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Extraction of Deep Brain Stimulation (DBS) source in SEEG using EMD and ICA

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Abstract— **In the context of drug resistant partial epilepsy, intra-cerebral electrical stimulation (Deep Brain Stimulation) constitutes one of the means of investigation to locate epileptic volume. This exogenous source can then activate the underlying epileptic networks and generate an electrophysiological reaction. The purpose of this work is to estimate and eliminate the overlapping electrical stimulation signal in order to subsequently explore the provoked underlying electrical activity. We propose here several methods to tackle this problem, using two different approaches based on different assumptions: BSS approach based on Independent Component Analysis (ICA) and non parametric decomposition - empirical modes decomposition (EMD) algorithms.**

I. INTRODUCTION

The general framework of this paper is the processing and the analysis of the electrical signals generated by different brain areas and recorded by intra-cerebral electrodes. This recording technique, Stereo-ElectroEncephalography (SEEG/depth EEG), is based on surgically implanted electrodes and it is exploited for drug-resistant epileptic patients candidates to surgery [3, 5, 8]. The main objective is to contribute to a precise localization of the epileptic zone and/or the epileptic network, needed before a possible surgical removal. In some cases, electrical stimulation is used to provoke clinical manifestations in order to detect which brain areas and functions are affected by the disease.

However, in order to access this underlying brain activity, one needs to distinguish between the propagated electric potentials (due to the stimulation) and the electrophysiological sources (generated or inhibited by the neuronal structures). The stimulation can be seen as a perturbation that has to be eliminated in order to analyze the signals produced as the response to the stimulation. Indeed this generator can evoke an electrophysiological reaction of the excited cerebral processes. However, this phenomenon which occurs during the stimulation can arise with low energy in relation to DBS. If some clinical symptoms appear to be characteristics of an epileptic seizure, then the stimulated zone can be regarded as epileptogenic. In fact, it is necessary to exploit a propagation model to understand and interpret how electric stimulation is propagated through the process. Moreover, the objective is to separate the stimulation considered here to be a perturbation source for the brain processes.

In the hypothetical case where the signal generated by DBS and the model of propagation were both perfectly known and validated, then the extraction of stimulation would be easy. Nevertheless, the model should take into account the contact of the electrode stimulation and the characteristics of brain tissues which are not clearly defined. In fact for this study we choose not to introduce a model of this signal.

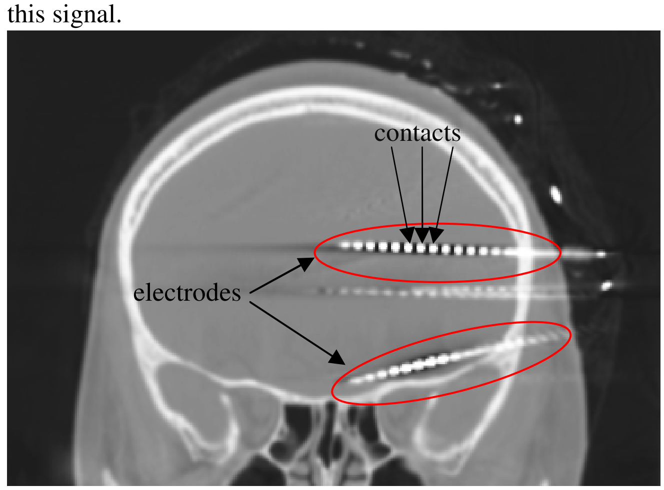

Fig. 1 Depth electrodes implantation scheme

The aim of this paper is to present several techniques in order to separate the stimulation activity from the background brain activity. The next section is dedicated to the acquisition protocol and it is followed by a modeling section. Next, we present the developed methods to identify the perturbation and we compare and discuss the obtained results.

II. DATA ACQUISITION

A SEEG recording of 14 patients was studied from intracerebral electrodes (Dixi Medical, Besançon, France) placed into the brain. The electrodes were not uniformly distributed in the brain, but were established according to the suspicion of the epileptic area. SEEG and video monitoring were performed using a Micromed® SystemPlus acquisition system. The signal was recorded at a 512 Hz sampling rate on a 128 channel amplifier (LTM 128 Headbox; Micromed, Italy). Electrical stimulation was injected as dipolar source between two contiguous contacts of one electrode. For one patient stimulating contact could vary between electrodes and between contacts of one electrode. We focus here on the specific type of stimulation using a current source that

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delivers a periodic pattern *p(t)* (1):

$$p(t)=\begin{cases}0 & -\dfrac{T}{2}<t<\tau \\ A & \tau\le t<0 \\ -A & 0\le t<\tau \\ 0 & \tau\le t<\dfrac{T}{2}\end{cases}, \quad (1)$$

where the amplitude *A* can vary from 0.2 to 3 mA, the period T = 20 ms and pulse width τ= 0.5 ms (see Fig. 2). The spectrum is thus made up the various harmonics.

