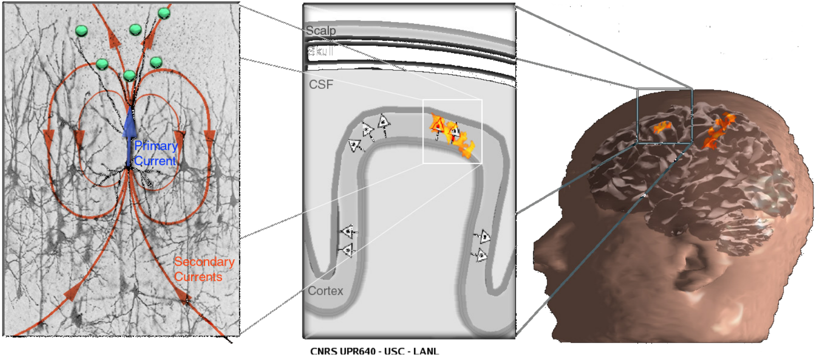
a.k.a

- “Source reconstruction”
- “Source imaging”
- “Cortical source estimation”
- “Inverse solution”

Outline

1. Introduction to Neuroimaging
2. **Forward problem: from Sources to Sensors**
   - **Forward problem and conductivity**
   - **Volume conduction**
   - **Solving the Forward problem**
3. Inverse Source Reconstruction
   - Regularized Source Reconstruction
   - Current Source Density Mapping
   - Surface Laplacian
4. Brain Computer Interfaces
   - Neuroimaging in BCI
   - Motor Imagery
   - Error-related Potential

Origin of brain activity measured in EEG and MEG



[Baillet et al., IEEE Signal Processing Mag, 2001]

Pyramidal neurons post-synaptic currents

Current perpendicular to cortical surface

Neurons in a macrocolumn co-activate

Conductivity σ

Relation between sources $\mathbf{J}^p$ and potential V

$$\nabla \cdot \sigma \nabla V = \nabla \cdot \mathbf{J}^p$$

- **Scalp, CSF, and gray matter:** σ isotropic ,
- **White matter:** σ anisotropic, depends on direction of fibers,
- **Skull:** σ inhomogeneous, anisotropic, holes.

Forward Problem of EEG:

compute potential V on sensors
supposing sources $\mathbf{J}^p$ and conductivity σ to be known

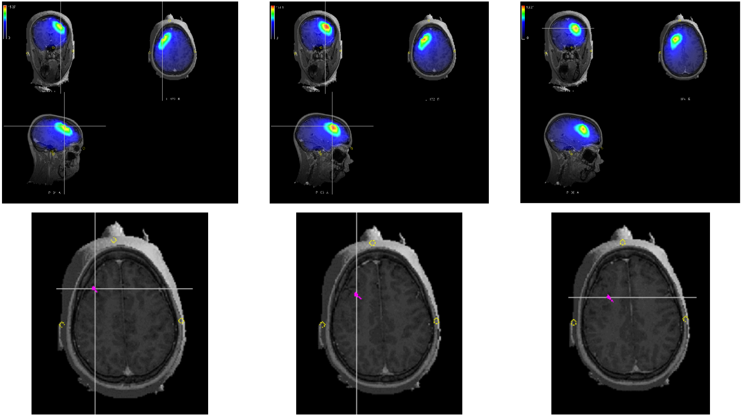
EEG sensitive to ratio $\sigma_{scalp}/\sigma_{skull}$ [Vallaghé, Clerc IEEE TBME 2009]

	$\sigma_{scalp}/\sigma_{skull}$
Rush & Driscoll [1968]	80
Cohen & Cuffin [1983]	80
Oostendorp & al. [2000]	15
Gonçalves, de Munck etal. [2003]	20 – 50

Challenge: calibrating σ non-invasively, in vivo:

