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Extracting the spike process from the EEG by spatially constrained ICA

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***Abstract*— Epileptic patients often show Interictal Epileptic Discharges (IED's) in the electroencephalogram (EEG) recorded between seizures. This epileptiform activity is in many cases related to the location of the seizure onset, and is believed to reflect the frequency of the seizures. We present a fully automated technique that is able to extract the IED's from the EEG, despite the obscuring artifacts. The presented technique is based on a multi-objective optimization by maximizing the signal's kurtosis and minimizing its distance to a defined template. Preliminary results show that this technique automatically extracts a source on which spike detection techniques should perform better than on the regular channel selection procedure.**

I. INTRODUCTION

Epilepsy is a disease affecting 0.5-1% of the population and which is characterized by the occurence of seizures, originating from within the brain by a simultaneous burst of neuronal activity. The effect of the seizures is affecting the patients' lifes since it is often associated with changes in consciousness and abnormal behaviour or physical malfunctioning. About 25% of the epileptic patients are suffering from refractory or drugresistant epilepsy, being in need of a surgical intervention to free them from future seizures or at least decrease their frequency. For this presurgical evaluations are necessary, including the positioning of the seizure onset. Since the neuronal activity can be measured in the EEG through potential distributions on the scalp, this makes it an excellent means for detecting the cerebral activities.

A. The spike process

Often, patients suffering from epilepsy show epilepsy related activity in between the occurrences of seizures. The spike process that is generated in the EEG gives in most cases a reliable estimate to the brain area related to the the seizure onset, making it a reliable tool for localization purposes. Next to these localization purposes, recent studies ask for a decent tool to summarize spike processes into statistics [3]. Few solutions have been offered, mostly offering the capability of spike counting on a single channel from the EEG. However, all of these techniques suffer from the sensitivity of the EEG to artifact introduction such as ocular movement, muscle contractions, electrode artifacts and the interference of the regular background activity. The challenge is to find a representation of the EEG in which the processes of interest are well separated from this background and the introduced artifacts. In this way, processing of the EEG is shifted toward processing of the appropriate partial signal, a task that is much easier to accomplish by physicians as well as by software.

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B. Blind Source Separation

Given n time series Y (nxN), it is always possible to have a representation in some signals X (mxN) that form a linear combination W (mxn) of Y, up to some noise η (mxN). Or, vice versa, the measurements could always be written as a linear combination $A = W^+$ (nxm) of the sources X, up to some noise μ (nxN). Here, W^+ denotes the pseudoinverse of A. Blind Source Separation (BSS) searches for this linear combination and the corresponding sources given the measurements. Assuming the noise level is neglegible, we obtain:

$$Y = AX \text{ or } X = WY. \tag{1}$$

This linear mixing model supports the EEG measurements very well[]. The rows in W or the columns in A are then the reflection of the activation each source component has at the corresponding electrode site, i.e. the corresponding topography. However, there is still a need to determine the method that is to be used in order to obtain as physiologically reasonable source components as possible.

II. METHOD

A. Preprocessing

Since the EEG consists of an amount of extracerebral artifacts that are mixed into the scalp potentials resulting from cerebral activities, there is a need to get rid of those artifactual components before the actual processing can take place. Recently, pSVD [1] has been developed, a method to extract the artifacts introduced by ocular movements from the EEG. Using a sliding window it removes the component if and only if it is associated to the first principal eigenvector and if the topography corresponds to one of the topographies from a template dictionary up to some error threshold. Since those are the only artifacts in the EEG's that really obscure the spike processes in the interictal EEG, we removed them prior to all other processing. The cleaned EEG, after centralization and normalization, is denoted as Y_c.