An example of 40 ms of recording during stimulation is presented in Fig. 3.

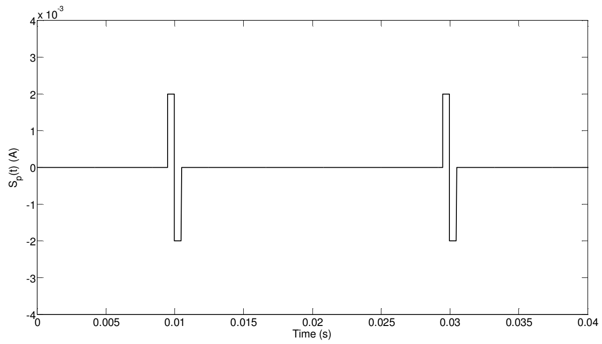

Fig. 2 Modeled stimulation.

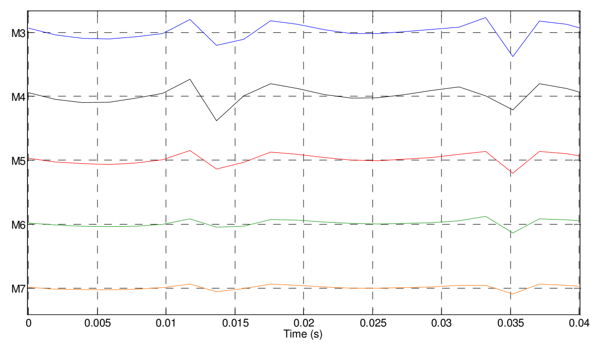

Fig. 3 Measured signals after the anti-aliasing filter.

III. Problem formulation

SEEG is the electrical activity measured in the brain produced by the electrical neuronal sources. The model of the SEEG activity is based on the quasi-static approximation of Maxwell's equations. Thus, the SEEG can be represented by a linear instantaneous mixture of dipolar sources. Under this assumption and in the absence of the stimulation, the electrical potential affecting the electrode *i* can be modeled as the weighted sum of different brain dipolar sources and the noise:

$$x_i(t)=\sum_{j=1}^{l} a_{i,j}\cdot s_j(t)+n(t), \quad (2)$$

where $a_{i,j}$ is the propagation (mixing) coefficient between the *j*-th source s_j and the *i*-th electrode. The external stimulation artifact appears in the model as a perturbation source by adding a weighted (propagated) stimulus signal to the measured signals in (2):

$$\begin{aligned} x_i(t) &= a_{i,p}\cdot s_p(t)+\sum_{j=1}^{n} a_{i,j}\cdot s_j(t) \\ &= b_{i,p}(t)+\sum_{j=1}^{n} b_{i,j}(t) \end{aligned}, \quad (3)$$

where $b_{i,p}(t)=a_{i,p}\cdot s_p(t)$ is the contribution of the perturbation source s_p at the electrode *i*, and $b_{i,j}(t)=a_{i,j}\cdot s_j(t)$ is the contribution of the source s_j at the electrode *i*. According to (3), we can reconstruct the depth EEG potentials not affected by the stimulation by estimating the mixing (propagation) coefficients $a_{i,p}$ and the perturbation source s_p. In the case of an independent stimulation signal, this problem can be solved by a BSS approach. Nevertheless, even if the stimulation signal was independent from the brain activity at the beginning of the process, some brain activity can be generated and then synchronized with the stimulation pattern producing correlated activity. Another possible approach in order to estimate the stimulation signal from the observed mixture is the Empirical Mode Decomposition (EMD) method. The advantage of this method over classical BSS is that it does not need any assumption about the observed mixture and its components are not necessarily independent or non-correlated.

IV. Methods

A. *Empirical Mode Decomposition (EMD)*

In general the EMD is a nonlinear and non-stationary data-driven decomposition method (N. E. Huang et al., 1998). EMD decomposes the signal into one finite set of Intrinsic Mode Functions (IMFs) which give the original signal when added together. The algorithm of EMD for a given signal $x(t)$ can be summarized as:

1. Find all extreme points of $x(t)$.

2. Interpolate between all maxima and minima points (separately), to obtain the upper and lower envelope.

3. Compute the mean m_1 of both envelopes.

4. Extract the detail $h_1=x(t)-m_1$

5. Repeat the steps 1 to 4 for k iterations (until detail h_k can be considered as $IMF_1=h_k$), due to errors which can arise by spline fitting processes.

6. Apply steps 1 to 5 for the residual $r_j=r_{j-1}-h_j$ in order to obtain all the *IMFs* of the signal (for the first residual $r_1=x(t)-h_1$).

