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Sparse EEG Source Localization Using Bernoulli Laplacian Priors

Facundo Costa*, *Student Member, IEEE*, Hadj Batatia, *Member, IEEE*, Lotfi Chaari, *Member, IEEE*,
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Abstract—Source localization in electroencephalography has received an increasing amount of interest in the last decade. Solving the underlying ill-posed inverse problem usually requires choosing an appropriate regularization. The usual ℓ_2 norm has been considered and provides solutions with low computational complexity. However, in several situations, realistic brain activity is believed to be focused in a few focal areas. In these cases, the ℓ_2 norm is known to overestimate the activated spatial areas. One solution to this problem is to promote sparse solutions for instance based on the ℓ_1 norm that are easy to handle with optimization techniques. In this paper, we consider the use of an $\ell_0 + \ell_1$ norm to enforce sparse source activity (by ensuring the solution has few nonzero elements) while regularizing the nonzero amplitudes of the solution. More precisely, the ℓ_0 pseudonorm handles the position of the nonzero elements while the ℓ_1 norm constrains the values of their amplitudes. We use a Bernoulli–Laplace prior to introduce this combined $\ell_0 + \ell_1$ norm in a Bayesian framework. The proposed Bayesian model is shown to favor sparsity while jointly estimating the model hyperparameters using a Markov chain Monte Carlo sampling technique. We apply the model to both simulated and real EEG data, showing that the proposed method provides better results than the ℓ_2 and ℓ_1 norms regularizations in the presence of pointwise sources. A comparison with a recent method based on multiple sparse priors is also conducted.

Index Terms—Electroencephalography (EEG), inverse problem, $\ell_0 + \ell_1$ norm regularization, Markov chain monte carlo (MCMC), source localization, sparse Bayesian restoration.

I. INTRODUCTION

ELECTROENCEPHALOGRAPHY (EEG) source localization is an ill-posed inverse problem that has been receiving an intensive attention in the literature and has been solved using several interesting methods. These methods can be classified into two main groups based on different models: 1) the dipole-fitting models that try to estimate the localization of a small number of dipoles and 2) the distributed-source models that assume that there is a large number of dipoles and try to estimate their amplitudes and orientations. The dipole-fitting models [1], [2] assume that the brain activity is concentrated in a small number of point-like sources and estimate the localization, amplitude, and orientation of a few dipoles (usually no more than ten) to explain the measured data. A particularity of these models is that they lead to solutions that can vary

extremely with the initial guess about the number of dipoles, their locations and their orientations because of the existence of many local minima in the optimized cost function [3]. To solve this problem, the MUSIC algorithm [4] and its variants R-MUSIC [5], RAP-MUSIC [6], and FINES [7] were developed. Another recent dipole-fitting model whose parameters are estimated using sequential Monte Carlo [8] formulates the EEG source localization as a semilinear problem due to the measurements having a linear dependence with respect to the dipole amplitudes and a nonlinear one with respect to the positions. If few and clustered sources are present in the underlying brain activity, the dipole-fitting algorithms generally yield good results [9], [10]. However, the performance of these algorithms can be altered in the case of multiple spatially extended sources [3]. On the other hand, the distributed source models represent the brain activity as a big number of dipoles (usually between 1.000 and 50.000) with fixed positions (that occupy either the entire volume or just the cortical surface of the brain), and estimate their amplitudes and orientations. Since the amount of dipoles is much larger than the number of electrodes, the problem to be solved is underdetermined and has an infinite number of possible brain activity distributions associated with the measured data. The EEG source localization problem is, therefore, known to be ill posed [3].

In order to choose from the possible solutions of the EEG source localization problem, a regularization trying to enforce desirable properties is usually applied. The minimum-norm estimation algorithm [11] tries to minimize the ℓ_2 norm of the solution favoring low power activity estimations. However, the resulting model also prefers weak surface power over strong depth power [3]. Several algorithms have tried to correct this problem including the weighted minimum norm, Loreta [12] and sLoreta [13]. Among these solutions, sLoreta can estimate the maximum excitation point with zero localization error in noiseless conditions [3]. A drawback of these algorithms is that they require to adjust a regularization parameter, which is usually performed with empirical methods such as cross validation, Bayesian estimation [14] or the L -curve method [15]. Another problem is that they overestimate the active spatial area in the cortex when the actual source activity is focal [3]. Motivated by the fact that realistic source activity is likely to be associated with few active brain regions at the same time, some algorithms that encourage sparse solutions have been developed. An ℓ_0 pseudonorm can be used to provide sparse solutions [16]. However, since the minimization of this norm requires a very expensive combinatory search, it is usually approximated by an ℓ_1 norm [17], [18] that is easier to handle with classical

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optimization techniques due to its convexity. These two types of regularizations have been shown to be equivalent under certain conditions [16].

In addition to the optimization techniques mentioned previously, it is also possible to estimate the brain activity by modeling its time evolution and applying Kalman filtering [19], [20] or particle filters [21]–[23]. Another way of looking for a solution with sparse properties is to consider Bayesian techniques with appropriate priors assigned to the model parameters. These Bayesian techniques have the advantage of estimating the model hyperparameters directly from the data using hierarchical algorithms. Note that Bayesian methods have been used both for dipole-fitting [24]–[27] and distributed source models [28]–[30]. In [29], Friston *et al.* developed the multiple sparse priors (MSP) framework in which they parcel the brain in different preselected regions and promote a sparse subset of these regions to be active. This is performed by using a Gaussian prior distribution for the brain activity and estimating its correlation matrix as a linear combination of predefined base matrices with finite support defined over each brain parcel. This method is designed to estimate brain activities that have multiple spatially extended sources and requires choosing a criterion for the prior parcellation of the brain in different regions and the selection of the base matrices. Even though the results of the MSP framework proved to be good in several scenarios, since our focus is to estimate point-like focal source activity, we propose to consider separate dipoles instead of grouping them together in different preselected regions. This avoids the need to select a criterion for brain parcellation and constructing the base matrices required by the MSP framework.

For these reasons, we propose to introduce a new algorithm relying on the ℓ_1 norm and ℓ_0 -pseudonorm regularizations. Since the ℓ_0 pseudonorm is too costly for direct implementation and the ℓ_1 norm does not always yield the same solution, we propose to combine them into a Bayesian framework to pursue sparse solutions. It can be easily shown that using a Laplace prior is the Bayesian equivalent of ℓ_1 norm regularization, whereas a Bernoulli prior can be associated with the ℓ_0 pseudonorm. As a consequence, we propose the use of a Bernoulli–Laplace prior in a distributed source model for the estimation of the activity of focal point-like sources. The combination of the two norms allows the nonzero elements to be localized (via the Bernoulli part of the prior) and their amplitudes to be estimated (with the Laplace distribution). Note that the Laplace distribution prior is able to estimate both small and high amplitudes due to its large value around zero and its fat tails. In addition one could introduce a spatial-regularizing prior to yield a region-based sparse solution equivalent to the MSP model without the preprocessing and associated hypotheses.