B. A template for the spike channel

In the presented method, we try to estimate the mixing channel of the spike process by using the principle of simultaneous neuronal activation. Since the spike is a direct consequence of a spontaneous neuronal activity burst, there is a high synchronization in the EEG at the moment of the spike. This prior knowledge is exploited by using the correlation matrix of the original signal matrix. Summation of the absolute values over the columns, and assigning the appropriate sign to the vector elements by using the summation of the signatures over the columns, results in a basic topography to start from. $C_{Y_cY_c}$ being the correlation matrix of Y_c, we obtain for the template topography:

$$\mathbf{t} = \sum_{i=1}^{n} C_{Y_cY_c}^{(i)} \cdot sign\left(\sum_{i=1}^{n} sign\left(C_{Y_cY_c}^{(i)}\right)\right), \qquad (2)$$

where $sign(a)$ represents the sign function, equal to 1 if $a \geq 0$, and -1 elsewhere.

C. Spike separation

The epileptic spike is more or less distributed according to a Laplacian distribution, which means that its kurtosis should be high. In the preprocessing, the high leptokurtic eye movement artifact has already been removed. Searching for a maximal kurtosis of the signal is thus a possible objective. Combining the maximization of kurtosis, while staying in the neighborhood of the template topography, results in a spatially constrained form of ICA. For simplicity of representation, there is only interest in the spike channel for now, which reduces W and X to the vectors $\mathbf{w}$ and $\mathbf{x}$, respectively, unless denoted otherwise. The two objectives are then given by $\mathbf{F}_1(\mathbf{w}) = \text{kurtosis}(\mathbf{w}X)$ and $\mathbf{F}_2(\mathbf{w}) = ||\mathbf{w},\mathbf{t}||$. We replace the kurtosis by a nonlinear function g, which is a more general and robust information theoretic measure [4]. For $\mathbf{F}_2$ we use the consine of the angle between the two vectors to represent their similarity, since this measure is bounded within $[-1,1]$, giving $\mathbf{F}_2(\mathbf{w}) = \text{abs}\left(\mathbf{w}^T\mathbf{t}\right)$. Both object functions are then to be maximized over $\mathbf{w}$. Combining both objectives results in a weighted addition of the form $\text{maximize}_{\mathbf{w}}\mathbf{F}(\mathbf{w})$, where $\mathbf{F}(\mathbf{w}) = \alpha\mathbf{F}_1(\mathbf{w}) + (1-\alpha)\mathbf{F}_2(\mathbf{w})$, and α is yet to be determined.

Maximization of the function $F(\mathbf{w})$ is a numerical problem that can be solved using the fixed-point algorithm [4], which is very efficient and statistically robust. The updating of the weight vector is then given by

$$\mathbf{w}(k+1) = \alpha\mathbf{F}_1(\mathbf{w}(k)) + (1-\alpha)\mathbf{F}_2(\mathbf{w}(k)) \qquad (3)$$

where

$$\begin{aligned}\mathbf{F}_1(\mathbf{w}(k)) &= \mathrm{E}\left\{Y_c g\left(\mathbf{w}(k-1)^T Y_c\right)\right\} \qquad (4)\\ &\quad - \mathrm{E}\left\{g'\left(\mathbf{w}(k-1)^T Y_c\right)\right\}\mathbf{w}(k-1)\\ \mathbf{F}_2(\mathbf{w}(k)) &= sign\left(\mathbf{w}^T\mathbf{t}\right)\mathbf{t}, \qquad (5)\end{aligned}$$

and g equals the hyperbolic tangent function, tanh.

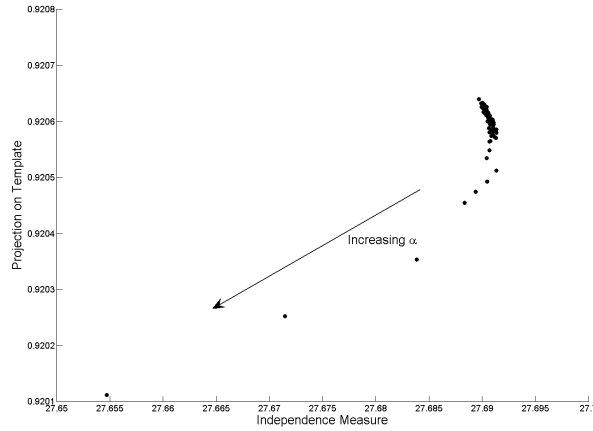

Fig. 1. An example of a realistic pareto front [pt0976 00:00:01 00:00:11]. For illustration purposes the resolution for α was chosen 0.01 and was limited between 0.01 and 0.98

III. RESULTS

A. Materials

The dataset was collected at the Reference Center for Epilepsy, at the Ghent University Hospital, Belgium. Data was used from 6 patients with diagnosed epilepsy, consisting of recordings of approximately 20 minutes of interictal EEG each. The EEG was registered using a Telefactor Beehive system at a sample rate of 200Hz. Twenty-one electrodes were placed on the patient's head according to the international 10-20 system with six extra electrodes to cover the temporal regions. All the EEG's showed interictal discharges (IED's) which were marked by a local physician.

