Source Localization of Subtopographies Decomposed by Radial Basis Functions

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Abstract. Functional neuroimaging methods give the opportunity of investigating human brain functioning. Mostly used functional neuroimaging techniques include Electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET) and optical imaging. Among these techniques EEG has the best time resolution, while fMRI has the best spatial resolution. High temporal resolution of EEG is an attractive property for neuroimaging studies. EEG inverse problem is needed to be solved in order to identify the locations and the strength of the electrical sources forming EEG/ERP topographies. Low spatial resolution of the scalp topography causes this localization problem more complicated. In this paper, a spatial preprocessing method, which separates a topography into two or more subtopographies is proposed. The decomposition procedure is based on defining a spatial map with radial basis functions which forms the subtopographies. A simulated data is used to exhibit the advantage of using this decomposition technique prior to EEG source localization. It is shown that the accuracy of the source localization problem is improved by using the subtopographies instead of using the raw topography.

Keywords: Subtopography, radial basis function, source localization.

1 Introduction

EEG is a record of the oscillations of brain electric potential recorded from the electrodes placed on the human scalp. Using these records, very rapid changes in electrical potentials can be measured. Hence, EEG is valuable for studying the timing of brain processes. Spatial distribution of the functional brain activity can be estimated by solving the neuroelectromagnetic inverse problem [1][2][3][4]. This problem has two types of solution; parametric and imaging. In the parametric solutions, brain electrical activity is modelled using a few number of electrical dipoles[5]. On the other hand, imaging type solutions try to estimate the activity using all possible spatial locations distributed in the brain[6]. The brain acitivity which is focal or distributed in space and nonstationary in time, motivated researchers to develop preprocessing methods before they apply source localization algorithms. The problem of identifying the individual EEG components in temporal domain are treated by proposing decomposition methods that involve the time, the frequency, the channel or their various combinations[8][7][9].

T. Dohi, I. Sakuma, and H. Liao (Eds.): MIAR 2008, LNCS 5128, pp. 108–115, 2008.
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In the spatial domain, EEG topographic maps are analyzed using 2D wavelet decomposition[10].

In this paper, a spatial preprocessing method is proposed prior to source localization algorithm. The method is based on defining the EEG topography with two or more subtopographies. A radial basis function is used to fit the raw topography by solving a non-linear least square optimization problem. This radial basis function formed the first subtopograpy and denoted as approximation while the remaining topography is assigned as the second subtopograpy which is called as detail or residual. Then electrical sources of these subtopographies are estimated by using Multiple Signal Classification algorithm (MUSIC) and standarized Low Resolution Electrical Tomography (sLORETA). The results of the subtopographic localization agreed with the simulation parameters while the localization of raw topographies biased the simulation parameters.

2 EEG Source Localization

EEG source localization problem is formulated in two stages; i)the forward and ii)the inverse problem. Forward problem is to determine the electrical potentials given the source location and strength parameters using a head model. Inverse problem, estimate these parameters from the measurements.

2.1 Forward Problem

Forward problem is defined to compute the electrial potential distribution over the scalp surface based on a head model. The head model is developped using average T1 weighted human brain MR data provided by Montreal Neurology Institute (MNI). Statistical Parameter Mapping software 2005 release (SPM05) which is developed by Wellcome Institute is used for 3D segmentation of the brain, skull and scalp.

The forward problem is solved by the Boundary Element Method (BEM) [12] which is a numerical approximation technique which partitions the surface of a volume conductor into closed triangular meshes. The human head is modelled as three homogeneous conductor layers; the outermost surface being the boundary of the scalp, and the intermediate and the innermost being the one for the skull and the brain, respectively. In order to apply the BEM, a realistic head model is formed and its surfaces are tesselated into triangles using marching cubes algorithm [11] as seen in Fig.2.1.