Influence of conductivity on localization

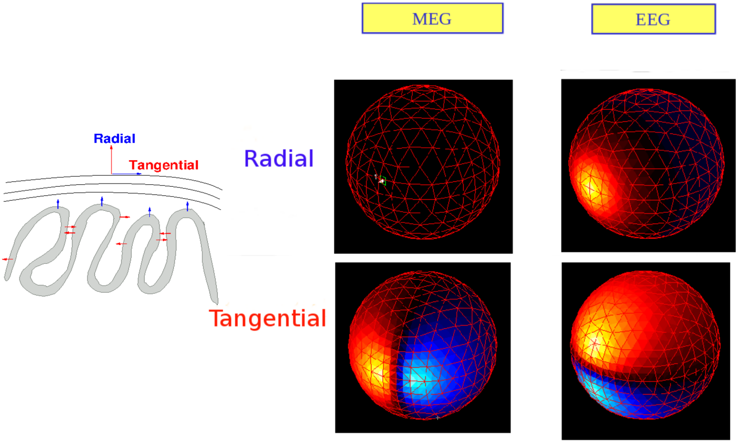
$\sigma_{\text{scalp}}/\sigma_{\text{skull}} = 80$ $\sigma_{\text{scalp}}/\sigma_{\text{skull}} = 40$ $\sigma_{\text{scalp}}/\sigma_{\text{skull}} = 20$



Averaged interictal spike.
Inverse reconstruction using MUSIC.

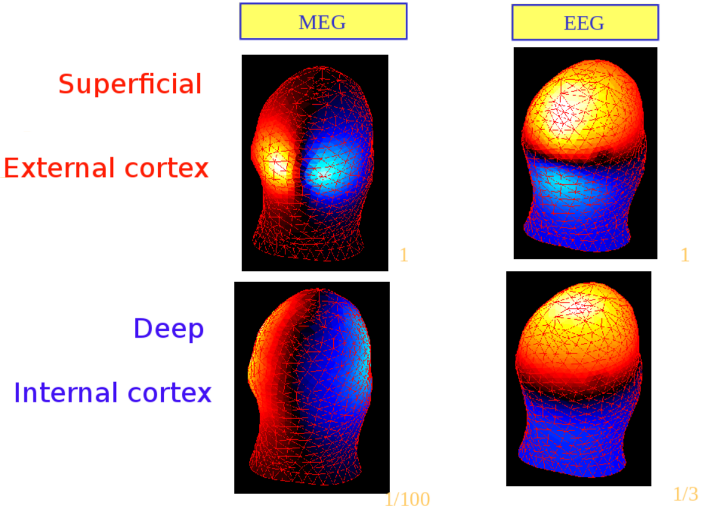
[courtesy of J-M Badier, La Timone]

Influence of orientation (spherical geometry)



[courtesy of S.Baillet]

Influence of depth (realistic geometry)



[courtesy of S.Baillet]

Consequences of volume conduction

Volume conduction produces a blurring effect

- not the same according to the modality (EEG, MEG, ECoG)
- EEG most diffuse (skull barrier)
- MEG more “transparent” to the skull
- ECoG under the skull, much less blurring.

Note: the spatial mixture is a curse, but also a blessing !

- EEG sensors sensitive to large areas of the cortex

Conversely intracerebral electrodes only sensitive to close-by regions.

Consequences of volume conduction

A good understanding of the spatial mixture (forward problem) provides a key to unmixing the data (inverse problem):

Consequences of volume conduction

A good understanding of the spatial mixture (forward problem) provides a key to unmixing the data (inverse problem):

Finding a spatial filter is like fitting a pair of glasses.

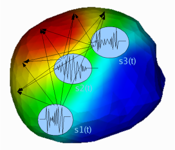
Consequences of volume conduction

The spatial mixture is instantaneous

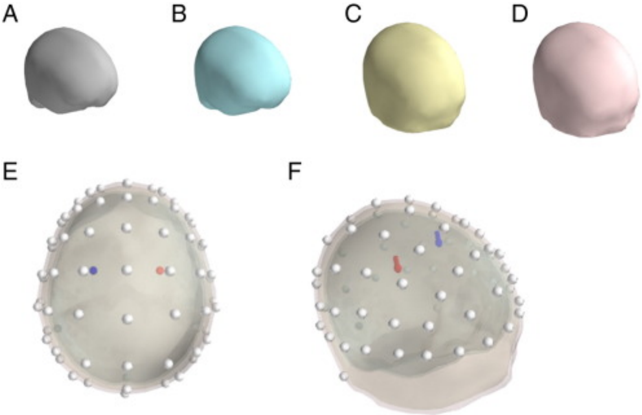
- electromagnetic waves propagate at speed of light
- no "echo effect", nor delay, at the frequencies of interest for EEG

