Incorporation of Functio-Anatomical *a priori* Knowledge into EEG Source Reconstruction

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Introduction

EEG and MEG are excellent means for the direct observation of neuronal activity in real time. However, the localizability of the underlying processes is limited. Sophisticated source localization techniques strongly depend upon additional knowledge or assumptions about the spatial structure of the underlying generators. Such additional information can be experiment specific, e.g. if we know from fMRI experiments, which brain regions are active with a certain stimulation or task, or general, e.g. the knowledge that certain patches of cortex are functionally homogeneous or that certain networks of regions preferentially react as a whole. We present a technique to incorporate information about the spatial structure of brain activity (e.g. activity networks from fMRI experiments or function-anatomical parcellations based on cytoarchitectonic, receptor-architectonics, or long-range fibre connections) into the low resolution electromagnetic tomography (LORETA) method [1]. .

Theory

The LORETA algorithm

The source reconstruction methods proposed here are based on the LORETA method [1].

$$J=(\Omega B^T B\Omega)^{-1}L^T\left(L(\Omega B^T B\Omega)^{-1}L^T\right)^{(-1)}M$$

The spatio-temporal data matrix M is mapped onto the spatio-temporal matrix of dipole strengths J. The forward model is represented by the leadfield matrix L. Ω denotes a diagonal matrix accounting for the leadfield normalization,

$$\Omega_{ii}=\|L_{.i}\|_2$$

The matrix B codes the spatial Laplacian operator. The superscript $^{(-1)}$ denotes the regularized inverse (e.g. by Tikhonov regularization or truncated SVD).

The Laplace operator

The Laplace operator on a 3-dimensional grid is defined for dipole i as:

$$\Delta_i\varphi=\sum_{j\in\Xi_i}\gamma_{ij}(\varphi_j-\varphi_i)$$

with Ξ_i being the set of neighbouring dipoles to dipole i and γ_{ij} being the weight of the edge connecting two nodes (dipoles), leading to the following definition of the Laplacian operator matrix:

$$B_{ii}=-1-\lambda_B$$

$$B_{ij}=\frac{\gamma_{ij}}{\sum_{k\neq i}\gamma_{ik}},\ j\in\Xi_i$$

where λ_B is a regularization parameter. This definition of the Laplacian differs from the one proposed by e.g. [1] in that dipoles with fewer neighbours (e.g. on the surface) are not excessively punished any more. The weights λ_{ij} are all 1 for a regular 3-dimensional grid. For a triangulated surface, e.g. the cortex or brain surface, the following solution is used [2].

$$\gamma_{ij}=\frac{1}{d_{ij}}\left(\frac{1-\cos\phi_{ij}^{+}}{\sin\phi_{ij}^{+}}+\frac{1-\cos\phi_{ij}^{-}}{\sin\phi_{ij}^{-}}\right)$$

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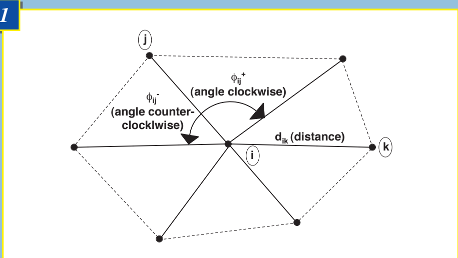

Incorporation of a priori knowledge on functional units

The basic principle is to restrict the smoothness criterion of the LORETA algorithm to dipoles, which are all within one functional unit. This can be done by defining the node neighbourhoods Ξ_i accordingly by combining the set of dipoles belonging to the unit containing the i^{th} dipole Ψ_i, with the set of grid neighbours of the same dipole θ_i.

We propose two algorithms:

(1) pLORETA (patch LORETA)

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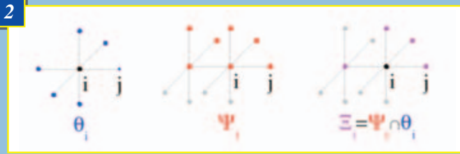

The smoothness is imposed the same way as with classical LORETA within the units (patches), but not across the patch boundaries.

(2) pacoLORETA (patch constraint LORETA)

$$\Xi_i=\Psi_i-\{i\}$$

All dipoles belonging to the same patch are considered neighbours, regardless of physical distance and direct neighbourhood.

Methods

Simulations were used to reveal some of the principal capabilities of the proposed algorithms.