In order to compute estimators associated with the proposed Bayesian model, we derive a Markov chain Monte Carlo (MCMC) method allowing samples to be generated according to the posterior of interest. These samples are then used to estimate the unknown model parameters. The resulting algorithm has several attractive properties, including the fact that it is able to estimate the model hyperparameters in an unsupervised framework and provides better estimations of the source activity than the traditional ℓ_2 or ℓ_1 norms.

This paper is organized as follows: The observation model is introduced in Section II. The Bayesian model proposed to estimate the unknown parameters is defined in Section III. Section IV studies a hybrid Gibbs sampler that will be used to generate samples asymptotically distributed according to the posterior of interest. Simulation results obtained with synthetic and real EEG data are reported in Section V. Section VI concludes the paper.

II. PROBLEM STATEMENT

The main objective of the EEG source localization problem is to estimate the brain activity of the patient from EEG measurements. It is well known that the activity can be represented as a continuous current distribution [31] that can be approximated by a discrete number of dipoles located in the brain [3], [31]. Therefore, we propose to model the brain activity by using a finite number of active dipoles located in the cortex. More precisely, we consider a distributed-source model with a fixed amount of dipoles with given locations. Since the electric potential at any point of the scalp can be calculated as a linear combination of the dipole amplitudes, the relationship between the potential at the scalp and the dipole amplitudes can be represented as follows [3], [31]:

$$\mathbf{y} = \mathcal{H}\mathbf{x} + \mathbf{e} \quad (1)$$

where $\mathbf{x} \in \mathbb{R}^{3M}$ contains the amplitudes of the M dipoles along the three spatial dimensions, $\mathbf{y} \in \mathbb{R}^N$ is the measurement vector acquired by the N electrodes, the $N \times 3M$ lead field matrix \mathcal{H} models the propagation of the electromagnetic field from the sources to the sensors [24], [32] and \mathbf{e} is an additive white Gaussian noise. Since the activity measured by an EEG is mainly generated by groups of neurons that are oriented orthogonal to the brain surface [31], [33], we assume the source orientations to be normal to the cortex. Moreover, as in many works [3], [28], [34], we limit the position of the dipoles to the cortex surface. As a consequence, the moment of each dipole can be determined using only one value, such that $\mathbf{x} \in \mathbb{R}^M$ and $\mathcal{H} \in \mathbb{R}^{N \times M}$. Note that even though the orientations of the dipoles are constrained, the directions of their currents are not known and have to be estimated by the algorithm (via the signs of the elements of \mathbf{x}) [3], [34].

The EEG source localization problem based on the observation model (1) mainly consists of estimating the vector \mathbf{x} from the observed data \mathbf{y} . The next section introduces a hierarchical Bayesian model appropriate to solve this inverse problem. The likelihood of this model and the priors assigned to its unknown parameters and hyperparameters are defined in the next sections.

III. BAYESIAN MODEL

A. Likelihood

It is very classical in EEG analysis to consider an additive white Gaussian noise with a variance σ_n^2 [3]. When this assumption does not hold, it is classical to estimate the noise covariance matrix from the data and to whiten the data before applying the algorithm [35]. This strategy will be considered in our experiments related to real data presented in Section V-C.

The Gaussian noise assumption for the noise samples leads to the following probability density function (pdf)

$$f(\mathbf{y}|\mathbf{x}, \sigma_n^2) = \left(\frac{1}{2\pi\sigma_n^2} \right)^{\frac{N}{2}} \exp\left(-\frac{\|\mathbf{y} - \mathcal{H}\mathbf{x}\|^2}{2\sigma_n^2} \right) \quad (2)$$

where $\|\cdot\|$ denotes the Euclidean norm.

B. Prior Distributions

The unknown parameter vector associated with the proposed model (1) is $\boldsymbol{\theta} = \{\mathbf{x}, \sigma_n^2\}$. In order to perform Bayesian inference, we assign priors to these parameters as follows.

1) *Prior for the Dipole Amplitudes*: In order to encourage sparse solutions whose nonzero elements have small amplitudes, we introduce the Bayesian analogous of an $\ell_0 + \ell_1$ regularization by using a Bernoulli–Laplace prior distribution for each element of the vector \mathbf{x} . The corresponding pdf for the i th element of \mathbf{x} is

$$f(x_i|\omega, \lambda) = (1 - \omega)\delta(x_i) + \frac{\omega}{2\lambda} \exp\left(-\frac{|x_i|}{\lambda} \right) \quad (3)$$

where $\delta(\cdot)$ is the Dirac delta function, λ is the parameter of the Laplace distribution, and ω the weight balancing the effects of the Dirac delta function and the Laplace distribution. Assuming the random variables x_i are *a priori* independent, the prior distribution of \mathbf{x} can be written as

$$f(\mathbf{x}|\omega, \lambda) = \prod_{i=1}^M f(x_i|\omega, \lambda). \quad (4)$$

2) *Prior for the Noise Variance*: A noninformative Jeffrey’s prior is assigned to the noise variance

$$f(\sigma_n^2) \propto \frac{1}{\sigma_n^2} \mathbf{1}_{\mathbb{R}^+}(\sigma_n^2) \quad (5)$$

where $\mathbf{1}_{\mathbb{R}^+}(\xi) = 1$ if $\xi \in \mathbb{R}^+$ and 0 otherwise. This prior is a very classical choice for a noninformative prior (see, e.g., [36] for motivations). Note that a more informative *prior* distribution related to the signal to noise ratio could also be investigated. However, we have chosen here to design an algorithm requiring as little prior information as possible.

C. Hyperparameter Priors

The hyperparameter vector associated with the previous priors is $\boldsymbol{\Phi} = \{\omega, \lambda\}$ as displayed in the direct acyclic graph of Fig. 1. This paper considers a hierarchical Bayesian model that allows the hyperparameters to be estimated from the data. This strategy requires to assign priors to the hyperparameters (referred to as hyperpriors) that are defined in this section.

1) *Hyperprior for ω* : An independent uniform distribution on $[0, \omega_{\max}]$ is assigned to the weight ω

$$\omega \sim \mathcal{U}_{[0, \omega_{\max}]} \quad (6)$$

where $\omega_{\max} \in [0, 1]$ is an upper bound on ω that is fixed in order to ensure a minimum level of sparsity.¹

¹We have observed that setting $\omega_{\max} = 0.5$ (instead of $\omega_{\max} = 1$) yields faster convergence of the sampler studied in Section IV.

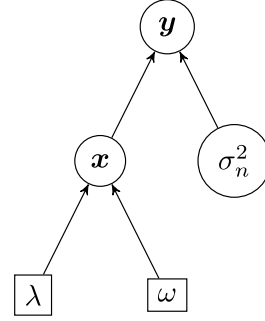


Fig. 1. Directed acyclic graph of the hierarchy used for the Bayesian model.