The algorithm ends when a monotonic signal is found to be residual.

In favour of EMD it has been shown from other similar methods like wavelet-like decomposition, that it decomposes a signal in a natural way without prior knowledge about the signal of interest embedded in the data series [4].

In our study of stimulation extraction, we use two modified versions of EMD:

- EMD presented in [10] is a modified version of Huang [6] in the 5th step (see the section IV. A). This is called EMDr further in the text.
- Multivariate EMD proposed in [9] which generates multiple n-dimensional envelopes by taking signal projections along different directions in n-dimensional spaces; these projections are then averaged to obtain the local mean. The direction vectors for taking projections are chosen to be based on polar and spherical coordinate system. This algorithm is later referred to as MEMD.

The measured EEG signal can be represented as a sum of Intrinsic Mode Functions (IMFs) as:

$$\hat{x}_i(t) = \sum_{j=1}^{M} IMF_{i,j}(t)\,, \qquad (4)$$

where M is the number of IMFs.

To estimate IMFs related to the perturbation source s_p , we used the sum of the first intrinsic mode functions as:

$$\widehat{s}_{i,p}(t) = \sum_{j=1}^{k} IMF_{i,j}(t)\,, \qquad (5)$$

where k is the index of the first local minimum of the correlation function $\mu_i(j) = Corr(x_i, IMF_{i,j})$ and it is calculated as:

$$k = \arg\min_{j<M} \mu_i(j)\,. \qquad (6)$$

We choose the sum of first IMFs as perturbation source because of high frequency components contained in the stimulation pattern.

B. Blind Source Separation Approach (BSS): Independent Component Analysis (ICA)

The objective of blind source separation is to recover all the independent sources from the observed measures. In general, these observations are modeled as a linear mixture of independent sources, both the mixing system and the sources being unknown [2].

The classical instantaneous linear mixing model is written

$$\mathbf{x} = \mathbf{A}\mathbf{s}\ , \qquad (7)$$

where $\mathbf{x}$ is a vector of observed data, $\mathbf{A}$ is the unknown mixing matrix and $\mathbf{s}$ is the vector of independent unknown sources.

In order to estimate the original sources, a reverse linear transformation $\mathbf{B}$ must be obtained such as:

$$\mathbf{s} = \mathbf{B}\mathbf{x}\,. \qquad (8)$$

Thus, source separation algorithms try to find an estimate of the matrix **B.** In the BSS framework, there are two major families of algorithms, those based on High Order Statistics (*HOS*), like fastICA [7], and those based on Second Order Statistics (*SOS*), like SOBIRO [1].

EMD (estimated stimulation): from one of the electrode measurements we estimate the Intrinsic Mode Functions (IMFs) by using the EMD algorithm, then we perform the subtraction between the measured signals and the sum of IMFs needed to construct the stimulation as follows (valid for both EMD versions):

$$\hat{\mathbf{x}}_{EMD} = \mathbf{x} - \hat{\mathbf{s}}_{p,EMD}\ . \qquad (9)$$

BSS-fastICA (estimated source and coefficients): assuming both the source and the propagation coefficients to be unknown, we estimate both of them by BSS. Normally, to obtain artifact free brain signals, the undesired source (stimulation signal $\widetilde{s}_p$) is chosen according to (10) and subtracted, weighted by the corresponding estimated mixing coefficients and the solution given by BSS (fastICA or SOBI) is:

$$\hat{\mathbf{x}}_3 = \mathbf{x} - \hat{\mathbf{k}}_{BSS} \cdot \hat{\mathbf{s}}_{p,BSS}\ . \qquad (10)$$

V. Results

We have applied stimulation estimation methods (presented in section 2) to 243 selected stimulations from 14 patients. However, to reduce the amount of data, we used those contacts, which belong to the stimulating electrode, because with them stimulation is measured with more energy. Finally, we acquired 2330 measurements of 9.8 contacts per stimulation on average.

In order to analyze in detail the efficiency of each method for all stimulation measurements, we have correlated the estimated stimulation (from different methods) with a one second long pattern of stimulation, taken from a clear, low noise measurement where no evidence of the cerebral activity was visible. The results for EMD are presented in the table 1.

Table 1
Analysis of EMD methods. Mean cross-correlation with pattern.

Method	k*	IMF_1	IMF_2	k=2	k=3	k=4
MEMD	0.860	0.511	0.319	**0.881**	0.878	0.871
EMDr	0.856	0.499	0.311	**0.876**	0.873	0.861

* IMFs are chosen, calculating indexes as shown in (6).

