Forward and Inverse EEG Source Modeling

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Motivation

• Why perform ICA?
• Why fit dipoles or distribution source models?
• Why measure EEG?!

• To obtain information about brain processes...
  – Time course of activities that produce the EEG signals
  – Locations of the activities that produce the EEG signals

R. Oostenveld, & S. Makeig, 2016
Scalp dynamics ≠ source dynamics

Cortex

Skull

Local Synchrony

Local Synchrony

Skin

Electrodes

Relative Independence

Equivalent Current Dipole

Spatial EEG Source Filtering

S. Makeig 2007
EEG source modeling

**Source Space**
- Electrical currents

**Sensor Space**
- Recorded potentials

**Forward head model**

**forward problem**
- Volume conduction through body tissues

**Inverse localization method**

**inverse problem**
Peri-neuronal currents

Closed field

Open field

R. Oostenveld, 2007
Symmetry, orientation and activation

radially symmetric, i.e. randomly-oriented

asynchronously activated

synchronously activated parallel-oriented

Closed field

Phase cancellation

Open field

A when recorded at a distance, dipolar field components dominate

R. Oostenveld, 2007
Many neurons need to sum their local field activities to be detectable at EEG electrodes. Synchronized neural activity produces large far field signals.
EEG volume conduction of dipolar field patterns ➔ effective sources

R. Oostenveld, 2007
The *equivalent* current dipole

R. Oostenveld, 2007
Equivalent current dipole modeling

1st IC source fit in an individual head model via EEGLAB

A. Delorme, ~2007
Independent cortical components

Equivalent dipoles

Single dipole component

Dual-symmetric dipole component
Physical/mathematical motivation

- Any current distribution can be written as a multipole expansion
- First term: monopole (must be 0)
- Second term: dipole
- Higher order terms: quadrupole, octopole, ...

In far-field recordings, the dipolar term dominates.

For convenience + accuracy, therefore

- **Dipoles** can be used as building blocks in distributed EEG effective source models
The linear forward problem

\[ X = LS \]

where \( L \) is the lead field matrix giving potential vector contributions \( X \) to each scalp electrode for all possible source contributions \( S \) (source space).

**Anatomical constraint:**
Sources are in the cortex & perpendicular to it.

Daunizeau, 2009
The linear forward problem

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Anatomical constraint: Sources are in the cortex & perpendicular to it.
Forward Head Models

• Electrical properties of tissue
  – Conductivity
  – Anisotropy

• Geometrical description
  – Spherical model? (less realistic)
  – Realistically shaped model

→ A **forward model** describes how the currents flow from all possible points of origin

R. Oostenveld, & S. Makeig, 2016
Forward Head Models

- Advantages of the **spherical** model
  - mathematically accurate
  - reasonably accurate
  - computationally fast
  - easy to use

- Disadvantages of the **spherical** model
  - inaccurate in some regions
  - difficult to align to head
Forward Head Models

• Advantages of a **realistic** head model
  – accurate solution for EEG
• Disadvantages of a **realistic** model
  – more work
  – computationally slower
  – numerically instable?
  – More difficult inter-individual comparisons

→ The pragmatic (easy, cheap) solution is to use a standard (mean) realistic head model (MNI).

R. Oostenveld, & S. Makeig, 2016
Forward Head Models

• Computational methods for volume conduction problem that allow realistic geometries
  – Boundary Element Method (BEM) models
  – Finite Element Method (FEM) models

• Geometrical description
  – Triangles (2-D) → BEM
  – Tetrahedra (3-D) → FEM

R. Oostenveld, & S. Makeig, 2016
Forward Head Models: BEM

- **Boundary Element Method (BEM) models**
  - description of head geometry by tissue compartments
  - Tissue in each compartment is assumed
    - homogenous
    - isotropic

Important tissue types
- Scalp
- Skull
- CSF
- Brain (grey matter / white matter)
- Use triangulated surfaces as boundaries
- Each surface should be closed (no holes)

R. Oostenveld, & S. Makeig, 2016
Boundary Element Method (BEM) models describe the head geometry by tissue compartments. Tissue in each compartment is assumed to be homogenous and isotropic.

Important tissue types include:
- Scalp
- Skull
- CSF
- Brain (grey matter/white matter)

Use triangulated surfaces as boundaries, ensuring each surface is closed (no holes).
Mapping sources of intracranial data recorded to plan brain surgery

Non-conductive ‘plastic layer’ (the ECoG electrode sheet and strip)
• EEG = ‘Potential differences between electrodes,’ a measure of summed current flowing through scalp.