2) *Hyperprior for λ* : Using similar arguments as for the noise variance σ_n^2 , a Jeffrey’s prior is assigned to λ in order to define the following noninformative prior

$$f(\lambda) \propto \frac{1}{\lambda} \mathbf{1}_{\mathbb{R}^+}(\lambda). \quad (7)$$

D. Posterior Distribution

Taking into account the likelihood and priors introduced previously, the joint posterior distribution of the model used for EEG source localization can be expressed using the following hierarchical structure:

$$f(\boldsymbol{\theta}, \boldsymbol{\Phi}|\mathbf{y}) \propto f(\mathbf{y}|\boldsymbol{\theta})f(\boldsymbol{\theta}|\boldsymbol{\Phi})f(\boldsymbol{\Phi}) \quad (8)$$

where $\{\boldsymbol{\theta}, \boldsymbol{\Phi}\}$ is the vector containing the model parameters and hyperparameters. Because of the complexity of this posterior distribution, the Bayesian estimators of $\{\boldsymbol{\theta}, \boldsymbol{\Phi}\}$ cannot be computed with simple closed-form expressions. Section IV studies an MCMC method that can be used to sample the joint posterior distribution (8) and build Bayesian estimators of the unknown model parameters using the generated samples.

IV. MARKOV CHAIN MONTE CARLO METHOD

This section considers a Gibbs sampler [36] that generates samples iteratively from the conditional distributions of (8), i.e., from $f(\sigma_n^2|\mathbf{y}, \mathbf{x})$, $f(\lambda|\mathbf{x})$, $f(\omega|\mathbf{x})$ and $f(x_i|\mathbf{y}, \mathbf{x}_{-i}, \omega, \lambda, \sigma_n^2)$. Note that this strategy showed interesting results for many image processing problems including image denoising [37], sparse image reconstruction [38], hyperspectral image unmixing [39], and fusion of hyperspectral and panchromatic images [40]. The next sections explain how to sample from the conditional distributions of the unknown parameters and hyperparameters associated with the posterior of interest (8). The resulting algorithm is also summarized in Algorithm 1.

A. Sampling According to $f(\sigma_n^2|\mathbf{y}, \mathbf{x})$

Using (8), it is straightforward to derive the conditional posterior distribution of σ_n^2 which is the following inverse gamma distribution

$$\sigma_n^2|\mathbf{x}, \mathbf{y} \sim \text{IG}\left(\sigma_n^2 \left| \frac{N}{2}, \frac{\|\mathbf{y} - \mathcal{H}\mathbf{x}\|^2}{2} \right. \right) \quad (9)$$

where $\|\cdot\|$ is the Euclidean norm.

Algorithm 1 Gibbs sampler.

Initialize \mathbf{x} with the sLoreta solution
repeat
 Sample σ_n^2 according to (9).
 Sample λ according to (10).
 Sample ω according to (11).
 for $i = 1$ to M **do**
 Sample x_i according to (12).
 end for
until convergence

B. Sampling According to $f(\lambda|\mathbf{x})$

By using $f(\mathbf{x}|\omega, \lambda)$ and the prior distribution of λ , it is easy to derive the conditional distribution of λ , which is also an inverse gamma distribution

$$\lambda|\mathbf{x} \sim \mathcal{IG}\left(\lambda \mid \|\mathbf{x}\|_0, \|\mathbf{x}\|_1\right) \quad (10)$$

where $\|\cdot\|_0$ and $\|\cdot\|_1$ are the ℓ_0 and ℓ_1 norms, respectively.

C. Sampling According to $f(\omega|\mathbf{x})$

Using $f(\mathbf{x}|\omega, \lambda)$ and the prior of ω it can be shown that the conditional distribution of ω is a truncated Beta distribution defined on the interval $[0, \omega_{\max}]$

$$\omega|\mathbf{x} \sim \mathcal{B}_{[0, \omega_{\max}]}(1 + \|\mathbf{x}\|_0, 1 + M - \|\mathbf{x}\|_0). \quad (11)$$

D. Sampling According to $f(x_i|\mathbf{y}, \mathbf{x}_{-i}, \omega, \lambda, \sigma_n^2)$

Using the likelihood and the prior distribution of \mathbf{x} , the conditional distribution of each signal element x_i can be expressed as follows:

$$f(x_i|\mathbf{y}, \mathbf{x}_{-i}, \omega, \lambda, \sigma_n^2) = \omega_{1,i}\delta(x_i) + \omega_{2,i}\mathcal{N}_+(\mu_{i,+}, \sigma_i^2) + \omega_{3,i}\mathcal{N}_-(\mu_{i,-}, \sigma_i^2) \quad (12)$$

where \mathcal{N}_+ and \mathcal{N}_- denote the truncated Gaussian distributions on \mathbb{R}^+ and \mathbb{R}^- , respectively. The vector \mathbf{x} can be decomposed on the orthonormal basis $B = \{\mathbf{e}_1, \dots, \mathbf{e}_M\}$ such that $\mathbf{x} = \tilde{\mathbf{x}}_{-i} + x_i\mathbf{e}_i$ where $\tilde{\mathbf{x}}_{-i}$ is obtained by setting the i^{th} element of \mathbf{x} to 0. Defining $\mathbf{v}_i = \mathbf{y} - \mathcal{H}\tilde{\mathbf{x}}_{-i}$ and $\mathbf{h}_i = \mathcal{H}\mathbf{e}_i$, the weights $(\omega_{l,i})_{1 \leq l \leq 3}$ are defined as

$$\omega_{l,i} = \frac{u_{l,i}}{\sum_{l=1}^3 u_{l,i}} \quad (13)$$

where

$$\begin{aligned} u_{1,i} &= 1 - \omega \\ u_{2,i} &= \frac{\omega}{2\lambda} \exp\left(\frac{(\mu_{i,+}^+)^2}{2\sigma_i^2}\right) \sqrt{2\pi\sigma_i^2} C(\mu_{i,+}^+, \sigma_i^2) \\ u_{3,i} &= \frac{\omega}{2\lambda} \exp\left(\frac{(\mu_{i,-}^-)^2}{2\sigma_i^2}\right) \sqrt{2\pi\sigma_i^2} C(-\mu_{i,-}^-, \sigma_i^2) \end{aligned} \quad (14)$$

and

$$\begin{aligned} \sigma_i^2 &= \frac{\sigma_n^2}{\|\mathbf{h}_i\|^2} \\ \mu_i^+ &= \sigma_i^2 \left(\frac{\mathbf{h}_i^\top \mathbf{v}_i}{\sigma_n^2} - \frac{1}{\lambda} \right) \\ \mu_i^- &= \sigma_i^2 \left(\frac{\mathbf{h}_i^\top \mathbf{v}_i}{\sigma_n^2} + \frac{1}{\lambda} \right) \\ C(\mu, \sigma^2) &= \frac{1}{2} \left[1 + \operatorname{erf}\left(\frac{\mu}{\sqrt{2}\sigma^2}\right) \right]. \end{aligned} \quad (15)$$

Finally, it is interesting to mention how to sample efficiently from (12), which will also be useful to define appropriate estimators (see Section IV-E). Since (12) is a mixture of three distributions, we introduce a discrete random variable b_i taking the value 0 with probability $\omega_{1,i}$ (corresponding to $x_i = 0$), the value 1 with probability $\omega_{2,i}$ (corresponding to $x_i > 0$), and the value -1 with probability $\omega_{3,i}$ (corresponding to $x_i < 0$). To sample from (12), we can draw the discrete random variable b_i , and generate x_i conditionally upon b_i . The role of the discrete random variable b_i is to detect whether x_i is zero, positive, or negative.