Nevertheless the spatial mixture also leads to a temporal mixture of signals

- effect on latencies
- effect on the frequency spectrum

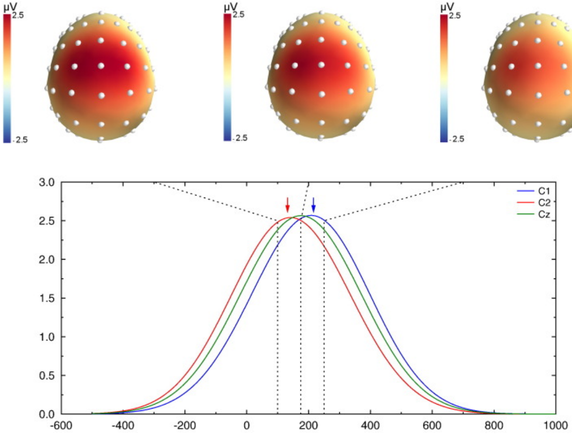


Volume conduction: temporal resolution



Dipole 1: under C1, amplitude peak: 100 ms
Dipole 2: under C3, amplitude peak: 250 ms
[Burle, Spieser et al, int J Psychophysiol. 2015]

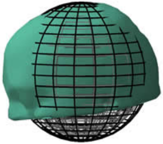
Volume conduction: temporal resolution



Volume conduction has an adverse effect on temporal resolution
→ model it in order to compensate for it

Solving the forward problem

- **simplest model: overlapping spheres**



✓ no meshing required

✓ analytical methods

× crude approximation of head conduction, especially for EEG

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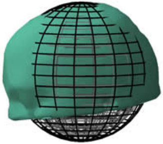
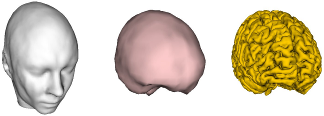


- **surface-based-model: piecewise constant conductivity**

✓ only surfaces need to be meshed

✓ Boundary Element Method (BEM)

× only isotropic conductivities



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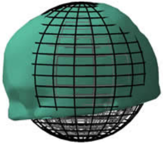

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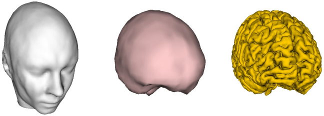
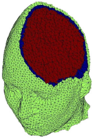


- **most sophisticated model: volume-based conductivity**

✓ detailed conductivity model,
(anisotropic: tensor at each voxel)

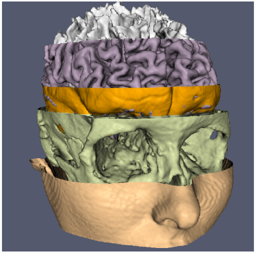
✓ Finite Element Method (FEM),

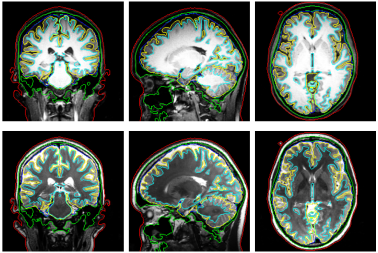
× huge meshes, difficult to handle

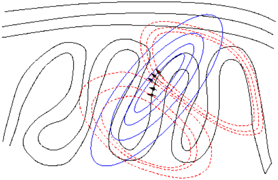


The forward problem: better matching specificities

- User-specific:
  - cortical foldings
  - tissue conductivities
  - tissue shapes
- Session-specific:
  - sensor positions