In table 1, for different selections of IMFs, we calculate the index m_{emd}:

$$m_{emd} = \frac{1}{N}\sum_{i=1}^{N} \max corr(s_{pp}, \widehat{s}_{i,p})\,, \qquad (11)$$

where $corr$ – cross-correlation, s_{pp} – pattern of stimulation, $\widehat{s}_{i,p}$ – estimated perturbation source from x_i and N – total number of measurements (from all patients). In the first column, for calculating $\widehat{s}_{i,p}$, IMFs are selected as indicated in (6), in the second and third columns – single IMF_1 and IMF_2, respectively, and in the others the sum of the first k^{th} IMFs is considered to be a stimulation source. We calculated the same mean cross-correlation given by (11) for ICA and SOBIRO estimated stimulation sources:

Table 2
Index of correlation for two algorithms of BBS

Method	Index m_{ICA}
Fast ICA	**0.853**
SOBIRO	**0.858**

As estimated stimulation for ICA and SOBIRO (table 2), we selected an independent source that gives the highest cross-correlation with the stimulation pattern, because, as we could see in this study, combining independent sources does not improve the correlation.

After estimating DBS, we visually inspected some stimulation cases where the presence of an underlying cerebral activity had been verified by neurologists. One case is shown in figure 4, where a brain discharge starts after 3 seconds of stimulation. However, in figure 5, we presented the spectrum of the same data from which the stimulation is eliminated using (8) and (9). The result spectrum (in red) is compared with the measurements (in blue). As we can see, the two types of methods resemble each other, but we presume that EMD separates stimulation from cerebral discharge more precisely, because fastICA and SOBIRO algorithms have left frequencies of the perturbation.

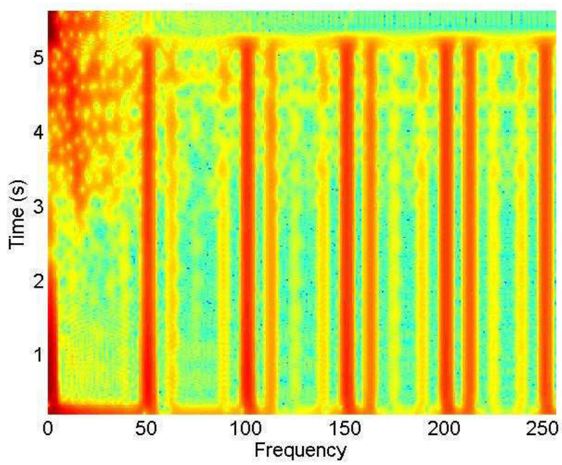

Fig. 4. Spectrogram of stimulation and brain discharge activity (starting after 3 seconds, at 5-25 Hz frequencies).

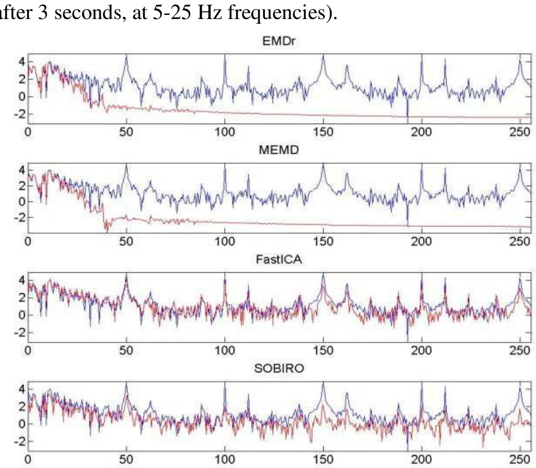

Fig. 5. FFT spectrum of EMDr MEMD, FastICA and SOBIRO stimulation eliminated data (in red) compared with data spectrum (in blue).

VI. Conclusion

We have presented one application in signal identification for SEEG signal processing methods based on different models with the same purpose of blind signal decomposition. The first family of methods presented here is Blind Source Separation (BSS). BSS has been successfully tested in many biomedical applications such as artifact detection.

The second family is the Empirical Mode Decomposition (EMD). The EMD is based on a signal decomposition which does not follow a particular model for its decomposed signals, i.e. there is not a matrix of coefficients that relates the measured signals with its decomposed signals. EMD has already been used in applications on non-stationary biomedical signal decomposition for some time. In this paper, we have shown one application for the EMD in SEEG signals and we have obtained slightly better results than those provided with the classical BSS algorithms. Therefore, from the correlation results illustrated in table 1 for EMD and table 2 for BSS, we can conclude that to identify DBS signal as presented here, BSS type methods are not the best choice. However, comparing EMDr and MEMD methods, we may say that the MEMD is very promising to analyze EEG and SEEG because of its multivariate nature. In further study we have planned to look at combined decomposition methods such as EMD together with ICA, SVD (Singular Value Decomposition) and SSA (Singular Spectrum Analysis) and use them for the applications of the SEEG signals (DBS together with epilepsy signals).

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