E. Parameter Estimation

In order to estimate the different parameters associated with the posterior (8) using the samples generated by the MCMC method described previously, we first detect the nonzero values of x_i corresponding to the nonzero dipole amplitudes. This detection can be easily achieved by using the generated discrete random variables b_i used to sample according to x_i . More precisely, we estimate b_i following the maximum *a posteriori* principle as the most likely value generated by the sampler.² Once we have detected whether x_i is zero, positive, or negative (i.e., once we have estimated b_i), we keep the vectors generated by the MCMC method satisfying these conditions for the different variables b_i and we estimate the dipole amplitudes, the noise variance and the hyperparameters using the mean of these vectors. In other words, we estimate the indicators b_i by the maximum *a posteriori* principle and the amplitudes x_i by the minimum mean square error (MMSE) principle, which corresponds to the mean of the posterior.

V. EXPERIMENTAL RESULTS

This section reports different experiments conducted to evaluate the performance of the proposed EEG source localization algorithm for synthetic and real data. In these experiments, our algorithm was initialized with the sLoreta solution obtained after estimating the regularization parameter by minimizing the cross-validation error as recommended by Pascual-Marqui *et al.* in [13]. The upper bound of the sparsity level was set to $\omega_{\max} = 0.5$, which is much larger than the expected value of ω .

²We have noted that when the number of zeros is close to the number of nonzeros, it can be interesting to promote the nonzero value, which will result in estimating a small dipole amplitude.

The results obtained with synthetic and real data are reported in two separate sections.

A. Synthetic Data

1) *Simulation Scenario*: Synthetic data with few pointwise source activations were generated using a realistic BEM head model with 19 electrodes placed according to the 10 – 20 international system of electrode placement. Three different kinds of activations were investigated: 1) single dipole activations, 2) multiple distant dipole activations, and 3) multiple close dipole activations. The default subject anatomy of the Brainstorm software [41] was considered. This model corresponds to MRI measurements of a 27-year old male using the boundary element model implemented by the OpenMEEG package [42]. The default brain cortex of this subject was downsampled to generate a 1003-dipole head model. These dipoles are distributed along the cortex surface and have an orientation normal to it, as discussed in the previous sections. The resulting head model is such that $\mathcal{H} \in \mathbb{R}^{19 \times 1003}$.

For each of the activations that are described in what follows, three independent white Gaussian noise realizations were added to the observed signal $\mathbf{H}\mathbf{x}$, resulting in three sets of measurements \mathbf{y} with an SNR of 20 dB. For each of these three noisy signals \mathbf{y} , four MCMC independent chains were run, resulting in 12 total simulations for each of the considered activations \mathbf{x} . The ℓ_1 and sLoreta methods were applied to the same three different sets of measurements \mathbf{y} resulting in three simulations for each activation.

2) *Performance Evaluation*: To assess the quality of the localization results, the following indicators were used.

- i) Localization error [3]: The Euclidean distance between the maximum of the estimated activity and the real source location is used to determine whether the algorithm is able to find the point of highest activity correctly or not.
- ii) Center-mass localization error [43]: The Euclidean distance between the barycenter of the estimated activity and the real source location allows us to appreciate if the activity estimated by the algorithm is centered around the correct point or if it is biased.
- iii) Excitation extension: The spatial extension of the spatial area of the brain cortex that is estimated to be active was considered in [43]. Since the synthetic data only contain pointwise sources, this criterion should ideally be equal to zero.
- iv) Transportation cost: This indicator evaluates the performance in a multiple dipole situation where the activity estimates from different dipoles may overlap. It is computed as the solution of an optimal mass transport optimization problem [44] considering the known ground truth to be the initial mass distribution and the activity estimated by the algorithm to be the target mass distribution. The activities associated with the ground truth and the estimated data are first normalized. The total cost of moving the activity from the nonzero elements of the ground truth to the nonzero elements of the estimated activity is then computed. It is obtained by finding the weights $w_{j \rightarrow k}$

that minimize

$$\sum_j \sum_k w_{j \rightarrow k} |\mathbf{r}_{x_j^{\text{nz}}} - \mathbf{r}_{\hat{x}_k^{\text{nz}}}| \quad (16)$$

where x_j^{nz} denotes a nonzero element of the ground truth, \hat{x}_k^{nz} is a nonzero element of the estimated activity and \mathbf{r}_d represents the spatial position of dipole d in Euclidean coordinates, with the following constraints for the weights (in order to avoid the trivial zero solution)

$$\sum_j w_{j \rightarrow k} = \hat{x}_k^{\text{nz}}, \quad \sum_k w_{j \rightarrow k} = x_j^{\text{nz}}. \quad (17)$$

Note that (16) defines a similarity measure between the amount of activity in the nonzero elements of the ground truth and the estimated solution. The minimum cost of (16) can be obtained using the simplex method of linear programming. The transportation cost of an estimated solution is finally defined as the minimum transportation cost calculated between the estimated solution and the ground truth. Since the activity has been normalized in the first step, this parameter is measured in millimeters.

The proposed method is compared to the more traditional weighted ℓ_1 norm [45] and sLoreta. The regularization parameter of sLoreta was computed by cross validation using the method recommended by Pascual-Marqui *et al.* in [13]. The weighted ℓ_1 norm was implemented using the alternating direction method of multipliers with the technique used by Boyd *et al.* in [46]. The regularization parameter was chosen so that $\|\mathbf{y} - \mathcal{H}\hat{\mathbf{x}}\| \approx \|\mathbf{y} - \mathcal{H}\mathbf{x}\|$ according to the discrepancy principle [47].

3) *Single Dipole*: The first kind of experiment consisted of activating only one dipole. Ten dipoles were randomly chosen from the 1003 dipoles of the head model. For each of these ten positions, a measurement vector \mathbf{x} was formed that had only the corresponding dipole activated (referred as single dipole activations #1 through #10). After generating the different sets of measurements \mathbf{y} , the localization error was found to be 0.00 mm for all the dipoles with the three methods. The other performance parameters are displayed in Fig. 2 showing the good performance of the proposed method (indicated by PM).

The brain activities detected by the proposed method and the weighted ℓ_1 norm solution are illustrated in Fig. 3 for a representative simulation. Our algorithm managed to perfectly recover the activity for 9 out of the 10 activations (with center-mass localization error, extension and transportation cost equal to 0.00 mm) for all simulations. The dipole corresponding to activation #7 was located precisely for some simulations and with very reduced error in the others. The mean transportation cost of the proposed method for activation #7 is 0.7 mm. In comparison, sLoreta has an excitation extension that is significantly larger (between 41 and 51 mm for the different dipole positions) (as expected for an ℓ_2 norm regularization) and a larger transportation cost (bigger than 55 mm in all cases). The weighted ℓ_1 norm regularization provides better estimations than sLoreta with a mean extension of up to 10 mm and transportation cost of up to 13 mm but is still outperformed by the proposed method.