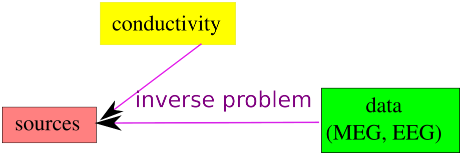


Taking care of these specificities (*forward* problem)
+ reconstructing brain activity (*inverse* problem)
leads to better information on brain activity
(more precise in space and in time)

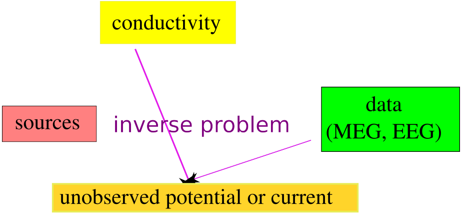
Outline

Inverse Problems

Inverse problems recover hidden information, using measurements and priors:



Source Reconstruction



Current Source Density Mapping

Forward vs. Inverse Problems

Forward problems are generally well-posed

- existence
- uniqueness
- continuity.

Conversely, inverse problems are generally ill-posed: either

- non-unique
- non-stable (non-continuous)

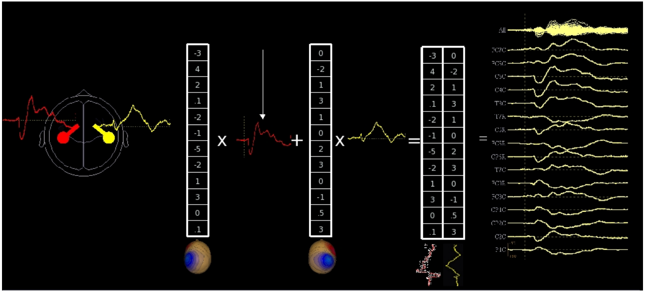
In ideal cases, inverse source reconstruction is unique.
It needs regularization to be stable.

From forward to inverse problem: the gain matrix

Measurements **M** resulting from two sources:

- source $s_1(t)$ at position $\mathbf{x}_1$, orientation $\vec{q}_1$
- source $s_2(t)$ at position $\mathbf{x}_2$, orientation $\vec{q}_2$

$$\mathbf{M}(t) = \begin{bmatrix} G_1(x_1, \vec{q}_1) \\ \vdots \\ G_m(x_1, \vec{q}_1) \end{bmatrix} \times s_1(t) + \begin{bmatrix} G_1(x_2, \vec{q}_2) \\ \vdots \\ G_m(x_2, \vec{q}_2) \end{bmatrix} \times s_2(t)$$



source: S. Baillet, Master MVA

From forward to inverse problem: the gain matrix

For n time samples $t_1 \dots t_n$,

$$\mathbf{M} = \mathbf{G}\,\mathbf{S}$$

where $\mathbf{S}$ contains the source amplitudes

$$\mathbf{S} = \begin{bmatrix} s_1(t_1) & \dots & s_1(t_n) \\ \vdots & \ddots & \vdots \\ s_N(t_1) & \dots & s_N(t_n) \end{bmatrix}$$

Gain matrix

Gain matrix $\mathbf{G}$ computed via the Forward Problem,
provides **a linear relationship** between source amplitudes and sensor data.

Source reconstruction: estimate **S** from **M**

Measurements on m EEG and/or MEG sensors.
The forward problem of volume conduction provides **G**:
a linear relationship between sources and sensor data:

$$\underbrace{\begin{bmatrix} M_1(t) \\ \vdots \\ M_m(t) \end{bmatrix}}_{\substack{m \times n \\ \mathbf{M}}} = \underbrace{\begin{bmatrix} G_1(x_1, \vec{q}_1) & \dots & G_1(x_p, \vec{q}_p) \\ \vdots & \ddots & \vdots \\ G_m(x_1, \vec{q}_1) & \dots & G_m(x_p, \vec{q}_p) \end{bmatrix}}_{\substack{m \times p \\ \mathbf{G} \text{ gain matrix}}} \underbrace{\begin{bmatrix} s_1(t) \\ \vdots \\ s_p(t) \end{bmatrix}}_{\substack{p \times n \\ \mathbf{S}}} + \mathbf{N}$$

$$\mathbf{M} = \mathbf{G}\,\mathbf{S} + \mathbf{N}$$

p sources $\gg$ m sensors

Regularized source reconstruction

Find sources **S** minimizing $\|\mathbf{M} - \mathbf{G}\,\mathbf{S}\|^2 + \lambda R(\mathbf{S})$
with $R(\mathbf{S})$: regularization.

