FOCAL AND ROTATIONALLY INVARIANT SOURCE RECONSTRUCTION FROM EEG/MEG

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***Abstract*— Simultaneous localization of close neuronal sources from EEG/MEG measurements is a challenging problem. To solve it, we here propose Focal Vector Field Reconstruction (FVR) as a new source imaging technique. The FVR objective facilitates at the same time sparsity and smoothness of the solutions while it is invariant with respect to rotations of the coordinate system. In the simultaneous localization of left and right somatosensory N20 generators from real EEG recordings, FVR outperforms state-of-the-art methods (such as LORETA and Minimum Current Estimate), as it is the only method that delivers correct location of the source in the somatosensory area of each hemisphere; in accordance with neurophysiological prior knowledge.*

***Keywords*— EEG/MEG, Inverse Problem, Sparsity, Smoothness, Rotational Invariance*

Introduction

Electroencephalography (EEG) and Magnetoencephalography (MEG) allow very accurate reconstruction of the time course of neuronal signals with a microsecond precision. Importantly both techniques are noninvasive and do not interfere with neuronal activities. However, the signal arriving at the sensors contains contributions from all areas of the brain, as well as external noise. It is of great scientific interest to infer the location of the underlying cerebral sources from the EEG/MEG measurements. This problem is called the EEG/MEG inverse problem.

The forward mapping from cerebral sources to sensors is well-defined and can be described mathematically with the help of a suitable model of the head. On the other hand, infinitely many source configurations will fulfill the forward equation. In other words, the inverse problem is ill-posed.

Imaging methods constrain the space of source configurations to a large but fixed number of dipolar current sources. These are arranged in a regular grid covering the whole brain (or optionally just the cortical areas).

Materials

We recorded 113-channel EEG of one male subject (26 years) during electrical median nerve stimulation. The relevant subset of EEG electrodes were positioned according to the international 10-20 system and the spatial positions were obtained using a 3D digitizer. The electrode positions were mapped onto the surface of the publicly available Montreal head [1], for which a realistic head model with three shells (brain, skull, skin) was created. A dipole grid with 7mm voxel distance was constructed fully inside the inner shell. The forward matrix L was obtained using semi-analytic expansions of the electric lead fields [2].

EEG data were recorded with sampling frequency of 2500 Hz, digitally bandpass-filtered between 15 Hz and 450 Hz. Left and right median nerves were stimulated in separate blocks by constant square 0.2 ms current pulses with intensities of approx. 9 mA (above motor threshold). The interstimulus interval varied randomly between 500 and 700 ms. About 1100 trials were recorded for each hand. Artifactual trials, as well as artifactual electrodes, were excluded from further analysis. For the remaining data, baseline correction was done based on the mean amplitude in the prestimulus interval (-100 ms to -10 ms). Finally, a scalp pattern was constructed by averaging the current amplitudes at 21 ms across 1946 trials (50% left hand, 50% right hand). By this means, the somatosensory N20 responses to left and right median nerve stimulation were captured with high signal-to-noise ratio.

The extracted pattern, as well as subaverages for left hand and right hand trials and the respective time courses are depicted in Fig. 1.

Methods

Let the measured scalp pattern be denoted by $\vec{x}$, a single dipole moment vector by $\vec{s}_i = (s_{i,x}, s_{i,y}, s_{i,z})^T$ and the vector of all dipole moments by $\vec{s} = (\vec{s}_1^{\,T}, \ldots, \vec{s}_N^{\,T})^T$. To infer $\vec{s}$ the functional

$$\hat{\vec{s}} = \arg\min_{\vec{s}} f(\vec{s}) \ \text{s.t.} \ \left\| L\vec{s} - \vec{x} \right\|_2 < \varepsilon \ , \quad (1)$$