Finally, 30 channel electrode locations (Fp1, Fp2, F7, F3, Fz, F4, F8, Ft7, Fc3, Fcz, Fc4, Ft8, T7, C3, Cz, C4, T8, Tp7, Cp3, Cpz, Cp4, Tp8, P7, P3, Pz, P4, P8, O1, Oz, O2) are registered to the scalp surface by spline interpolation using the T1 weighted MR data, the inion-nasion and pre-auricular coordinates, and the 10-20 Electrode Placement System.

The forward EEG equation can be written as in Eq.1,

$$V = HJ = HML \tag{1}$$

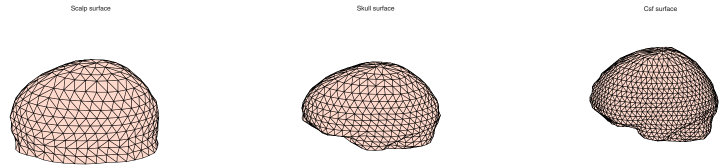

Fig. 1. Scalp, skull and csf surfaces are tessellated with 1000,1000,2000 surfaces respectively

where $V \in \Re^{Nv,1}$ is the electrical potential vector measured by scalp electrodes (N_v is the number of voxels in the brain gray matter volume), $H \in \Re^{Ne,3\times Nv}$ is the lead field matrix (Ne is the number of electrodes), $J \in \Re^{3\times Nv}$ is the current density orientation vector, $M \in \Re^{3\times Nv,Nv}$ contains the normal vectors to the cortical surface at each voxel and $L \in \Re^{Nv,1}$ is the current density amplitude vector.

2.2 Inverse Problem

The inverse problem estimates the source positions and their strength from multichannel EEG data. The solution space for the inverse problem is restricted to the gray matter. A voxel is labeled as a gray matter if it satisfied two conditions: Its probability of being gray matter is higher than that of being white matter and its probability of being gray matter is higher than that of being cerebrospinal fluid (Csf). 3D solution space is sampled with a resolution of $2mm \times 2mm \times 2mm$ and $N_v = 43277$ points are obtained. Two different inverse solutions are implemented based on realistic head model.

As a parametric method, the MUSIC scanning algorithm; this method is based on subdividing the brain tissue into a 3D grid and computing the spatial power spectrum with an eigenbased approach for each voxel element. In order to do this, the transfer function H in Eq.1 has to be computed numerically.

MUSIC algorithm

– Compute the correlation matrix of V.

$$R = \frac{1}{N}(VV^T) \tag{2}$$

– Eigenvalue decomposition of R

$$R = [\Phi_s \Phi_n]\Lambda[\Phi_s \Phi_n]^T \tag{3}$$

(Φ_s and Φ_n: signal and noise eigenvector matrices)
(Λ: $\lambda_1 > \lambda_2 > ...\lambda_M$, eigenvalues of R)

– Compute the forward matrix H and its singular value decomposition on each voxel.
$\forall$i$\in$ Solution space

$$H_i = U_{H_i} S_{H_i} V_{H_i}^T \tag{4}$$

(U_{H_i} and V_{H_i}: left and right eigenvector matrices)
($\Sigma_{H_i} : \sigma_1 > \sigma_2 > ...\sigma_N$ singular values of H_i)

– Compute the spatial power spectrum Z_i

$$Z_i = \lambda_{min}(\frac{1}{U_{H_i}^T \Phi_n \Phi_n^T U_{H_i}}) \tag{5}$$

– Find maximum value of Z_j where $1 \leq j \leq Nv$
j is the index of the activity.

As an imaging method,

sLORETA. The solution of the regularized, weighted minimum norm problem in Eq.6 is defined as Eq.7 by Pascual-Marqui [13],

$$min(||V - HML||^2 + \alpha L^T W L) \tag{6}$$

where $W \in \Re^{Nv,Nv}$ is a known symmetric weight matrix and $\alpha > 0$ is the regularization parameter.

$$L = W^{-1}(HM)^T((HM)W^{-1}(HM)^T + C)^{\dagger}V \tag{7}$$

where $C \in \Re^{Ne,Ne}$ is the sensor noise covariance matrix.