- Activity is modelled on a grid (2586 nodes) covering the brain surface.
- EEG is simulated at 85 electrodes covering the entire scalp.
- Employed algorithms: weighted minimum norm [3], LORETA, pLORETA, pacoLORETA
- Regularization of the Laplace operator λ_B=0.1.
- Regularization of leadfield matrix using Tikonov method with $\alpha=0.001\cdot tr(L\Omega BB^T\Omega L^T)/n$.
- White noise was added to simulated EEG data, SNR=1…100.
- Subdivision of brain surface into functional units for forward simulation and as *a priori* knowledge.
- Original and reconstructed activation are compared by means of spatial correlation.

Results

- pacoLORETA solutions are dominated by *a priori* information, while pLORETA still yields acceptable results, if the *a priori* information is incorrect (Fig. 1, rows 2 and 3).
- If the *a priori* information is correct, pLORETA yields results nearly as perfect as pacoLORETA (Fig. 1, rows 1 and 4, see also Fig. 2).
- Noise did not affect pLORETA or pacoLORETA any worse than the classical methods.
- For SNR≥4, the beneficial effect of the *a priori* knowledge is still preserved (see Fig. 1, last row).

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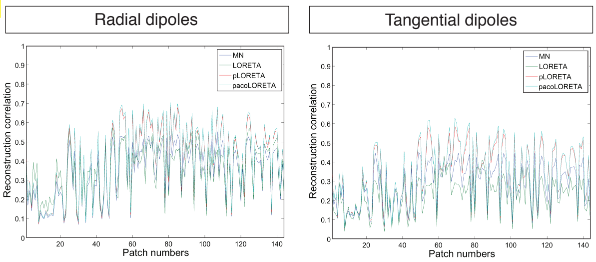
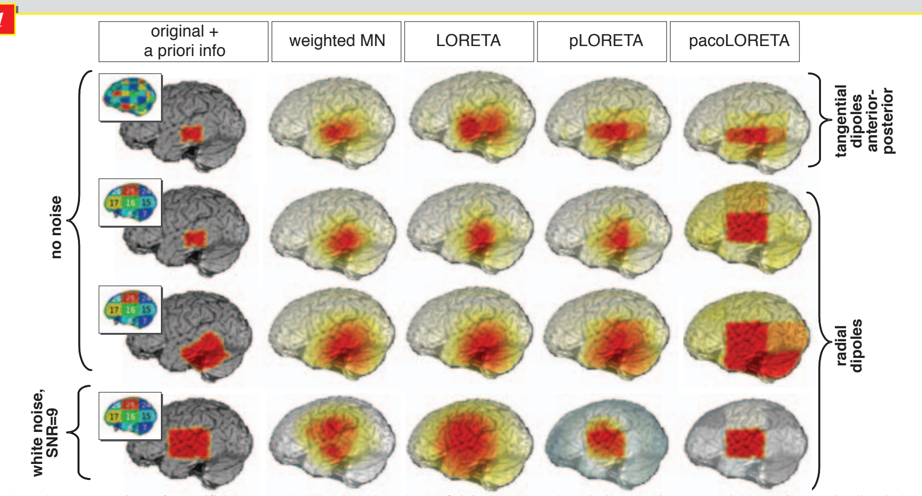


Spatial correlations between original and reconstructed sources for noise free data and congruous knowledge (corresponding to top row in Fig. 1)

1



Example reconstructions of an artificial extended source using various methods. A priori knowledge (checkerboard pattern, see small insets in first column) has been introduced. Original source and a priori knowledge are in agreement (top and bottom rows) or in disagreement (middle rows). Dipole orientations are either tangential (posterior-anterior direction) or radial.

Discussion

If one can be sure on the functional units defined as *a priori* knowledge, i.e. if the source reconstruction only has to decide, which units are on or off, the pacoLORETA algorithm is very effective. However, this situation is quite rare in practice. On the other hand, the pLORETA algorithm still makes use of the introduced *a priori* information without completely derailing if this information is wrong or incorrect. In case the EEG data and the function-anatomical *a priori* information cannot be reconciled, pLORETA follows the EEG data. This allows more flexible formulations of *a priori* knowledge, e.g. defining boundaries where they are known (e.g. between the lobes) and leaving open, whether the defined patches are internally homogeneous or can be further subdivided. An obvious extension to the proposed algorithm would be to allow fuzzy boundaries or overlap between patches. This would make it easier to introduce realistic information into the solution and to impose just the right amount of constraint.

References

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