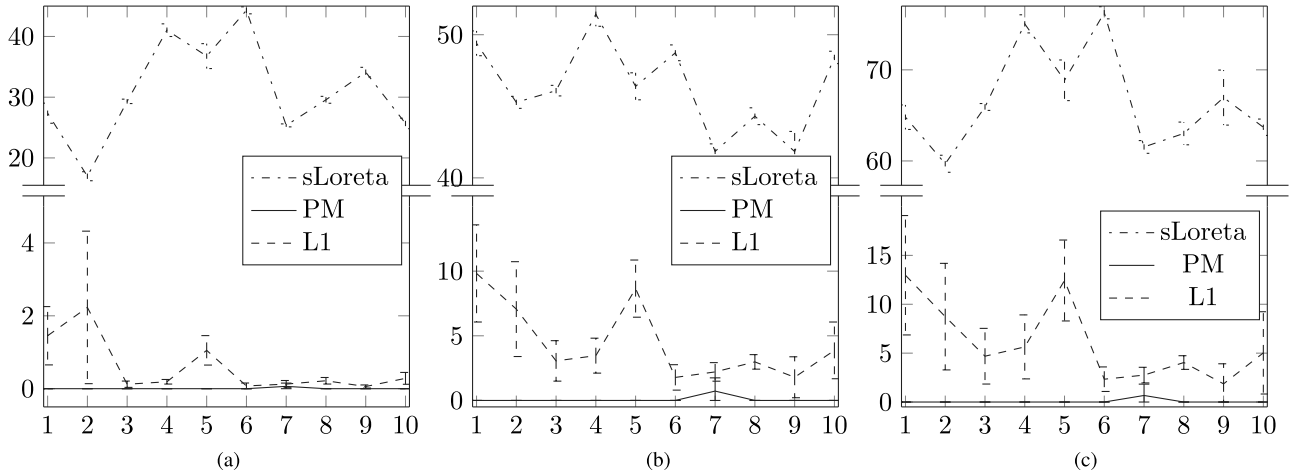


Fig. 2. Simulation results for single dipole experiments. The horizontal axis indicates the activation number. The error bars show the standard deviation over 12 Monte Carlo runs.

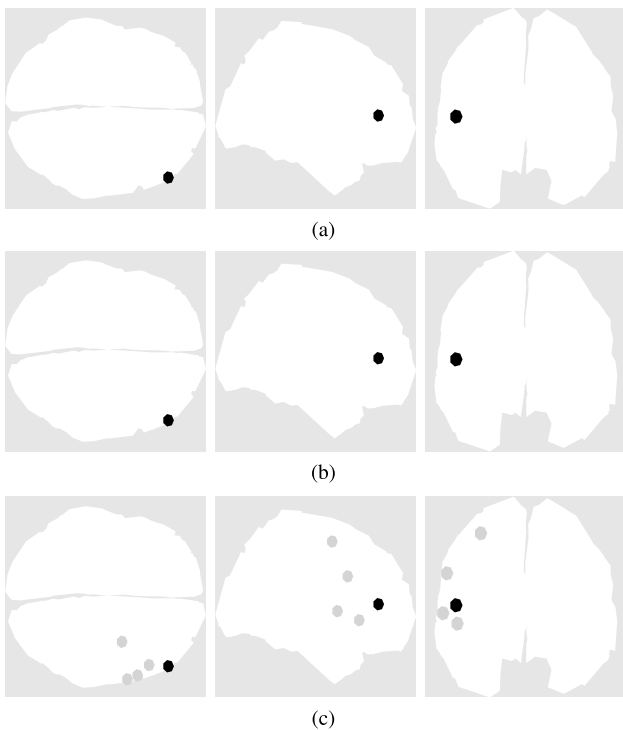


Fig. 3. Brain activity for one single dipole experiment (activation #5).

In addition, Fig. 4 shows the histograms of the samples of σ_n^2 , ω , λ , and the amplitude of the active dipole x_i for one of the simulations corresponding to activation #3 as a representative case. It is shown that the ground truth values of ω (the proportion of nonzeros $1/1003$), σ_n^2 and x_i are inside the support of their histograms and are close to their estimated mean values, i.e., close to their MMSE estimates.

4) *Multiple Distant Dipoles*: The second kind of experiments evaluates the performance of the proposed algorithm when several dipoles are activated at the same time and when these activated dipoles have distant space positions. More precisely, we chose randomly the following sets of dipoles from the 1003 dipoles present in the head model.

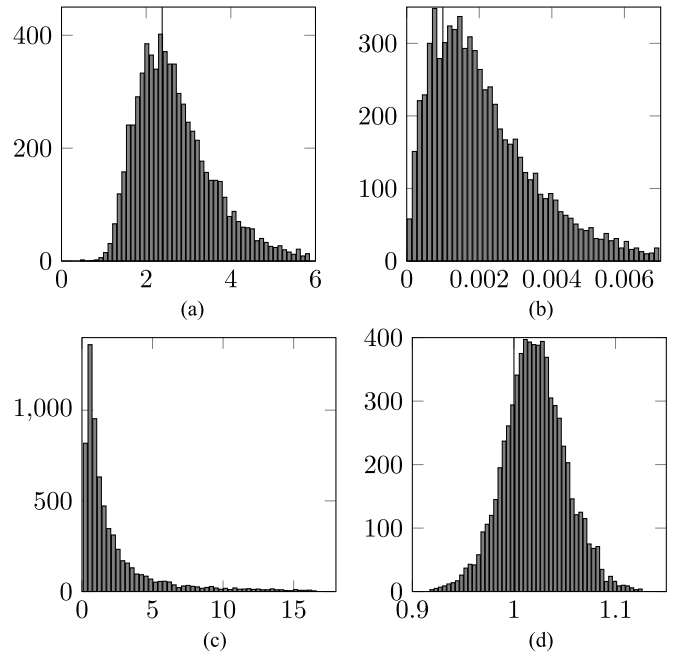


Fig. 4. Histogram of samples generated by the MCMC method for one of the single dipole simulations. The estimated mean values and ground truth are indicated in the figures.

- i) Two pairs of $N = 2$ simultaneous dipoles spaced more than 100 mm (activations #1 and #2).
- ii) Two sets of $N = 3$ simultaneous dipoles spaced more than 100 mm (activations #3 and #4).

For each of these four sets of dipoles, a vector \mathbf{x} having only the corresponding active dipoles was formed and the measurements \mathbf{y} were calculated as described previously.

