Methods for Processing Magnetoencephalograph and Electroencephalography Signals

Gabriel Cabrera Ocola

April 2025

1 Introduction

Signal processing plays a critical role in the analysis and interpretation of neural data, providing the foundation for extracting meaningful information from complex biological signals. This report outlines a selection of essential signal processing techniques, with particular emphasis on their relevance to neurophysiological research. The content presented serves as a demonstration of methodological proficiency within the context of the NeuroTUM Student Club, aiming to support ongoing efforts in the integration of computational tools in neuroscience.

2 Source Analysis

2.1 Source Localization

The cerebral activity can be described in two currents, a primary and a secondary. The primary currents(red) are generated by the synaptic activation of the brain cells, with origin in the dendrites and flow across the neuron. This intracellular currents are responsible of the electromagnetic fields that can be measured outside the skull and also induce the secondary currents(blue) in the surrounding tissue.

In Magnetoencephalography (MEG), the magnetic field produced by the primary current is measured. MEG is less affected by the skull, because the magnetic fields are not disturbed much by skull or scalp,

On the other hand, Electroencephalography (EEG) measures electrical potentials in the scalp, which are generated by secondary currents. because of that the precise localization of the dipoles can be difficult without a proper head model.

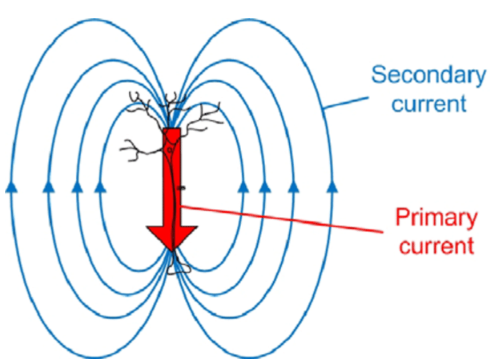

Figure 1 Becker, H. (2014). Neuron modelled as current dipole.

Source localization implies a number of crucial processes, starting with anatomical and spatial information, such as the head model, source model (usually a 3D grid inside the brain), and the exact locations of the electrodes or MEG sensors (Channels). The computation of the *forward solution*, which estimates the signal at the sensors given a hypothetical source distribution, requires this anatomical arrangement.

In parallel, the measured functional data (EEG or MEG) is preprocessed. Techniques such as **Independent Component Analysis (ICA)** are commonly applied at this stage to isolate and remove artifacts or to separate functionally independent brain sources. ICA assumes that the observed signals aren't too correlated, and aims to unmix them without prior knowledge of the mixing process. In EEG analysis, ICA can help reveal brain components that contribute more directly to the signal of interest. Delorme, A. and Makeig, S. (2004).

The forward model and preprocessed data are then combined in the *inverse solution* step, which attempts to estimate the most likely sources in the brain that generated the observed signals. Finally, statistical analysis and visualization tools are used to interpret the results.

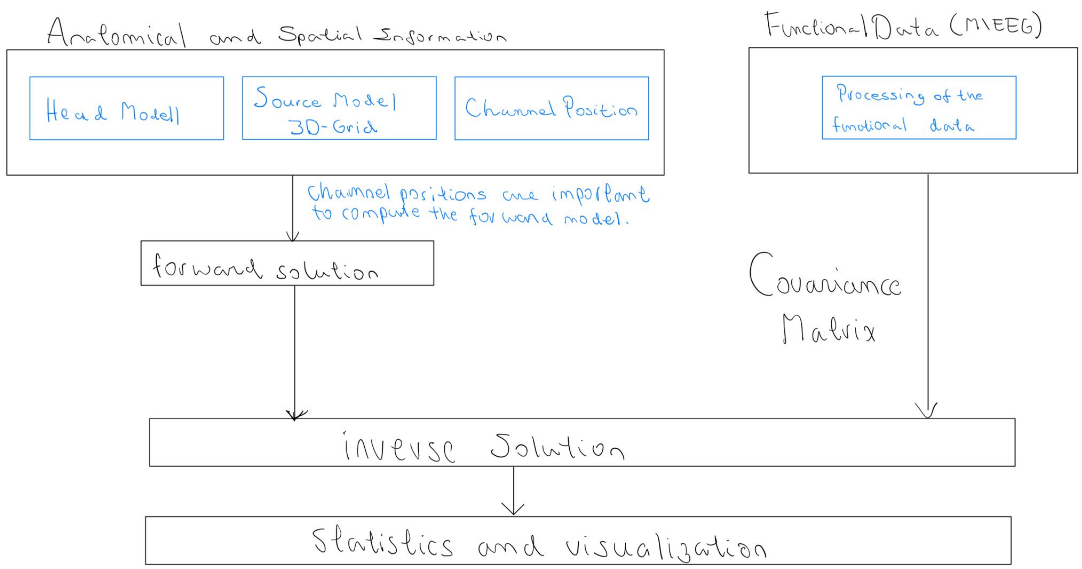

Figure 2. Pipeline for EEG/MEG Source Localization

2.2 Beamforming and Filter Design

This method focus in the contribution of the position of a single brain cell q_0, and not the complex field. Beamformers don't estimate the amplitude or the gain of the brain cell, but the variance of the signal over a period of time. In this context the Variance $\approx$ electric potential.

$$\mathrm{Var}[y(t)] = \frac{1}{T}\sum_{i=0}^{T}(y(i) - \overline{y})^2$$

This helps us knowing how active is this region during a period of time T instead of the exact value.
Beamforming assumes that the time-courses of different sources are uncorrelated. Why is Beamforming frequently used if it doesn't give us the exact value?. The M/EEG is noisy and variable, it estimate the average energy in this point, this has a positive part, because we get robust data against the noise of the signal (other brain cells) and interference.