Computation of weight matrix W is defined in [13] with a simple algorithm.

3 Spatial Decomposition by Radial Basis Function

An RBF is a real-valued function whose value depends only on the distance from the origin, so that $\theta(x) = \theta(||x||)$; or alternatively on the distance from some other point c, called a center, so that $\theta(x, c) = \theta(||x - c||)$. Any function θ that satisfies the property $\theta(x) = \theta(||x||)$ is a radial function.

Two different RBF; a gaussian as in Eq.8 and a morlet function as in Eq.9 kernels are selected to approximate the input image. RBF is fitted to the EEG 2D topography by solving Eq.10 using nonlinear least squares optimization. The mesh images of 2D gaussian and morlet RBFs are seen in Fig.2.

$$V_t(x, y) = \sum_{i=1}^{Nf} a_i e^{-\frac{(x - x_{c_i})^2}{\sigma_{x_{c_i}}^2} - \frac{(y - y_{c_i})^2}{\sigma_{y_{c_i}}^2}}. \tag{8}$$

$$V_t(x, y) = \sum_{i=1}^{Nf} a_i e^{-\frac{(x - x_{c_i})^2}{\sigma_{x_{c_i}}^2} - \frac{(y - y_{c_i})^2}{\sigma_{y_{c_i}}^2}} cos(k_i(x - x_{c_i}))cos(l_i(y - y_{c_i})). \tag{9}$$

where V_t is the approximated 2D scalp topography for an instance of time, x_{c_i} and y_{c_i} are coordinates of the center points, N_f is the number of RBFs and a_i is the weighting coefficient of RBF.

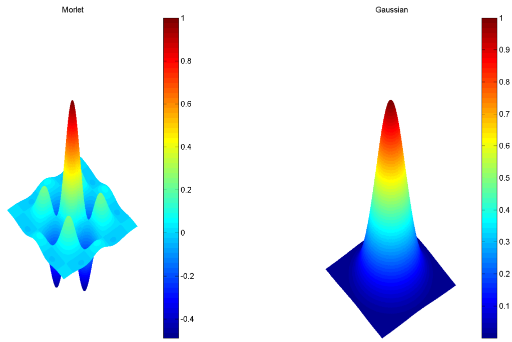

Fig. 2. Mesh images of 2D RBF gaussian kernel and morlet kernel, respectively

The nonlinear least square optimization tries to adjust the parameters of the kernel function V_t using Eq.10

$$\min ||(V_o(x, y) - V_t(x, y)|| \tag{10}$$

where V_o is the raw 2D scalp topography.

4 Validation of the Method

In order to validate the RBF decomposition method, a simulated multichannel EEG data is generated using BEM. Two stationry radial point sources are assumed; one being superficial while the other being deeper in the brain. Forward problem is solved for these point sources using BEM over the predefined head model given in Fig.2.1 and the topograhies are shown in Fig.3. The inverse problem is solved using both sLORETA and MUSIC for the total topographic

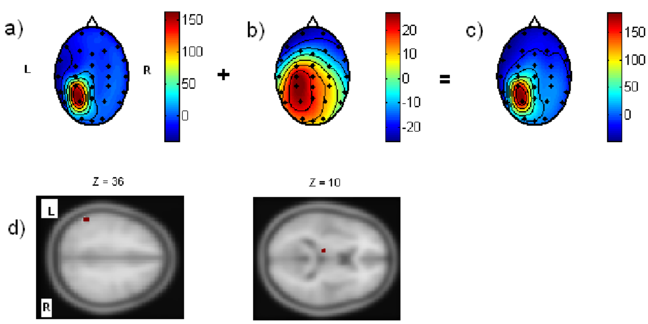

Fig. 3. 2D topography of simulation data for the a)superficial source and b)deeper source. c) Superimposition of these two subtopographies. d)Location of the superficial and deeper source, respectively.