The brain activities associated with two representative simulations corresponding to two and three dipoles are illustrated in Figs. 5 and 6. The activation #2 associated with two distant dipoles displayed in Fig. 5 is an interesting case for which the weighted ℓ_1 norm regularization fails completely to recover one of the dipoles. The activation #4 displayed in Fig. 6 shows that the proposed method detects an activity more concentrated in

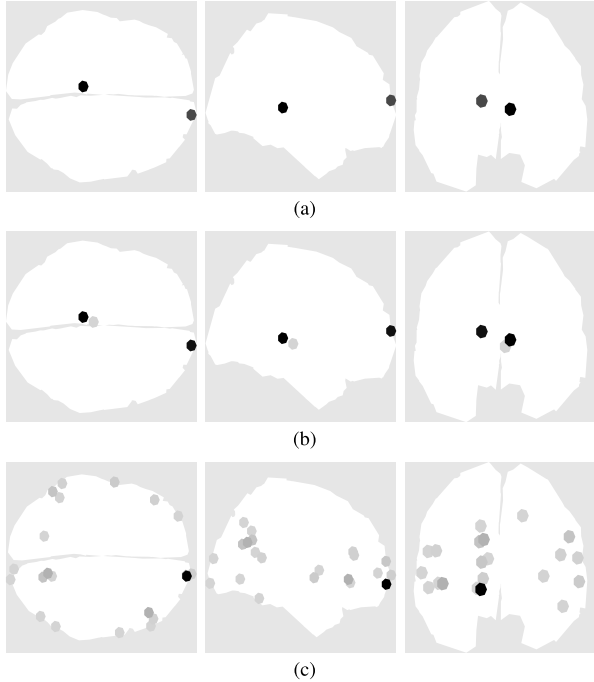


Fig. 5. Brain activity for a multiple distant dipole experiment (activation # 2 that has two active dipoles).

the activated dipoles while the ℓ_1 norm regularization provides less-sparse solutions.

Quantitative results in terms of transportation costs are displayed in Fig. 7 for the different experiments. The transportation costs obtained with the proposed method are below 3.6 mm in all cases and are clearly smaller than those obtained with the other methods. Indeed, the sLoreta transportation costs are between 50 and 62 mm, and the transportation costs associated with the weighted ℓ_1 norm regularization are between 3.9 and 13 mm, except for the activation #2, where it fails to recover one of the dipoles as previously stated.

5) *Multiple Close Dipoles*: The third kind of experiments evaluates the performance of the proposed algorithm for active dipoles that have close spatial positions. More precisely, we randomly chose the following sets of dipoles.

- i) Two pairs of dipoles spaced between 49 and 51 mm (activations #1 and #2).
- ii) Two pairs of dipoles spaced between 29 and 31 mm (activations #3 and #4).
- iii) Two pairs of dipoles spaced between 9 and 11 mm (activations #5 and #6).

For each of these six sets of dipoles, a vector \mathbf{x} having only the corresponding active dipoles was formed and the measurements \mathbf{y} were simulated as described previously.

Fig. 10 compares the transportation costs obtained with the different methods. Since it is much harder to distinguish the activity produced by two close dipoles, the transportation costs associated with the proposed method and the weighted ℓ_1 norm regularization are considerably higher than those obtained previously. However, the transportation costs obtained with the proposed algorithm are still below those obtained with the two other estimation strategies. Some interesting cases can be

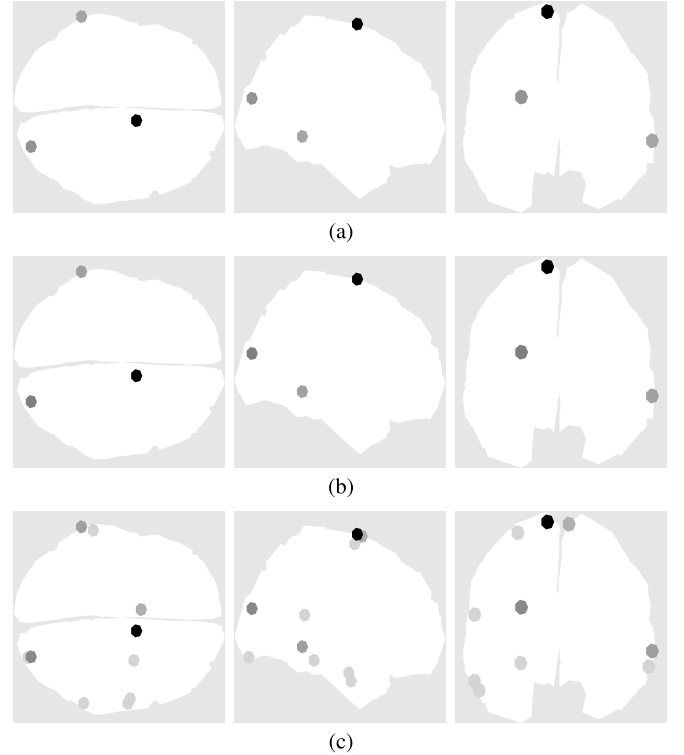


Fig. 6. Brain activity for a multiple distant dipole experiment (activation # 3 that has three active dipoles).

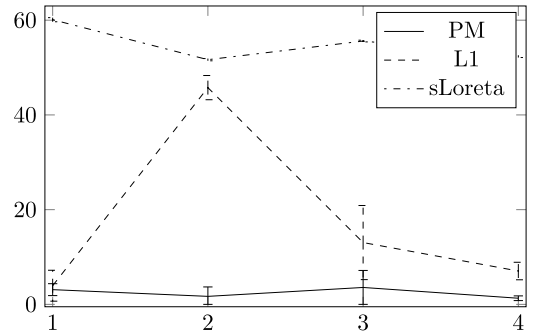


Fig. 7. Transportation cost for multiple distant dipoles experiments, the horizontal axis indicates the activation number (1 and 2: two active dipoles, 3 and 4: three active dipoles). The error bars show the standard deviation over 12 Monte Carlo runs.

observed in Figs. 8 and 9. Fig. 8 corresponds to one case where both algorithms fail to identify two dipoles and fuse them into a single dipole located in the middle of the two actual locations. In this particular activation, our algorithm adds considerably less extra activity than the weighted ℓ_1 norm regularization. In the case illustrated in Fig. 9, the proposed method correctly identifies two dipoles (but moves one of them from its original positions) while the weighted ℓ_1 norm regularization estimates a single dipole located very far from the two excited dipoles.

B. Computational Cost

This section compares the computational cost of the different algorithms (weighted ℓ_1 norm, sLoreta, and the proposed method) that were run on a modern Xeon CPU E3-1240 at

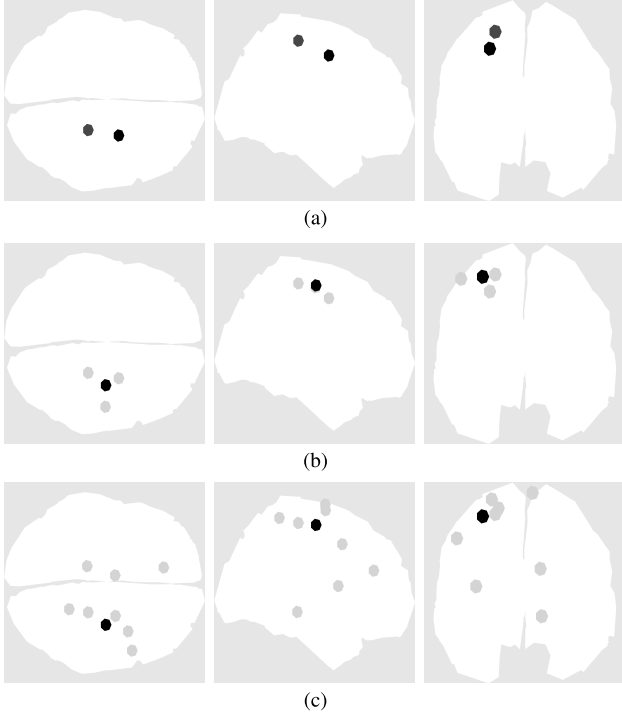


Fig. 8. Brain activity for multiple close dipoles (activation # 4 that has a 30-mm separation between dipoles).