- Forward Model

  Source To Data : $\mathbf{Y} = \mathbf{H(q)} \cdot q^T + Noise$

  Transfermatrix H(q): Nx3 Matrix that represent all the solutions to the forward problem given unity dipoles in x, y ,z direction at the position q_0

$$\begin{bmatrix} h_{1x} & h_{1y} & h_{1z} \\ h_{2x} & h_{2y} & h_{2z} \\ \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots \\ h_{Nx} & h_{Ny} & h_{Nz} \end{bmatrix} \cdot \begin{bmatrix} \quad q(t) \quad \end{bmatrix} + Noise = \begin{bmatrix} \\ \quad \mathbf{Y(t)} \quad \\ \\ \end{bmatrix}$$

  The consequences of a bad modelling of H(q) Matrix, it will suppres source activity (for the source q). That why during the filter design we ensure that:

$$w(q_0)_i^T \cdot H(q_0)_j = \begin{cases} 1, & \text{if i = j} \\ 0, & \text{if i} \neq \text{j} \end{cases} \quad \text{for } q \in \Omega \tag{1}$$

  where Ω represent the brain volume.

  The second condition cannot generally be fulfilled. Hence we minimize the variance of the filter output.

- Inverse Model

  Data to Source : $w^T \cdot \mathbf{Y} = q$

  Estimation of q with a spatial filter w

$$\begin{bmatrix} \quad w^T \quad \end{bmatrix} \cdot \begin{bmatrix} \\ \quad \mathbf{Y(t)} \quad \\ \\ \end{bmatrix} = \begin{bmatrix} \\ \hat{q}(t) \\ \\ \end{bmatrix}$$

  In this step, we derive the weights w that minimize the output variance of the filter, subject to a constraint on the signal. The variance of the output a is expressed as $\text{Var}[q] = w^T C_y w$, where C_y is the covariance matrix of the measurements Y. To find the optimal weights under this constraint, we use a Lagrange multiplier approach, which leads to the solution:

$$w^T = \left(H^T C_y^{-1} H\right)^{-1} H^T C_y^{-1}$$

  This ensures that the filter passes the desired signal while minimizing the noise and interference from other sources

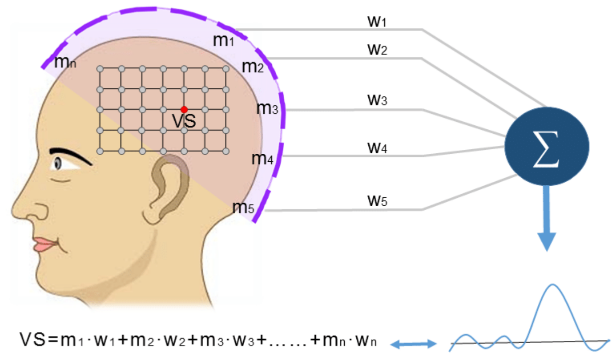

Figure 3. Migliorelli, C. (2017) Schematic representation of beamforming analysis.

Spatial sensitity and leakege
As told before we want to minimize or filter the interference of the other sources. We can have an idea of how this filter should look like (Figure 3) but that type of filter are imposible to make. That's why when the filters are applied, the result is a blur representation of the real source activity. This reflects the inherent limitations in inverse solutions for EEG/MEG data.

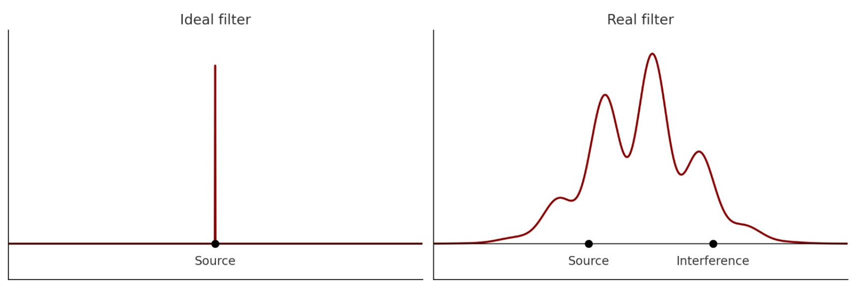

Figure 3. Ideal and Real Source Filters

2.3 Dipole fitting

Contrary to Beamforming
Find the dipole position that matches the measured field in the best possible way Dipole Fit Problems: • The number of sources must be known in advance. • Applicable only for a small number of source. The restriction to a very limited number of possible sources leads to an unique solution. MNE-Python or FieldTrip for EEG/MEG source modeling.

2.4 Artifacts Detection though MNE-Python

2.5 dasdas

3 Bibliography

- Becker, Hanna. (2014). Denoising, separation and localization of EEG sources in the context of epilepsy.
- Migliorelli, Carolina. (2017). Methods for noninvasive localization of focal epileptic activity with magnetoencephalography.

- Delorme, A., and Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of Neuroscience Methods, 134(1), 9–21.