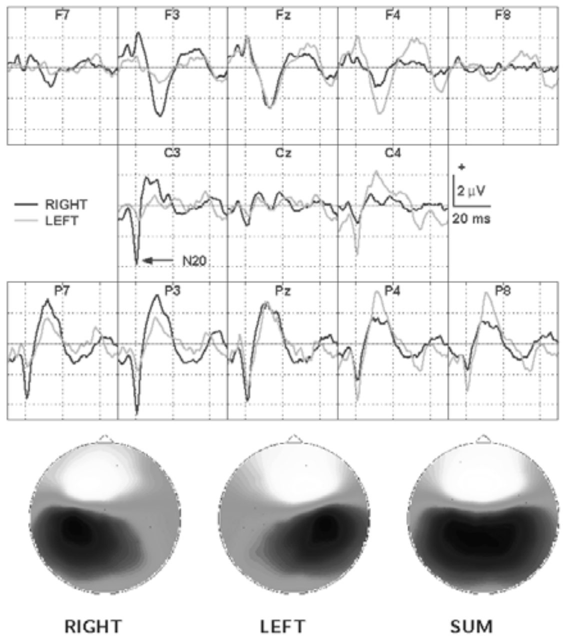

Figure 1: Somatosensory evoked responses to left and right median nerve stimulation. TOP: Time courses between 10 ms and 70 ms. BOTTOM: scalp pattern at 21 ms.

consisting of a goodness-of-fit term and an additional quality criterion (regularizer), has to be minimized. In this paper, the fitness parameter ε was chosen according to the estimated noise level of the EEG measurement.

As in general $\vec{s}$ is much larger than $\vec{x}$ (in our case there are ~6000x3 variables compared to ~100 measurements), many different assignments of $\vec{s}$ will fullfill the fitness criterion. A sensible choice of f is therefore crucial. Common inverse imaging methods encode in f either the preference for smoothness (i.e. LORETA [3], Minimum l_2-norm (MNE) [4]) or sparsity of the sources (Minimum Current Estimates (MCE) [5]). Both assumptions are reasonable, as a) the activation should be similar in adjacent voxels and b) in most experimental setups only a small number of voxels will be active. However, source configurations that are optimal in only one of the two aspects seem to perform poorly in the other one, as in practice the estimated sources of LORETA and MNE are often too distributed to be neurophysiologically plausible, while MCE solutions lack spatial continuity even in very small intervals. Furthermore, the estimated currents of conventional sparse methods are biased towards the axes of the coordinated system, a problem for which so far only workarounds have been proposed [6, 7].

In this paper we combine the preferences for smoothness and sparsity by simply minimizing a linear combination of two suitable objectives. For inducing sparsity, we minimize the l_1-norm of the current amplitudes

$$sp(\vec{s}) = \sum_{i=1}^{N} \left\| W_i \vec{s}_i \right\|_2 , \tag{2}$$

where 3x3 weighting matrices W_i are included in order to normalize the impact of sources from different depths in the cost function. The weights are defined based on a voxel-wise variance/covariance estimate (see [8, 9]), which means that. large currents at brain sites with high a-priori uncertainty are suppressed. It is easy to show that (2) is rotation-invariant, unlike the approach of [5], which minimizes the l_1-norm of stacked current vectors.

We define a smoothness measure with the help of a linear spatial Laplacian operator D (for the definition see [9])

$$sm(\vec{s}) = \left\| WD\vec{s} \right\|_2 , \tag{3}$$

where W is a blockdiagonal Matrix composed of the W_i.

The regularizer of FVR finally reads

$$f_{FVR}\ (\vec{s}\,) = sp(\vec{s}) + \lambda\ sm(\vec{s})\,. \tag{4}$$

In our study, we set $\lambda = 10^{-2} cm^2$, i.e. we treat sparsity more important than smoothnes.

Note that FVR has already been introduced in [9], where, however, the smoothness criterion was differently defined (as sparsity of the Laplacian transformed sources, corresponding to a „simplicity“ measure).