  – However, only a tiny fraction of brain source currents pass through the skull.

  – Therefore a forward head model should describe brain, skull, and scalp tissues as accurately as possible.

  – Skull is the most resistive, therefore knowing its conductance most important.
Forward head models: Modeling the skull

• Problems with skull modeling:
  – Poorly visible in an anatomic MRI (T2) image
  – Thickness varies regionally
  – Conductivity is not homogeneous (isotropic?)
  – Complex geometry at front and base of skull

 → **Skull conductivity** varies across individuals and has no direct measurement method.
Next, we present simulation results on the effects of using incorrect skull conductivity values on equivalent dipole source localization. In the 1970’s and 1980’s, the adult brain-to-skull conductivity ratio was reported to be near 80:1 (Cohen 1983; Rush 1968), a value still commonly used for EEG source localization. However, more recent studies have found this ratio to be lower, as low as 15:1 (Oostendorp 2000). For example, a 2005 study on adult epilepsy patients undergoing pre-surgical evaluation using simultaneous intra-cranial and scalp EEG recordings estimated average brain-to-skull conductivity ratio as 25:1 (Lai 2005).

Here, we used the four-layer reference BEM model for subject S1 and set the forward-model (ground truth) brain-to-skull conductivity ratio to 25:1. We then solved the inverse source localization problem using the same head model incorporating the assumed (and still commonly used) value of 80:1. This produced large equivalent dipole localization errors of up to 31 mm (Figure 13, top row). When we used the four-layer head-shape warped MNI template model to solve the inverse problem (Figure 13, middle row) the errors were still larger and more evenly distributed across the cortical region (Figure 4 bottom row). The estimated positions of the simulated dipoles generally moved towards the scalp surface. Conversely, when the brain-to-skull conductivity ratio was mis-estimated as 15:1 instead of 25:1 (Figure 13, bottom row), the estimated dipole locations moved towards the center of the brain, with error magnitudes up to 13 mm. Thus, correct modeling of skull conductivity is an important factor for EEG source localization, quite possibly outweighing the choice of head model.
The FEM volume conductor model

To make a Finite Element Method (FEM) head model:

• **Tesselate the 3-D volume into solid tetrahedra**
  - Contains a large number of 3-D elements
  - Each tetrahedron can have its own conductivity
  - Each tetrahedron can have its own *anisotropy* (direction-dependent conductivity differences)

• **FEM is the more complete numerical method (⟩ BEM)**
  – But is computationally expensive
  – Note: Accurate conductivities are not known, particularly for skull (and scalp?).
Head Modeling Errors

Electrode & MR image co-registration
Head geometry errors
EXCLUSION of white matter
Two few electrodes
Poor distribution of electrodes
Mis-estimation of skull conductivity!
Electromagnetic source localization using realistic head models (Dipfit, NFT)

Solve the forward problem using realistic head models (BEM)

Mesh generation

Simple Map

Sensor Localization

Signal Processing

Source Image

Magnetic Resonance Imaging (MRI)

Segmentation

Electroencephalography (EEG)

Zeynep Akalin Acar, ‘06
The MNI Head Model

- 4-layer
  - 16856 nodes
  - 33696 elements

- 3-layer
  - 12730 nodes
  - 25448 elements

Brain
CSF
Skull
Scalp
FEM models

BEM models

6-month old

adult

NFT

Akalin Acar & Makeig, 2010
NIST

Source space

Cheng Cao, 2012

Scalp map

Patch-based SBL

sLORETA

Load MRI

Start Freesurfer

Cortical source space

FP Solution with BEM

FP Solution with FEM

Component indices

Select Source Localization Method

Start Source Localization

Visualization
Head Model Generation Summary

- **Subject-specific Head Model (NFT)**
  - From whole head T1 weighted MR of the subject
  - 4-layer realistic BEM model

- **MNI Template Head model (DIPFIT)**
  - From the MNI head
  - 3-layer and 4-layer template BEM model

- **Warped MNI Template Head Model (NFT)**
  - Warp MNI template to EEG sensors

- **Spherical Head model (deprecated)**
  - 3-layer concentric spheres
  - Fitted to EEG sensor locations
  - Not accurate
Inverse source localization

• Single and multiple dipole models
  – Minimize error between the model and the measured potential/field

• Distributed dipole models
  – Seek perfect fit to the measured potential or field
  – Must minimize some additional source constraint
    • LORETA assumes a smooth source current distribution
    • Minimum Norm (L2), min. total cortical $|\text{current}|^2$
    • Minimum Current (L1) min. total cortical $|\text{current}|$

• Note: L2/L1 need some weighting scheme to keep source models from being too broad & superficial.