B. Optimal Parameter Values

The optimal parameter value of α in equation 3 is dependent on the presented dataset. For each dataset an optimization takes place by doing a pareto front analysis. This implies that the original objective functions are taken and their optimal results are returned for each value of α. However, this is computationally very inefficient and thus the stepsize of α has been limited to 0.05, thus having 19 possible values in the set $]0,1[$. Moreover, all values below 0.9 are distributed in the objective space with a very small variance. Increasing α beyond 0.9 decreases the optimum, which supports our choice.

The optimal value for α is found by choosing the value for which the Euclidian norm of the vector $\mathbf{J}_\alpha = [\mathbf{F}_1(\mathbf{w}^*|\alpha)\ \mathbf{F}_2(\mathbf{w}^*|\alpha)]$ is maximal. A pareto front with the direction of increasing α is given in fig. 1. The objective space contains a high density in the neighborhood of $\alpha = 0$, thus favoring low values over high ones. This is a direct consequence of the different scales of the object functions and optimal solutions are to be found in the proximity of $\alpha = |\frac{\mathbf{F}_2}{\mathbf{F}_2-\mathbf{F}_1}|$.

C. Measure of Performance

Since it is difficult to place objective measures on the evaluation of spike recognition within the EEG, we return to

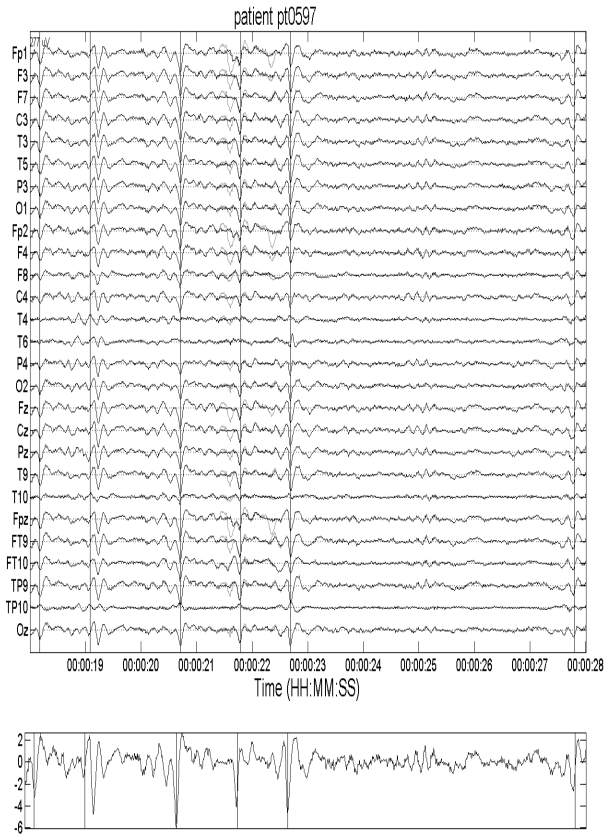

Fig. 2. EEG fragment and its associated spike channel (gray: before filtering, black: after eye movement artifact removal)

