LOCALIZATION OF EXTENDED INTRACEREBRAL CURRENT SOURCES: APPLICATION TO EPILEPSY

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ABSTRACT

We propose a new method for localizing intracerebral current sources at the origin of epileptic spikes from non-invasive EEG/MEG data. This method was designed to account for three main constrains. First, most relevant spike generation models assume that sources are extended, i.e. spatially distributed over a focal or muti-focal area. Second, the background activity of the brain also contributes to EEG/MEG signals recorded during epileptic events. In this context, it can be seen as a penalizing Gaussian and spatially correlated noise. Third the array manifold is usually corrupted by errors due to the complexity of the conduction head volume. The proposed method is an adaptation of the well-established MUSIC method, that allows for the localization of Extended Sources (ExSo) assuming that all current dipoles comprised in the extended source are synchronous. In addition, we use Higher Order (HO) statistics, which are asymptotically insensitive to a Gaussian noise of unknown spatial coherence and which offer a greater robustness with respect to modeling errors. The method is called $2q$-ExSo-MUSIC ($q \geq 2$) as it combines the ExSo-MUSIC principle with the use of HO statistics. Using computer simulations of EEG signals, it is shown to highly increase the performance of classical MUSIC-like algorithms when physiologically relevant models for current sources and for volume conduction are considered.

I. INTRODUCTION

Numerous source localization methods based on accurate signal processing techniques have been proposed to interpret MagnetoEncephaloGraphic (MEG) and ElectroEncephaloGraphic (EEG) data either to better understand normal brain functions or to localize, in a non-invasive way, the origin of abnormal signals. In particular, in the context of drug resistant partial epilepsy, source localization methods have been widely applied to interictal epileptiform signals (interictal spikes) that are considered as a marker of the patient's epilepsy (although their spatial relationship with ictal discharges still remains under study). As compared to ictal discharges, interictal spikes appear frequently on surface recordings, with a high of signal to noise ratio, and most often result from the activity of extended, i.e. spatially distributed, intracerebral sources.

On the one hand, numerous methods based on Minimum Norm Estimates (MNE, see [7] for a review) solve this particular ill-posed inverse problem by estimating in a tomographic way the activity of sources at each location of the brain volume under some regularization constraints. The popular methods LORETA [14] and sLORETA [12] have been the most commonly used and are particularly adapted to extended sources [7], [13]. These methods proved to be efficient in various situations but still suffer from blurred resolution [7], [8], [13].

On the other hand some methods solve the inverse problem by estimating the leadfield vectors of a finite number of non-normal sources only. For instance, Second Order (SO) MUSIC-like [2], [10], [11], [17] techniques can localize a number of sources equal to at most the number of scalp electrodes minus one, while the Higher Order (HO) MUSIC-like [1], [3], [4], [16] algorithms can process underdetermined mixtures of sources (i.e. more sources than scalp data). Nevertheless, a high degree of spatial independence between the different source activities is required in such methods to successfully localize such a large number of signals. In the same way, the different sources to be localized do not have to be too spatially close. However, in focal epilepsy, these assumptions are probably too strong. As a result, and despite their very good asymptotic properties [3], [15], [18], the MUSIC-like approaches are not always appropriate to identify extended sources. To overcome these difficulties, a particular SO MUSIC-like method, called Distributed Signal Parameter Estimator (DSPE), was originally proposed in the context of radiocommunications [21]. The intent was to find the directions of arrival of electromagnetic Extended Sources (ExSo). In this paper, we show that this method has a great interest for the EEG/MEG localization problem.

Indeed, we adapted the original DSPE method to the EEG/MEG localization problem first by giving the model

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of EEG/MEG data obtained from spatially distributed sources located on the neocortex and second by proposing a technique to avoid the high-cost exhaustive search of all possible ExSo locations and shapes. The resulting 2-ExSo-MUSIC method was then upgraded in order to allow for a use of HO statistics instead of the SO ones, giving birth to the $2q$-ExSo-MUSIC ($q \geq 2$) technique. The use of HO statistics makes the method more robust with respect to both a Gaussian noise with unknown spatial coherence and to modeling errors. The method was evaluated using a computational model of scalp EEG generation that accounts for extended cortical sources of epileptic spikes and for realistic head model. Simulation results described in section IV show that the combination between the ExSo-MUSIC concept and HO statistics highly improves the performance of the 2-ExSo-MUSIC and of classical SO and HO MUSIC-like approaches. Although extended tests on real data are necessary, the proposed method seems to constitute a promising tool to localize the origin of normal or pathological EEG/MEG signals.