Regularized Source Reconstruction

Finding **S** that minimizes

$$C(\mathbf{S}) = \|\mathbf{M} - \mathbf{G}\,\mathbf{S}\|^2 + \lambda R(\mathbf{S})$$

Many options for regularization $R(\mathbf{S})$.

L^2 regularization:

$$R(\mathbf{S}) = Tr(\mathbf{S}^T\mathbf{S})$$

Minimum Norm solution **S**

$$\mathbf{S} = \mathbf{G}^T(\mathbf{G}\mathbf{G}^T + \lambda\mathbf{I})^{-1}\mathbf{M}$$

Can be seen as a spatial filter applied to the measurements.

[Adde Clerc Keriven 2005]

Current Source Density mapping

Cortical Source reconstruction : sometimes cumbersome

- cortical surface highly convoluted, difficult to segment
- high number of vertices

Alternative approach: mapping current sources on a simpler surface
Recall that electric potential satisfies

$$\nabla \cdot \sigma \nabla V = \nabla \cdot \mathbf{J}^{\mathrm{p}}$$

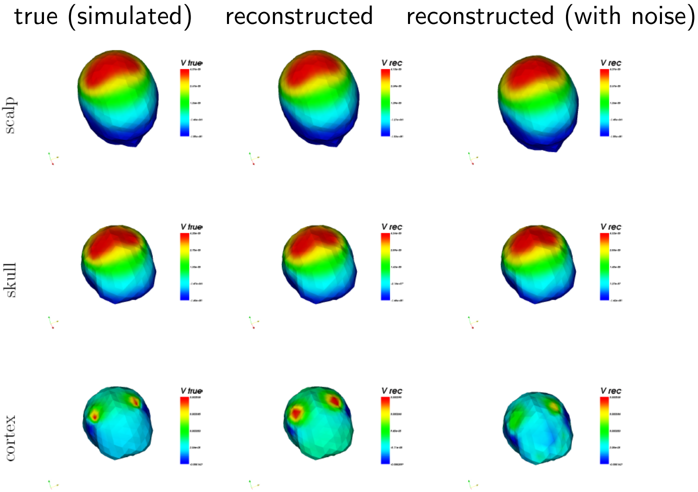
so outside the brain $\nabla \cdot \sigma \nabla V = 0$.

Cortical Mapping principle

Reconstruct the normal current on the pial surface, given that

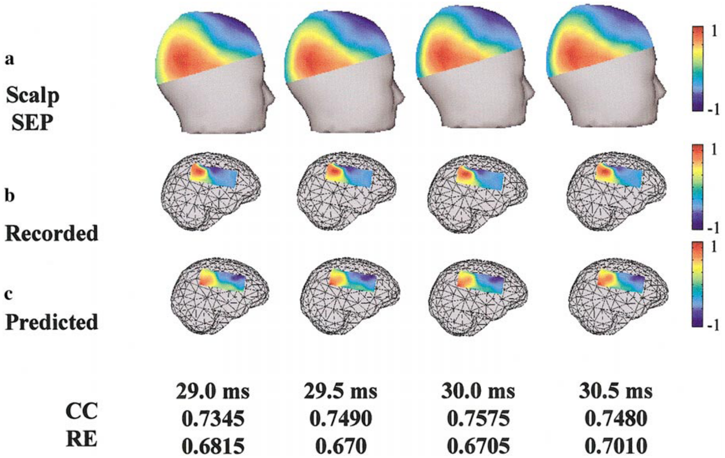
- $V = \mathbf{M}$ on sensors,
- $\nabla \cdot \sigma \nabla V = 0$ outside the brain .