R. Oostenveld, & S. Makeig, 2016
Inverse methods

Spatial filtering approaches

– **Scan whole brain** with single dipole and compute the filter output at every location (using sensor covariance)
  
  • MUSIC
  
  • *Beamforming* (e.g., LCMV, SAM, DICS)

– **Perform ICA decomposition** (higher-order statistics) on the *continuous* data.
  
  • ICA gives the projections of the sources to the scalp surface \(\rightarrow\) ‘simple’ maps!

→ ICA solves ‘the first half’ of the inverse problem: ‘What?’

→ ICA gives ‘simple’ source maps, helping to locate: ‘Where?’

R. Oostenveld, & S. Makeig, 2016
Single or multiple dipole models

• Manipulate source parameters to **minimize error** between measured and model data
  – The **position** of each source
  – The **orientation** of each source
  – The **strength (magnitude)** of each source

• **Dipole orientation** and **strength** together correspond to the “**dipole moment**,” estimated linearly

• **Dipole position** is estimated non-linearly by source parameter estimation

R. Oostenveld, & S. Makeig, 2016
DIPFIT: Dipole fitting

1. Coarse fit step
   • Define a grid with possible dipole locations
   • Compute optimal dipole moment at each location
   • Compute value of goal-function (fit to given map)
   • Plot value of goal-function on the grid → find best fit.
   • Number of evaluations:
     – single dipole, 1 cm grid: \( \sim 4,000 \)
     – single dipole, \( \frac{1}{2} \) cm grid: \( \sim 32,000 \)
     – BUT two dipoles, 1 cm grid: \( \sim 16,000,000 \)

R. Oostenveld, & S. Makeig, 2016
2. Fine fit step

Start with the initial guess from coarse fitting

– Evaluate the local derivative of the goal (fit) function
– Then “walk down hill” to the most optimal solution

Number of iterative steps required = ~100
By Simulation: The median geometric error in dipole localization using the MNI template head model warped to measured electrode positions is only 4 mm.

BUT Additional dipole error contributors:
- Electrode co-registration error
- ICA numerical error (not enough data?)
- Source model geometry error
- Conductance value error (skull)
Distributed source models

• The position of the source is not estimated as a whole
• Instead, On a pre-defined *source space* grid (3-D volume or cortical 2-D sheet)
  – Dipole strength is estimated *at each grid element*
  – In principle, a linear problem, easy to solve, BUT...
    • More “unknowns” (parameters) than “knowns” (channels, measurements), so ...
    • An infinite number of solutions can explain the data perfectly (not necessarily physiologically plausible!)
  – Therefore, additional source constraints are required ...
High-Resolution Distributed Source Localization using a multiscale patch basis

0. Build a high-res. cortical surface mesh; give each voxel an oriented dipole.

1. Compute a ‘dictionary’ of Gaussian patches conforming to the cortical surface centered at each cortical mesh voxel.

2. Use a ‘sparsifying’ approach to find the sum of the fewest of these patches that together produce the given source scalp or grid map.
• An electromagnetic **forward head model** is required to interpret the sources of scalp maps

• Interpretation of scalp maps in terms of brain source distributions is “**inverse** source estimation”

→ Mathematical techniques are available to aid in interpreting scalp maps as arising from particular brain sources

→ These require an **inverse source model**, i.e. assumptions about the possible locations and nature of the sources (i.e., what attributes make them **physiologically plausible**).

→ Then search for the **most plausible** source model.

R. Oostenveld, & S. Makeig, 2016
Summary-2

• Inverse modeling
  – Model assumption for volume conductor
  – Model assumption for source (i.e. dipole)
  – Additional assumptions on source

• Single point-like sources

• Multiple point-like sources

• Distributed sources
  – Different mathematical solutions
    • Dipole fitting (linear and nonlinear)
    • Linear estimation (regularized)

R. Oostenveld, 2007
• If we have MRI of the subject
  – Subject specific head model
  – Distributed source localization

• If we don’t have the MRI
  – Warped 4-layer MNI model (NFT)
  – Dipole source localization

• **Skull conductivity estimation** is as important as the head model used (SCALE)

• White matter modeling does not have a huge effect on source localization – excepting deep sources ...
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