II. MODEL AND ASSUMPTIONS

The method was tested on simulated data consisting of scalp EEG signals containing epileptic spikes rising from a focal source extending over the neocortex. The spatio-temporal model for this source as well as the forward problem solution are described in [6]. In brief, it starts from the fact that the neocortex is organized as a network of neuronal populations and that the activity of the neocortex is the major contribution to the scalp EEG. According to these assumptions, the source model is based on the combination between a distributed dipole layer accounting for the spatial features of the sources (folded surface) and a model of coupled neuronal populations (accounting for the time-course associated to the dipole sources). The electrical contribution of each population is represented by a current dipole which location and orientation are constrained by a realistic mesh of the neocortical surface. The mesh is composed of M triangles, at the barycenter of which a dipole is oriented orthogonally to the surface. Let $\boldsymbol{\rho}_m$ be the position of the m-th dipole of the mesh. The corresponding dipole intensity $\Delta_m\{s(\boldsymbol{\rho}_m, t)\}$ is defined as the time-course $\{s(\boldsymbol{\rho}_m, t)\}$ weighted by the surface Δ_m of the m-th triangle. $\{s(\boldsymbol{\rho}_m, t)\}$ is generated by a physiologicaly relevant model described in [22], in which the parameters can be adjusted to obtain an epileptic (interictal spike) or a background activity. The connection from one population located in $\boldsymbol{\rho}_i$ to another located in $\boldsymbol{\rho}_j$ is characterized by one parameter K_{ij} representing the degree of excitatory input from $\boldsymbol{\rho}_i$ to $\boldsymbol{\rho}_j$ [22]. Appropriate setting of coupling parameters K_{ij}'s between populations allows for building extended epileptic sources (so-called patch) composed of strongly coupled populations with hypersynchronized activity. It is noteworthy to mention that abnormally-high level of synchronization in epileptic tissue has been reported in numerous experimental [20] and clinical studies [19] over the past decades. As a result we can assume [22]:

H1) The dipole time-courses of an extended source are synchronous;

H2) The time-courses of dipoles belonging to the same extended source have the same amplitude;

In order to mathematically formulate the EEG/MEG model, the index of dipoles in the epileptic patches are stored into set Θ. The latter is partitionned into P sets θ_p such that dipole index in θ_p belong to the same extended source, i.e. their corresponding time-courses are all quasi-synchronous but asynchronous with dipole time-courses associated to other sets θ_p. Consequently, the EEG/MEG vector $\boldsymbol{x}(t)$ resulting from the epileptic activities of the P patches, and measured at a set of N scalp electrodes, can be written as following:

$$\boldsymbol{x}(t) = \sum_{p=1}^{P} \sum_{m \in \theta_p} \boldsymbol{a}(\boldsymbol{\rho}_m) \Delta_m s(\boldsymbol{\rho}_m, t) + \boldsymbol{\nu}(t) \qquad (1)$$

The noise vector process $\{\boldsymbol{\nu}(t)\}$, independent from the epileptic activities, regroups i) the contribution of the normal dipoles, assumed to be Gaussian with spatially correlated intensities, and ii) artifacts as ocular/muscular/heart activities. As these latter perturbations can be almost totally removed by denoising techniques [5], we assume here that $\{\boldsymbol{\nu}(t)\}$ is almost entirely due to the background activity. In brief we have:

H3) The noise is Gaussian, independent of the epileptic activities, with unknown spatial coherence.

The leadfield vector $\boldsymbol{a}(\boldsymbol{\rho})$ describes the relationship between the dipole intensity at location $\boldsymbol{\rho}$ and the surface EEG/MEG data at each electrode. This vector is obtained in a realistic head model that consists in three nested homogeneous compartments shaping the brain, the skull and scalp [23]. Under **H1**), we can consider that, there is a time-course $\{s_p(t)\}$ which is approximately common to all dipoles of the p-th extended source. Therefore, the EEG/MEG model (1) can be roughly factorized as following:

$$\boldsymbol{x}(t) \approx \sum_{p=1}^{P} s_p(t) \sum_{m \in \theta_p} \boldsymbol{a}(\boldsymbol{\rho}_m) \Delta_m + \boldsymbol{\nu}(t) \qquad (2)$$