Cortical Mapping



[Clerc Kybic Physics Med Biol 2007]

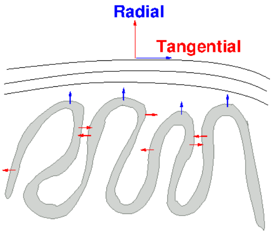
Cortical Mapping



[He Neuroimage 2002]

Surface Laplacian

Even more simple: only requiring scalp surface



On a given surface, one can define:

Tangential directions: x and y

Radial direction: z.

Surface Laplacian:

$$\Delta_S V = \frac{\partial^2 V}{\partial x^2} + \frac{\partial^2 V}{\partial y^2}$$

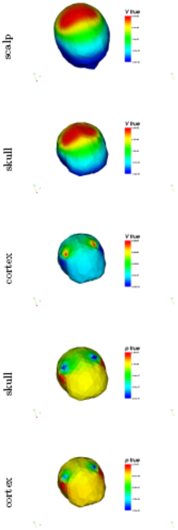
related to volume Laplacian:

$$\begin{aligned} \Delta V &= \frac{\partial^2 V}{\partial x^2} + \frac{\partial^2 V}{\partial y^2} + \frac{\partial^2 V}{\partial z^2} \\ &= \Delta_S V + \frac{\partial^2 V}{\partial z^2} \end{aligned}$$

In regions with no sources, $\Delta V = 0$ so on the scalp

$$\Delta_S V = -\frac{\partial^2 V}{\partial z^2}$$

Surface Laplacian: measures skull current



$$\Delta_S V = -\frac{\partial^2 V}{\partial z^2}$$

and $-\frac{\partial^2 V}{\partial z^2} \simeq \frac{1}{z_{scalp} - z_{skull}} \left(\frac{\partial V}{\partial z}(z_{skull}) - \frac{\partial V}{\partial z}(z_{scalp}) \right)$

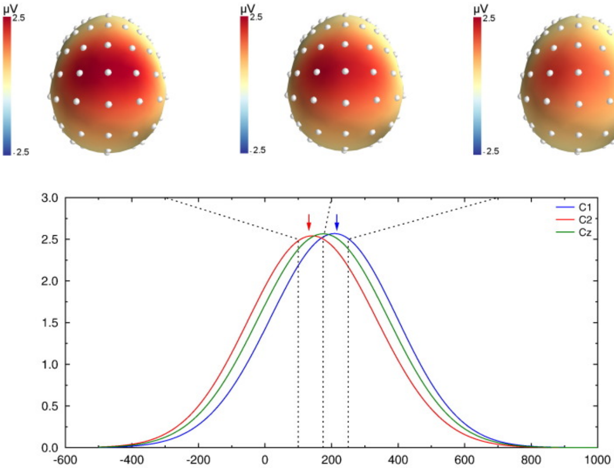
$\frac{\partial V}{\partial z} = 0$ on the scalp surface, because $\sigma = 0$ outside (air).

Therefore

$-\frac{\partial^2 V}{\partial z^2}$ proportional to $\frac{\partial V}{\partial z}$ on outer skull.

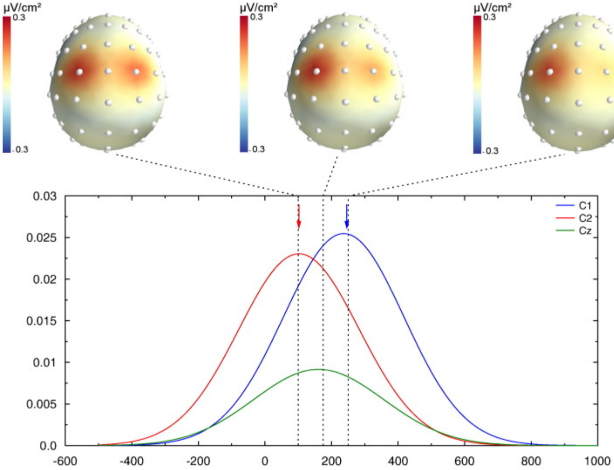
The Surface Laplacian $\Delta_S V$ is a spatial filter which approximates the normal skull current.