3.4-GHz processor using a MATLAB implementation. In the case of the weighted ℓ_1 norm, we used the stopping criterion recommended by Boyd *et al.* in [46]. The proposed method was run with four parallel chains (as stated in Section V-A1) until the potential scale reduction factor of all the generated samples was below 1.2 as recommended in [48]. The average running times of each of the methods are presented in Table I. As we can see, the weighted ℓ_1 norm is three orders of magnitude slower than sLoreta (taking seconds instead of milliseconds), while the proposed method is three orders of magnitude slower than the weighted ℓ_1 norm. Note that the first two algorithms seem to have a running time that does not depend on the kind of simulations while the proposed method is faster for simpler cases and slower for more complex dipole distributions. Having a higher computational cost is a typical disadvantage of MCMC sampling techniques when compared to optimization approaches. However, it is important to note that our algorithm is able to estimate its hyperparameters in one run while the other two require to be run several times in order to set their regularization parameters by cross validation for instance.

C. Real Data

Two different sets of real data were considered. The first one consists of an auditory evoked response while the second one is the evoked response to facial stimulus. In addition to the weighted ℓ_1 norm regularization, we also compared our results with the MSP algorithm [29] using the default parameters in the SPM software.³

³The SPM software is freely available at <http://www.fil.ion.ucl.ac.uk/spm>.

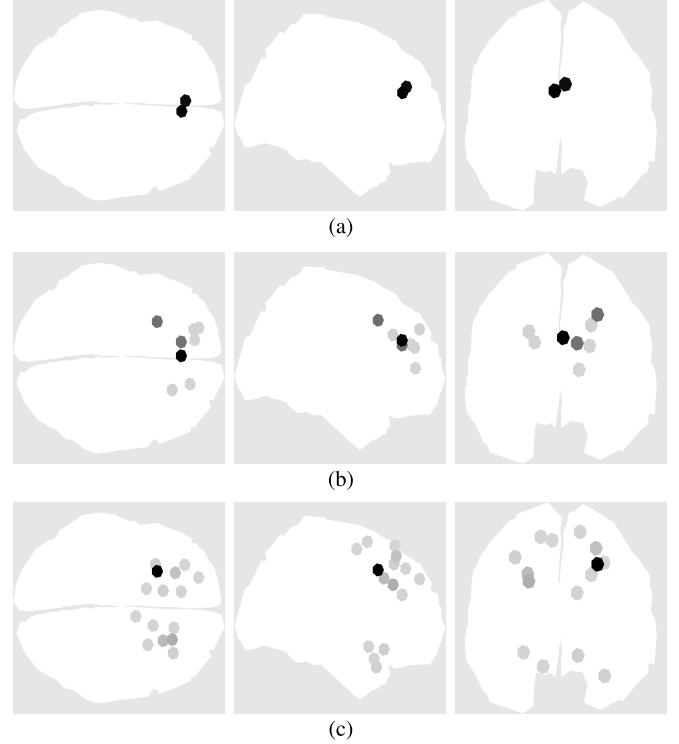


Fig. 9. Brain activity for multiple close dipoles (activation # 6 that has a 10-mm separation between dipoles).

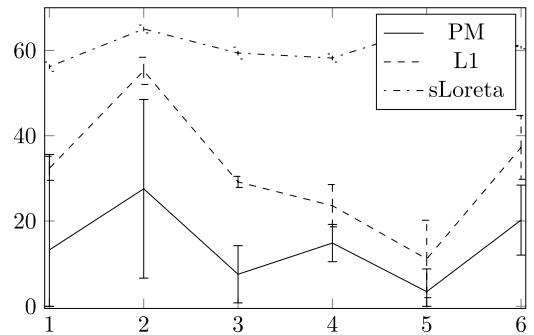


Fig. 10. Transportation cost for multiple close dipoles experiments. The horizontal axis indicates the activation number (1 and 2: 50-mm separation, 3 and 4: 30-mm separation, 5 and 6: 10-mm separation). The error bars show the standard deviation over 12 Monte Carlo runs.

TABLE I
COMPUTATION COSTS OF THE DIFFERENT ALGORITHMS (IN SECONDS)

Experiment Type	sLoreta	ℓ_1 Norm	Proposed Method
Single dipole	3.65×10^{-3}	1.09	651.9
Multiple distant dipole	3.64×10^{-3}	0.84	886.6
Multiple close dipole	3.61×10^{-3}	0.91	1128.0

1) *Auditory Evoked Responses:* The used dataset was extracted from the MNE software [49], [50]. It corresponds to an evoked response to left-ear auditory pure-tone stimulus using a realistic BEM head model sampled with 60 EEG electrodes at 600 samples/s. The samples were low-pass filtered at 40 Hz and

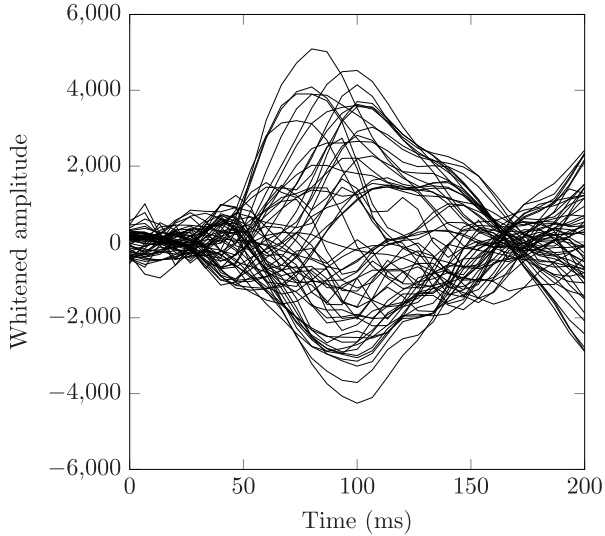


Fig. 11. EEG measurements for the real data application.

downsampled to 150 samples/s. The noise covariance matrix was estimated from 200 ms of data preceding each stimulus and was used to whiten the data. Fifty one epochs were averaged to generate the measurements \mathbf{y} .

The sources associated with this example are composed of 1844 dipoles located on the cortex with orientations that are normal to the brain surface. One channel that had technical artifacts was ignored resulting in an operator $\mathcal{H} \in \mathbb{R}^{59 \times 1884}$. We processed the eight time samples corresponding to $80 \text{ ms} \leq t \leq 126 \text{ ms}$, i.e., associated with the highest activity period in the EEG measurements as displayed in Fig. 11.