So, by defining the ExSo leadfield vector $\boldsymbol{h}(\theta) = \sum_{m \in \theta} \boldsymbol{a}(\boldsymbol{\rho}_m) \Delta_m$, the ExSo mixing matrix $\boldsymbol{H}(\Theta) = [\boldsymbol{h}(\theta_1), \ldots, \boldsymbol{h}(\theta_P)]$ and the ExSo source vector $\boldsymbol{s}(t) = [s_1(t), \ldots, s_P(t)]^{\mathsf{T}}$, the EEG/MEG data vector can be approximately written:

$$\boldsymbol{x}(t) \approx \boldsymbol{H}(\Theta) \boldsymbol{s}(t) + \boldsymbol{\nu}(t) \qquad (3)$$

Formulation (2) is a particular case of a more general model of distributed sources previously proposed in the radiocommunication context [21]. Therefore, the DSPE method [21], which is based on this more general model, is of great interest for our EEG/MEG localization problem involving the particular model (2).

III. EEG/MEG LOCALIZATION METHODS OF EXTENDED SOURCES

To solve the EEG/MEG localization problem, we further assume following hypothesis:

H4) The number P of extended sources is known;

H5) The HO marginal cumulants of all extended source activities is non-zero;

III-A. From the DSPE method to the 2-ExSo-MUSIC algorithm

The DSPE method [21] is capable of localizing extended sources from the observation data by potentially estimating the P parameters θ_p. The method is highly inspired of the well-known 2-MUSIC method [11], [17]. Under **H3**) and Using (3), the covariance matrix of the EEG/MEG data $\{\boldsymbol{x}(t)\}$ has roughly the following algebraic structure:

$$\boldsymbol{C}_{2,\boldsymbol{x}} \approx \boldsymbol{H}(\Theta)\boldsymbol{C}_{2,\boldsymbol{s}}\boldsymbol{H}(\Theta)^{\mathsf{T}} + \boldsymbol{C}_{2,\boldsymbol{\nu}} \tag{4}$$

where $\boldsymbol{C}_{2,\boldsymbol{s}}$ and $\boldsymbol{C}_{2,\boldsymbol{\nu}}$ are the signal and noise covariance matrices, respectively. The signal subspace, denoted by $\mathsf{Span}\{\boldsymbol{H}(\Theta)\boldsymbol{C}_{2,\boldsymbol{s}}\boldsymbol{H}(\Theta)^{\mathsf{T}}\}$ is also spanned by the P vectors $\boldsymbol{h}(\theta_p)$. As a result, the projection of $\boldsymbol{h}(\theta)$ onto the signal subspace is maximal if and only if $\theta = \theta_p$, for $1 \leq p \leq P$. By the same token, the projection of $\boldsymbol{h}(\theta)$ onto the subspace orthogonal to the signal subspace, called noise subspace, is minimal if and only if $\theta = \theta_p$, for $1 \leq p \leq P$. In practice, since $\boldsymbol{H}(\Theta)$ and $\boldsymbol{C}_{2,\boldsymbol{s}}$ are unknown, the signal subspace is built from an EVD of the symmetric matrix $\boldsymbol{C}_{2,\boldsymbol{x}} - \boldsymbol{C}_{2,\boldsymbol{\nu}}$, which requires either a perfect knowledge of $\boldsymbol{C}_{2,\boldsymbol{\nu}}$ or at least a spatial independence of the noise process. Then, the eigenvectors associated with the P highest eigenvalues, ordered in matrix $\boldsymbol{E_s}$, span the signal subspace. The eigenvectors associated with the $N-P$ lowest eigenvalues, sorted in matrix $\boldsymbol{E_\nu}$, span the noise subspace. Consequently, two equivalent estimations of the P sets θ_p, one based on the signal subspace and the other one based on the noise subspace, can be obtained by looking for either the P maxima of $\Upsilon(\boldsymbol{h}(\theta), \boldsymbol{E_s})$ and the P minima of $\Upsilon(\boldsymbol{h}(\theta), \boldsymbol{E_\nu})$, respectively, where:

$$\Upsilon(\boldsymbol{h}, \boldsymbol{E}) = \boldsymbol{h}^{\mathsf{T}}\boldsymbol{E}\boldsymbol{E}^{\mathsf{T}}\boldsymbol{h}/\|\boldsymbol{h}\|^2 \tag{5}$$