Surface Laplacian: spatial and temporal resolution



[Burle, Spieser et al, int J Psychophysiol. 2015]

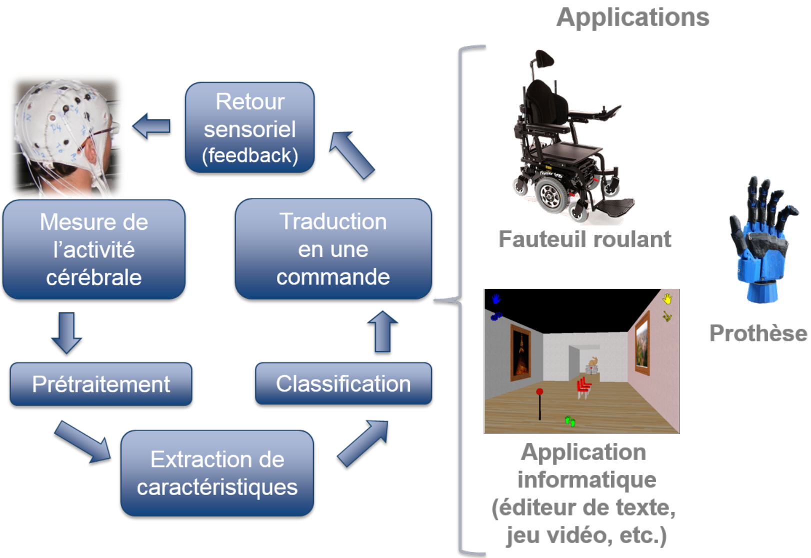
Surface Laplacian: spatial and temporal resolution



[Burle, Spieser et al, int J Psychophysiol. 2015]

Outline

Brain Computer Interfaces



Neuroimaging in BCI

Current BCI practice analyses signals at sensor level,
with signal processing / Machine Learning techniques

Advantages of features in source space rather than sensor space:

- features closer to actual brain activity
- neuroscientifical interpretation
- better alignment of features (across reference, montages, sessions, subjects...)

Note:
Other fields (e.g. psychology) are realizing the benefits of analyzing sources rather than scalp potentials.
[Kayser Tenke, Editorial Int J Psychophysiology 97 (2015)]

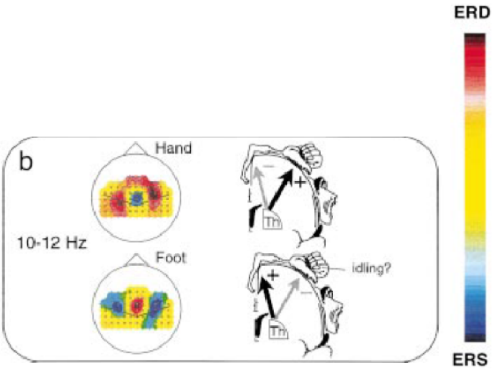
Motor imagery classification

32nd Annual International Conference of the IEEE EMBS
Buenos Aires, Argentina, August 31 - September 4, 2010

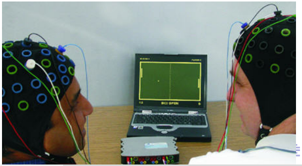
Reconstruction of cortical sources activities for online classification of electroencephalographic signals.