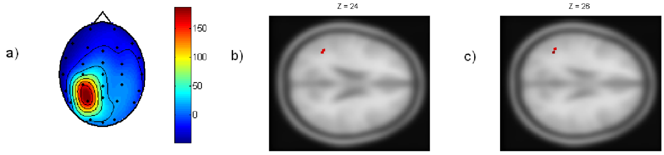

Fig. 4. a)Topography of the simulated superimposed raw data. b)Source localization result of this topography by MUSIC and c)by sLORETA.

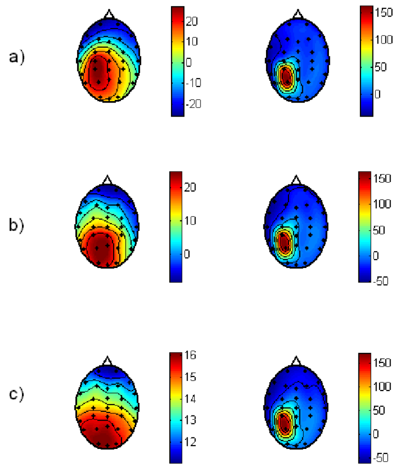

Fig. 5. a) Original raw subtoporaphies. b) Approximation and detail subtopographies decomposed using Morlet RBF and c)Gaussian RBF kernels.

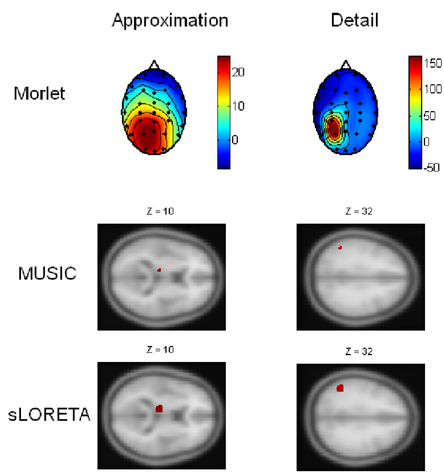

Fig. 6. 2D topographies of decomposed subtopographies based on Morlet RBF. Source localization of the corresponding topographies using MUSIC and sLORETA algorithms.

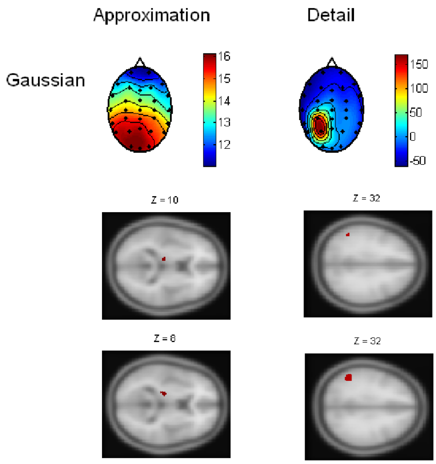

Fig. 7. 2D topographies of decomposed subtopographies based on Gaussian RBF. Source localization of the corresponding topographies using MUSIC and sLORETA algorithms.

activity. Both of the inverse methods could not localize the deeper source as shown in Fig.4. After the RBF decomposition, two suptopographic maps are obtained and their superimposition yielded the original EEG topography. Results of the RBF decomposition method for two kernel functions are shown in Fig.5. When these decomposed topographies are individually localized, it can be observed that the predefined sources can be easily discriminated as shown in Fig.6 and Fig.7 . Superficial source is localized from the approximation output while the deeper source is estimated from the detail output.

5 Conclusion

When a strong or superficial source exists, weak or deep sources remain invisible and localization results indicate that the activity is close to the strong source [14]. In our simulation case, deep and superficial sources can not be separated from the source localization of raw data. Moreover, localization methods interpreted the activity as one source located between the locations of superficial and deep source. Spatial decomposition of EEG simplifies the complexity of scalp topography into two subtopographic maps produced by individual EEG sources prior to their source estimation. Localization of these subtopographies gives us the original source configuration of the simulation. By this simulation it is shown that, spatial RBF decomposition helps us to enhance the accuracy and reliability of the source localization problem.

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