Note that the authors of [21] chose to implement the DSPE method with a search of P minima, which corresponds in our context to :

$$\{\hat{\theta}_1^{\text{DSPE}}, \ldots, \hat{\theta}_P^{\text{DSPE}}\} = \arg\min_{\theta} \Upsilon(\boldsymbol{h}(\theta), \boldsymbol{E_\nu}) \tag{6}$$

However, as far as the EEG/MEG localization problem is considered, the DSPE method should not be used in its original form. The search of maxima should be prefered in terms of numerical complexity, say:

$$\{\hat{\theta}_1, \ldots, \hat{\theta}_P\} = \arg\max_{\theta} \Upsilon(\boldsymbol{h}(\theta), \boldsymbol{E_s}) \tag{7}$$

Indeed, in such a context the number N of scalp data will be generally much greater than the number P of ExSo's and the computation of $\boldsymbol{E_s}$ will be less costly than the computation of $\boldsymbol{E_\nu}$. Next, in the EEG/MEG context, two more important problems appear using directly the DSPE method. First, the multidimensional maximization (6) would be very hard to achieve since no exact solution exists and the exhaustive exploratory search would be too costly. Indeed, each ExSo potential solution has a shape, a size and a location, that involves too many degrees of freedom. Therefore, we propose to limit the possible θ to spiral-like patches $\tilde{\theta}$, parameterized by the position of the center and the number of dipoles. However, it is highly probable that none patch θ_p belongs to the grid $\{\tilde{\theta}\}$ whatever its resolution. So, even if the estimated solution $\hat{\theta}_p$ is as close as possible to the real patch θ_p, this estimate will be biased most of the time. This difficulty can be overcome by searching not only one spiral-like patch but a union of several spiral-like patches with possibly non-empty intersections, which attempts to totally recover the expected patch θ_p. The question is: how to identify the different patches of this union? We show in the sequel that it is sufficient to take in the grid the points $\tilde{\theta}$, which metric is greater than a given threshold λ. Thus, the new 2-ExSo-MUSIC estimate is given by:

$$\hat{\Theta}^{\text{2-ExSo-MUSIC}}(\lambda) = \bigcup\{\tilde{\theta}, \Upsilon(\boldsymbol{h}(\tilde{\theta}), \boldsymbol{E}_{2,\boldsymbol{s}}) \geq \lambda\} \tag{8}$$

Such an approach requires both the following assumption:

H6) For every Θ, it exists at least one threshold λ_1 such that for every λ greater than or equal to λ_1, the estimate $\hat{\Theta}^{\text{2-ExSo-MUSIC}}(\lambda)$ is a subset of Θ.

and the following proposition:

P1) For every Θ, it exists at least one threshold λ_2 such that for every λ lower than or equal to λ_2 the estimate $\hat{\Theta}^{\text{2-ExSo-MUSIC}}(\lambda)$ entirely recovers Θ.

will be proved in a longer paper. Now, it is noteworthy that $\hat{\Theta}^{\text{2-ExSo-MUSIC}}(\lambda)$ grows up as λ decreases. As a result, hypothesis **H6**) and proposition **P1**) mean that the estimate $\hat{\Theta}^{\text{2-ExSo-MUSIC}}(\lambda)$ grows up inside Θ as λ decreases to λ_1. Next, when λ decreases from λ_1 to λ_2, $\hat{\Theta}^{\text{2-ExSo-MUSIC}}(\lambda)$ grows up both inside and outside Θ. When λ_2 is reached, Θ is totally recovered but parts of the estimate are outside of Θ unless $\lambda_2 = \lambda_1$. Eventually, when λ decreases from λ_2 to 0, $\hat{\Theta}_{\text{2-ExSo-MUSIC}}(\lambda)$ grows up only outside of Θ. In brief, being beyond λ_1 garantuees an estimate only in the true Θ and being below λ_2 ensures that Θ is entirely recovered.

Consequently, the value of λ has to be choosen between λ_2 and λ_1 as a compromise between being only in Θ and totally recovering Θ. This compromise will be studied in the computer result section through ROC curves [8]. In practice the covariance of the Gaussian noise $\{\boldsymbol{\nu}(t)\}$ is unknown, thus matrix $\boldsymbol{C}_{2\,\boldsymbol{x}} - \boldsymbol{C}_{2\,\boldsymbol{\nu}}$ cannot be computed and the signal subspace cannot be estimated properly. Consequently, the use of HO cumulants through the $2q$-ExSo-MUSIC $(q \geq 2)$ method proposed hereafter is able to overcome this problem.