Joan Fruitet and Maureen Clerc

2010



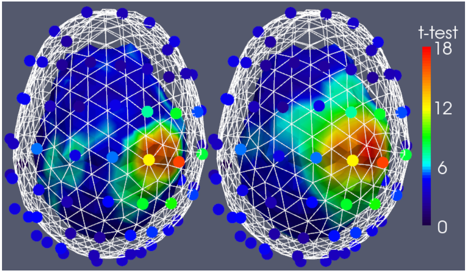
CEA LETI



Online classification in Source/Signal space

Goal:

- Comparison of a classification task in Source/Signal space
- Various preprocessings:
  - Sensor measurements
  - Spatial Laplacian
  - (Weighted) Minimum norm
  - Beamformed



Minimum Norm Beamforming

discrimininative features

[Fruitet Clerc EMBC 2007]

Binary Classification of Imagined Movements

Method	right/left	right/feet	left/feet	average
No reconstruction	68%	75%	71%	**70,9%**
Spatial Laplacian	69%	81%	75%	**75,1%**
Minimum-Norm	76%	82%	72%	**76,6%**
Weighted MN	77%	81%	74%	**77,2%**
Beamformer	75%	75%	74%	**74,7%**

Cortical Source Reconstruction, a form of spatial filtering, **improves feature discrimination**.

Error-related Potential

Online extraction and single trial analysis of regions contributing to erroneous feedback detection

Matthew Dyson[a], Eoin Thomas[b], Laurence Casini[a], Boris Burle[a]

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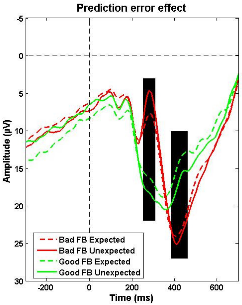
Highlights

- We extract discriminatory error-related activity in the source space from BCI EEG.
- Source features allow single trial classification of error feedback in noisy EEG.
- We assess whether automatically extracted EEG activity is functionally interpretable.

2015

cf Transfer Learning challenge on Kaggle

Error-related Potential



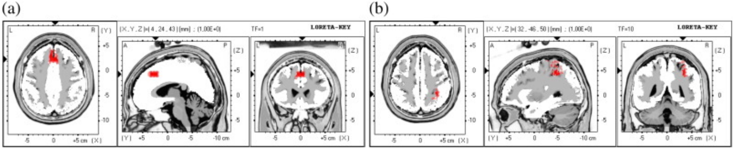
Potentials averaged over many repetitions

Goal:
Detecting the Error Potentials in individual signals
Needs supervised classification
Training data = labeled signals (error / no-error)
Challenge:
Detection with little or no training data

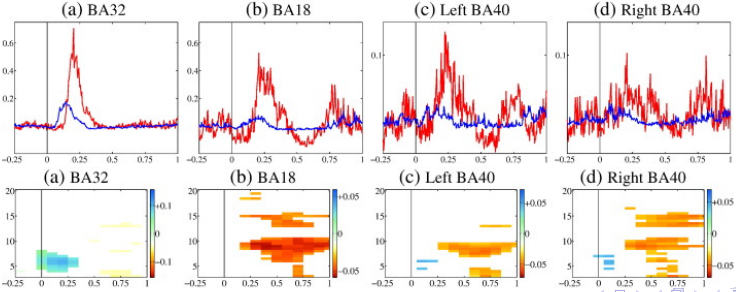
Error-related Potential

Using prior information on

- Error Potential source location (Anterior Cingulate Area)
- Error Potential source orientation (vertical, upward)



FuRIA algorithm Lotte et al IEEE T Sig Proc 2009



Conclusion

Imaging Brain Activity:

- brings out relevant activities
- allows to interpret results
- allows to understand mechanisms

But to be ued in practise important to find a compromise between

- **complexity** of models
  - subject-specific geometries ?
  - number of structures, of tissue boundaries ?
  - type of inverse problem ?
- **usability** of methods
  - imaging as investigation / interpretation
  - imaging for limiting calibration data
  - features must be extracted in real-time (¡.100 ms)

Contributors to this presentation

Inria Sophia Antipolis	Marseille LNC	INSERM Lyon
Maureen Clerc	Boris Burle	Jérémie Mattout
Théodore Papadopoulo	Matthew Dyson	Manu Maby
Joan Fruitet	Laurence Casini	Margaux Perrin
Eoin Thomas	Franck Vidal	

Support from:

Agence Nationale de la Recherche (projet CoAdapt)
Inria project-lab BCI-LIFT

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