Results

Fig. 2 illustrates the main properties of the inverse methods LORETA and MCE compared to that of FVR using definition (4). The current density domain was simplified to a straight line of 300 scalar sources. Three source configurations, consisting of either three Hanning windows, two boxcar windows or a single sine wave, were simulated. Source reconstruction was performed based on noisefree “measurements”, which were obtained by smoothing and subsampling the sources. Apparently, only FVR is able to recover the exact number of sources in all three cases. LORETA is not able to distinguish all three sources in the Hanning example. Instead, one estimated source is placed exactly in between two true sources. MCE estimates consist of spikes, the number and locations not always being in line with the true source configuration.

The localization results of left and right N20 generators are shown in Fig. 3. The FVR solution (according to [9]) shows two major patches, one in each contralateral somatosensory cortex. LORETA estimates only one large active region over the central area, with the maximum lying exactly in between. The MCE solution consists of several small patches scattered across the whole somatosensory area.

Discussion

The proposed method FVR behaves satisfactory both on synthetic and real data. In the real world example, the inverse solution of FVR is the only one that is in good agreement with the localization of the hand areas reported in the literature [10, 11]. In contrast, LORETA fails to distinguish the two true sources and spuriously merges them. MCE estimates too many sources in the somatosensory areas.

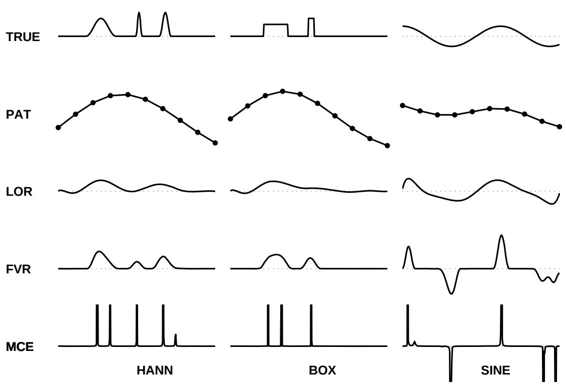

Figure 2: Characteristics of LORETA, FVR and MCE in a one-dimensional toy example.

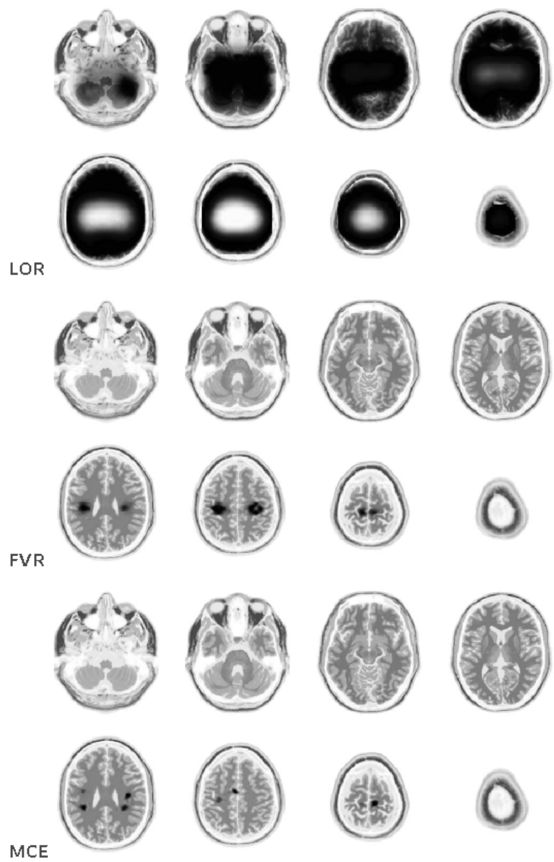

Figure 3: Eight consecutive axial slices (2 cm spacing) of the brain overlaid with the average estimated activity (dipole amplitudes) per interval according to the inverse solutions of LORETA (LOR), FVR and MCE.

It was pointed out in [9] that the characteristic shape of FVR estimates allows for a simple spatial partitioning of the source distribution into components. By means of this analysis a clearly artifactual source was easily detected in the FVR estimate but was indistinguishable mixed with the physiological sources in the LORETA estimate.

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