III-B. The $2q$-ExSo-MUSIC $(q \geq 2)$ techniques

The $2q$-th order statistical matrix of $\{\boldsymbol{x}(t)\}$, $\boldsymbol{C}_{2q,\,\boldsymbol{x}}$, that contains all $2q$-th order cumulants of $\{\boldsymbol{x}(t)\}$, can be approximately written as a function of $\boldsymbol{H}(\Theta)$ using the multilinearity property enjoyed by cumulants. Besides, under **H3**, $\boldsymbol{C}_{2q,\,\boldsymbol{x}}$ does not depend on noise $\{\boldsymbol{\nu}(t)\}$ since the HO of a Gaussian random variable is zero. More precisely, we get [3]:

$$\boldsymbol{C}_{2q,\,\boldsymbol{x}} \approx \boldsymbol{H}(\Theta)^{\otimes q} \boldsymbol{C}_{2q,\,\boldsymbol{s}} [\boldsymbol{H}(\Theta)^{\otimes q}]^{\mathsf{T}} \qquad (9)$$

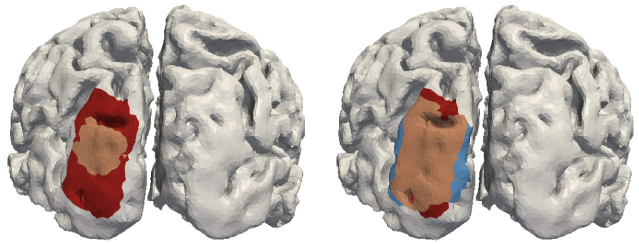
where the $(N^q \times P^q)$ matrix $\boldsymbol{H}(\Theta)^{\otimes q}$ is the Kronecker product of $\boldsymbol{H}(\Theta)$ by itself q times, the $(P^q \times P^q)$ matrix $\boldsymbol{C}_{2q,\,\boldsymbol{s}}$ is the $2q$-th order source statistical matrix. Then, the $2q$-th order signal subspace can be defined as the vector space spanned by the column vector of $\boldsymbol{H}(\Theta)^{\otimes q} \boldsymbol{C}_{2q,\,\boldsymbol{s}} [\boldsymbol{H}(\Theta)^{\otimes q}]^{\mathsf{T}}$. Thus, under **H5**) and appropriate rank conditions, the P vectors $\boldsymbol{h}(\theta_p)^{\otimes q}$ belong to the $2q$-th order signal subspace and the projection of $\boldsymbol{h}(\theta)^{\otimes q}$ onto it let $\boldsymbol{h}(\theta)^{\otimes q}$ unchanged if and only if $\theta = \theta_p$, $1 \leq p \leq P$. In practice the EVD of $\boldsymbol{C}_{2q,\,\boldsymbol{x}}$ allows for building a basis $\boldsymbol{E}_{2q,\,\boldsymbol{s}}$ of the $2q$-th order signal subspace, where $\boldsymbol{E}_{2q,\,\boldsymbol{s}}$ is the eigenmatrix associated to the non-zero eigenvalues of $\boldsymbol{C}_{2q,\,\boldsymbol{x}}$. Then, we define the $2q$-ExSo-MUSIC metric by $\Upsilon(\boldsymbol{h}(\theta)^{\otimes q}, \boldsymbol{E}_{2q,\,\boldsymbol{s}})$ and the $2q$-ExSo-MUSIC estimate is given by:

$$\hat{\Theta}^{2q\text{-ExSo-MUSIC}}(\lambda) = \bigcup \{\tilde{\theta}, \Upsilon(\boldsymbol{h}(\tilde{\theta})^{\otimes q}, \boldsymbol{E}_{2q,\,\boldsymbol{s}}) \geq \lambda\} \qquad (10)$$

This requies to extend of hypothesis **H6**) and **P1**) to order $2q$. As at order 2, such extension are valid in our EEG/MEG localization context and will be shown in a longer paper. To illustrate the proposed scheme and especially the interest in the concatenation of spiral-like patches, we give in figure 1 the global maximizer of the 4-ExSo-MUSIC metric and the estimate (10) for $\lambda = 0.998$.