The sum of the estimated brain activities over the eight time samples obtained by the proposed method, the weighted ℓ_1 norm regularization and the MSP algorithm are presented in Fig. 12. The proposed method consistently detects most of the activity concentrated in both the ipsilateral and contralateral auditory cortices. The weighted ℓ_1 norm regularization detects the activity in the right cortex in a similar position, but moves the activity detected in the left cortex to a lower point of the brain that is further away from the auditory cortex. The MSP algorithm finds the activity correctly in the auditory cortices but spreads it around a region instead of focusing it on a small number of dipoles. This is due to the fact that both the proposed method and the weighted ℓ_1 norm promote sparsity over the dipoles while MSP promotes sparsity over preselected brain regions that depend on the parcellation scheme used.

2) *Face-Evoked Responses*: The data used in this section are one of the sample datasets available in the SPM software. It were acquired from a face perception study in which the subject had to judge the symmetry of a mixed set of faces and scrambled faces. Faces were presented during 600 ms with an interval of 3600 ms (for more details on the paradigm see [51]). The acquisition system was a 128-channel ActiveTwo system with a sampling frequency equal to 2048 Hz. The data were downsampled to 200 Hz, and after artifact rejection, the 299

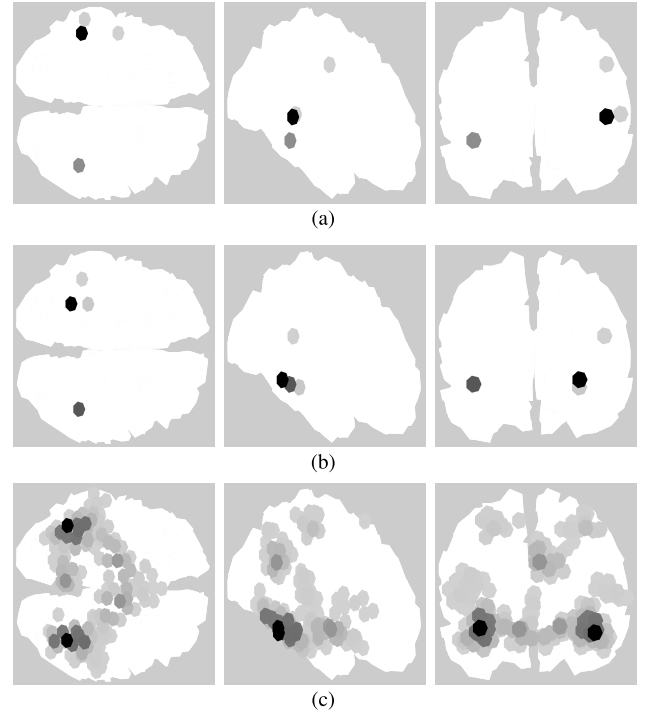


Fig. 12. Brain activity for the auditory evoked responses from 80 to 126 ms.

epochs corresponding to nonscrambled faces were averaged and lowpass filtered at 40 Hz. The head model is based on a T1 MRI scan of the patient downsampled to have 3004 dipoles, resulting in an operator $\mathcal{H} \in \mathbb{R}^{128 \times 3004}$.

The brain activities detected by the three algorithms for $t = 160 \text{ ms}$ (time sample with highest brain activity) are presented in Fig. 13. The MSP method locates the activity spread over several brain regions due to its prepartitioning of the brain. In particular, it locates activity in the lateral and posterior regions. In comparison both the weighted ℓ_1 norm and the proposed method focus the activity closer to the fusiform regions of the temporal lobes, areas of the brain that are speculated to be specialized in facial recognition [52]. Note that the proposed method provides the most focal solution of the three. It is interesting to note that the MSP algorithm divides the brain in symmetric parcels in both hemispheres, which very often causes the solution to have a high degree of symmetry while the other two methods only rely on the measurements to estimate the brain activity.

VI. CONCLUSION

This paper proposed a new Bayesian model for EEG source localization promoting sparsity for the dipole activities via a Bernoulli–Laplace prior. To compute the Bayesian estimators of this model, we introduced an MCMC method sampling the posterior distribution of interest and estimating the model parameters using the generated samples. The resulting EEG source localization strategy was compared to ℓ_2 norm (sLoreta) and weighted ℓ_1 norm regularizations for synthetic data and with

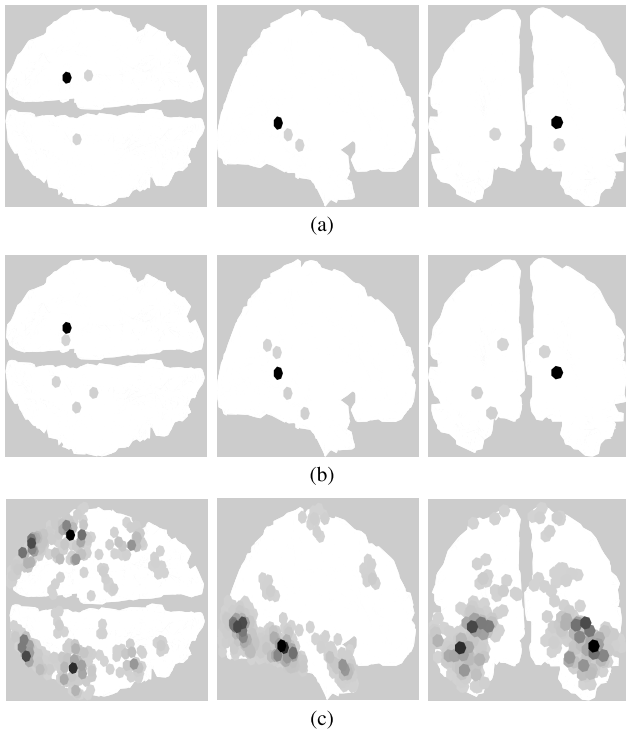


Fig. 13. Brain activity for the faced evoked responses for 160 ms.

the MSP algorithm for real data, showing promising results in both cases. More precisely, several experiments with synthetic data were constructed using single and multiple dipoles, both for close and distant locations. For the single dipole scenario, the proposed algorithm showed better performance than the more traditional l_2 - and l_1 norm regularizations in terms of several evaluation criteria used in the literature. In multiple dipole scenarios, the estimated activities from different dipoles can overlap, making the classical evaluation criteria difficult to apply. In order to assess the performance in these scenarios, we proposed a new evaluation criterion denoted as transportation cost defined as the solution of an optimal mass transportation problem. This criterion showed that the proposed localization method performed better than the standard l_2 norm and weighted l_1 norm regularizations. We also considered two sets of real data consisting of the evoked responses to a left-ear auditory stimulation and to facial stimulus, respectively. In both cases, the algorithm showed better performance than the weighted l_1 norm regularization and the MSP method to estimate brain activity generated by point-like sources.

Future work includes adapting the proposed model for multitemporal EEG signals and generalizing the Bayesian model to cases where the head model is not known perfectly.

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