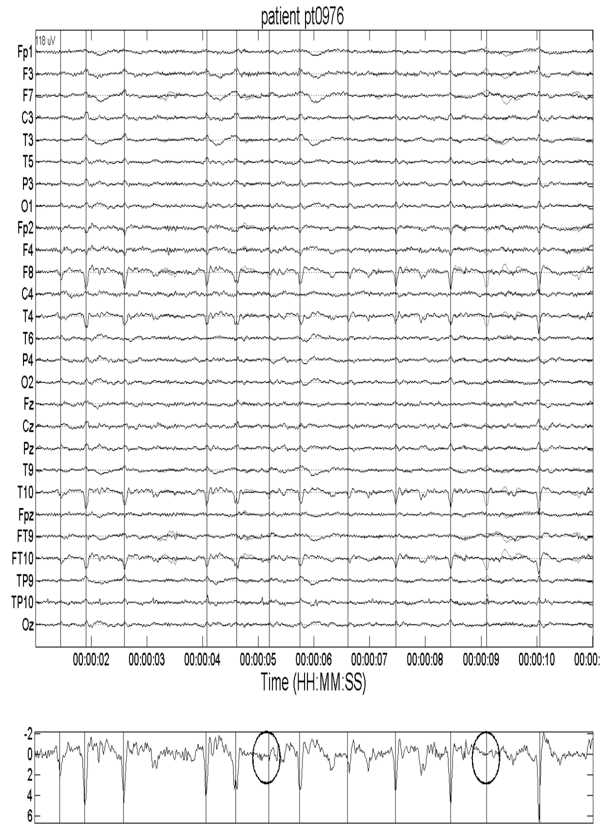

Fig. 3. EEG fragment and its associated spike channel: the eye artifact removal has been to greedy. Circles indicate the time instances where the pSVD got mislead (gray: before filtering, black: after eye movement artifact removal)

basic subjective channel evaluation. We assume that in the recovered spike channel s, at least the indicated IED's are present next to some additional epileptic interictal activities. The spikes are marked by physicians, which allows to increase the objectivity of the evaluation. In fig. 2,3, two examples are presented wherein the spike has been extracted after choosing an optimal α-value for the problem at hand. In both cases the extracted channel returns the smoothly contoured IED's. However, in fig. 3 the eye artifact removal has been to greedy. As a consequence the signal Y_c didn't contain all of the spikes that were originally present in the EEG. The spike extraction performs well under these conditions, extracting all the remaining spikes.

The extraction of the IED is independent on the type of epilepsy. As can be seen from both results in fig. 2,3, no distinction is made between generalized or focal activity, with an equal performance in both scenario's. This points at a wide applicability, a property that is essential when working on interictal EEG's stemming from a large patient population.

Since there is no objective measure available up till now, it rests us to say that all instances that were visually inspected agreed to the terms given above. Although the spikes were present in the extracted channel, and care had been taken, some of the channels still needed a manual reversal of their polarity in order to be consistent with the data.

IV. DISCUSSION

The method has shown nice convergence properties and is statistically sound, returning the spike channel no matter the initialization of the variables and parameters thanks to the possibility of detecting the optimal working point on the pareto front.

In case there are topographies of the IED's close to the topographies of eye movement artifacts, the IED's are picked up as being eye movement artifacts and thus removed by pSVD. This inconvenience can be solved by adapting the pSVD method, in which a learning process is introduced to learn the typical IED topography for the reviewed patient. By constraining the pSVD by an extra rule not to extract topographic maps associated to IED's, the EEG will be left untouched at those specific time instances. Both methods will benefit from mutual information exchange. However, a direct consequence is that one of the most favorable properties of pSVD, its real time analysis, will then be violated.

V. CONCLUSION AND FUTURE WORKS

A. Conclusions

A fully automated method was found to successfully extract a signal containing the spikes that were present in the cleaned EEG itself. The reduction of a higher dimensional dataset to one enhanced channel eases the process of spike detection in a later stage. Making the manual channel selection obsolete and suppressing the background should make future analysis with automatic spike detection methods much more robust.

B. Future Works

A lot of work is yet to be done in order to see whether spike detection programs will really benefit from this enhancement. To be able to present sound statistics, there is a need for a larger dataset of scored epileptic EEG's by multiple physisian's to decrease the subjectivity and increase the statistical validity. In the near future, tests will be carried out for the spike detection program developed within our group [2], to see whether the performance can increase using this method as a preprocessing step. A next step would be the analysis of the ictal EEG, making use of the described method, possibly in a slightly alternated form.

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