IV. COMPUTER RESULTS

In order to evaluate the reliability of the proposed method regarding the contribution of the new ExSo scheme and the HO statistics, the performance of 2-ExSo-MUSIC and 4-ExSo-MUSIC were studied for a single patch using computer simulations. In addition both methods were compared with the classical $2q$-MUSIC $(q = 1, 2)$ algorithms [3] used as propsed in [9] for 2-MUSIC. For the comparison, the ROC curves [8] was used where the mathematical expectation of the True Positive Fraction (TPF) and the False Positive Fraction (FPF) are estimated from L trials as a function of a given threshold λ as following:



(a) Global maximizer (b) Concatenation of spiral-like patches

Fig. 1. Localization of a 1000 mm^2 left occipital ExSo by 4-ExSo-MUSIC. The real patch is red, the true estimated parts are beige, and the false estimated parts are blue. (a) Global maximizer of the 4-ExSo-MUSIC metric. (b) Union of 20 spiral-like patches.

$$\widehat{\textbf{TPF}}(\lambda) = \frac{1}{L} \sum_{\ell=1}^{L} \frac{S_{\text{in}}^{\ell}(\lambda)}{S_{\text{p}}}$$

$$\widehat{\textbf{FPF}}(\lambda) = \frac{1}{L} \sum_{\ell=1}^{L} \frac{S_{\text{out}}^{\ell}(\lambda)}{S_{\text{b}} - S_{\text{p}}}$$

where S_{in}^{ℓ} is the well-recovered surface at the ℓ-th trial, S_{p} is the patch surface, S_{out}^{ℓ} is the wrong detected surface at the ℓ-th trial and S_{b} is the brain surface. For each threshold λ, the corresponding couple $(\widehat{\textbf{TPF}}(\lambda), \widehat{\textbf{FPF}}(\lambda))$ gives a point of the ROC curve. Moreover, to analyze the performance of the methods as a function of the surface interictal spike power, the Mean Spike-to-Background Ratio (MSBR) is introduced. It is defined by:

$$\text{MSBR} = 10 \log (\overline{\sigma}_s^2 / \overline{\sigma}_b^2) \qquad (11)$$

where the mean power $\overline{\sigma}_s^2$ of the surface EEG/MEG spikes $\{\boldsymbol{x}_s(t)\}$ and the mean power $\overline{\sigma}_b^2$ of the surface EEG/MEG background $\{\boldsymbol{x}_b(t)\}$ are defined by:

$$\overline{\sigma}_s^2 = \mathsf{E}[\|\boldsymbol{x}_s(t)\|^2] \quad \text{and} \quad \overline{\sigma}_b^2 = \mathsf{E}[\|\boldsymbol{x}_b(t)\|^2] \qquad (12)$$

IV-A. A MSBR based study

For this study, a patch of 1000 mm^2 is placed in the left occipital gyrus (as in fig. 1). The MSBR is set by varying, at the level of source activities, the amplitude of the spikes, leaving the background activity unchanged. We give in Tab. I the value of $\widehat{\textbf{TPF}}(\lambda)$ corresponding to $\widehat{\textbf{FPF}}(\lambda)$ equal to 5.10^{-3}. In addition, we give in figure 2 the complete ROC curve of the four methods for a MSBR equal to 6.1 dB that is assumed realistic for the considered patch.

MSBR (dB)	18.3	13.0	10.7	8.9	6.1	3.3
4-ExSo-MUSIC	.878	.878	.881	.879	.869	.751
4-MUSIC	.298	.300	.302	.302	.301	.294
2-ExSo-MUSIC	.879	.841	.786	.630	.165	0
2-MUSIC	.298	.277	.247	.199	.067	0

Table I. $\widehat{\mathbf{TPF}}(\lambda)$ as a function of the MSBR for a fixed $\widehat{\mathbf{FPF}}(\lambda) = 5.10^{-3}$. In gray the MSBR considered as realistic for a 1000 mm^2 occipital gyrus patch.

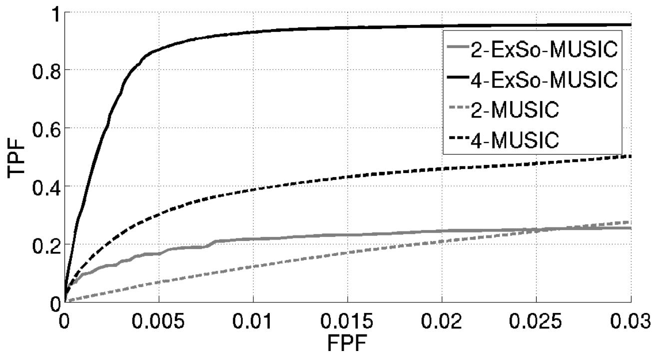


Fig. 2. ROC of the methods for a MSBR equal to 6.1 dB

For the highest value of MSBR, say 18.3 dB, 2-ExSo-MUSIC and 4-ExSo-MUSIC show the best performance. Beside, the performance of 4-ExSo-MUSIC stays stable as the MSBR decreased until 6.1 dB, and dropped to 75.1% of TPF for a 3.3 dB MSBR. On the contrary, the performance of the 2-ExSo-MUSIC method gradually decreases with MSBR and its TPF vanishes for 3.3 dB. For 2-MUSIC and 4-MUSIC the performance follow 2-ExSo-MUSIC and 4-ExSo-MUSIC respectively, but with an important shift to the bottom. Figure 2 shows that the TPF increases quickly until 85% and is then almost stable for the 4-ExSo-MUSIC method. The TPF of the three other methods increases much slowly. We deduce from these results that i) the algorithms based on HO statistics are more robust to the presence of a strong background activity as their performances stay longer stable with decreasing MSBR, and ii) that the ExSo scheme raises the method performance for a given statistical order.

IV-B. A Modeling error based study

Although the head/source models are more and more realistic, modeling errors are still present. To study the impact of these errors, we applied a Gaussian perturbation of variance σ_e to the source leadfield vectors when the observations are computed; i.e. $\tilde{\boldsymbol{a}}(\boldsymbol{\rho}) = \boldsymbol{a}(\boldsymbol{\rho}) + \boldsymbol{\varepsilon}$ where $\boldsymbol{\varepsilon}$ is a random vector which elements are zero-mean Gaussian random variables of variance σ_e^2. Consequently, the leadfield vectors used to solve the inverse the problem are slightly different from the leadfield vectors used to compute the surface EEG. We performe the evaluation of the modeling error robustness using an occipital gyrus patch of 1000 mm^2. The amplitude of the spike in the source activities was adjusted to get a relatively high MSBR of 13 dB in order to not disadvantage the SO methods. The results are given on table II where the variance of the modeling error varies from 0 to 10^{-2}. It appears that the HO MUSIC-like methods are almost

σ_e^2	0	10^{-4}	10^{-3}	10^{-2}
4-ExSo-MUSIC	.878	.866	.779	.545
4-MUSIC	.301	.300	.245	.126
2-ExSo-MUSIC	.841	.732	.362	0
2-MUSIC	.303	.261	.102	0

Table II. $\widehat{\mathbf{TPF}}(\lambda)$ of a 1000 mm^2 occipital gyrus patch as a function of the variance of the modeling error for a $\widehat{\mathbf{TPF}}(\lambda) = 5.10^{-3}$. The MSBR is equal to 13 dB.

not affected by a modeling error of variance 10^{-4} and a little by a modeling error of variance 10^{-3}. For a strong modeling error ($\sigma_e = 10^{-2}$), HO methods are still able to localize although the performance decreases strongly, while the SO methods become inefficient. These results confirm the fact that the use of HO statistics increases the robustness of methods to modeling errors.

V. CONCLUSION

The $2q$-ExSo-MUSIC method ($q \geq 1$) presented in this paper is based on two main principles. First, it consists in an adaptation of the DSPE algorithm to the EEG/MEG localization problem. This adaptation gives rise to an novel algorithm called 2-ExSo-MUSIC. Second, an extension of this algorithm to any statistical order $2q$ was introduced. The ExSo principle is shown to improve the performance of classical MUSIC-like methods when the sources are spatially extended. In addition, the use of HO statistics improves the robustness both to low mean spike-to-background ratio and to modeling errors. Results obtained on simulations are promising. The next step is to perform additional evaluations for new scenarii in which the sensitivity to parameters like the patch location and size, like the number of patches and like the number of electrodes will be tested. We will also compare the results of the $2q$-ExSo-MUSIC technique with others popular methods as LORETA and sLORETA. Finally, another issue for forthcoming works will aim at reducing the numerical complexity of our method.

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