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Detection of Epileptic High Frequency Oscillations Using Support Vector Machines

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Abstract— **Recently, several studies have proved that High Frequency Oscillations (HFOs) of [80-500] Hz are reliable biomarkers for delineating the epileptogenic zone. The total duration of HFOs is extremely short compared to the entire duration of EEG dataset to be analyzed. Therefore, visual marking of HFOs is time-consuming and laborious process. In order to promote the clinical use of HFOs oscillations as reliable biomarkers of epileptogenic tissue and to conduct large-scale investigations on cerebral HFOs activities, several automatic detection techniques have been proposed over the past few years. In the present framework, we propose a novel approach for detecting HFOs based on Support Vector Machines (SVM). Our method is subsequently compared with six other methods. HFOs detection performance is evaluated in terms of sensitivity, false discovery rate, area under the ROC curve and execution time. Our results demonstrate that SVM approach yields low false detection (FDR = 6.36%) but, in its current implementation, is moderately sensitive to detect HFOs with a sensitivity of 71.06%.**

Keywords—*Epilepsy, EEG, Automatic Detection, High Frequency Oscillations, Support Vector Machines.*

I. INTRODUCTION

Epilepsy is one of the most neurological disorders, with prevalence between 0.5 and 1% of the world population [1]. For numerous patients with drug-resistant epilepsy, besides transcranial direct current stimulation, surgical resection represents an alternative therapeutic solution. Recently, a number of studies suggested that both interictal and ictal [1], [2] HFOs in the [80–500] Hz frequency band may be specific and reliable surrogate biomarkers of the epileptic seizure zone (SZ). In addition, there is clinical evidence elucidating that HFOs can have a significant influence for a good understanding of the fundamental neural mechanisms underlying epileptic phenomena [3]. To date, higher durations, higher rates as well as higher powers of HFOs patterns have been observed within the SZ [4]-[7]. Beside, some studies on human have also shown that the resection of brain structures with high HFOs rates has led to good post-surgical outcomes [8], [9]. Some studies also suggested that HFOs could be used for predicting the onset timing of epileptic seizures [10]-[12] and that their occurrence rate was significantly correlated with the seizure frequency in epileptic patients [13]. In addition, this occurrence rate generally remains confined to the same regions during both ictal and interictal periods [14], [15]. These previous results have proved the strong role of HFOs and their relationship with epileptogenesis.

The duration of an HFO oscillation is approximately comprised between 10 and 100 ms. However, the average occurrence rate of an HFO is equal to 9.5 ± 17.5 /mn [16]. According to these values, the total duration of HFOs is extremely short compared to the total length of EEG datasets. Therefore, visual identification of HFOs in lengthy EEG data is extremely tedious and time consuming, and fatigue can easily lead to false identification [16], [17]. By contrast, automatic detection of HFOs presents advantages for neurologists and researchers since this procedure is objective and fast compared to visual marking.

In this paper, we propose a novel method of HFOs detection using Support Vector Machines (SVM) technique. In order to evaluate the efficiency of our SVM based approach, we compare its performance with six other existing methods previously implemented by our team and other research groups. The first method, referred as RMS, is based on Root Mean Square. The second one, called CMOR, is based on Complex Morlet wavelet. The third method, named BUMP, uses the modeling

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of bumps for detection of HFOs. The fourth method is based on Matching Pursuit (MP). The fifth method is mainly based on Hilbert Huang Transform (HHT) and the last one, named DECISION TREE, is a decision-tree based technique [18]. In our case, HFOs detection performance is assessed based on sensitivity, False Discovery Rate (FDR), Area Under the ROC Curve (AUC) and Execution Time (ET). The structure of the paper is organized as follows: Section II presents the clinical EEG database as well as a detailed description of the SVM technique and the retained features. In Section III, we detail the visual marking procedure and the performance metrics. Section IV describes the main results followed by a discussion before giving some conclusion in Section V.

II. Materials and Methods

A. Database

In the present study, the database was recorded using the EEG Stellate Harmonie Routine at the Montreal Neurological Institute and Hospital of Canada. During acquisition, the data was filtered by a low-pass analog filter with a cutoff frequency equal to 500 Hz. Subsequently, the filtered data was sampled at a frequency of 2000 Hz. The sampled data was then quantified using an encoder of 16 bits. The EEG channels used to test and assess the different methods were selected based on the following two criteria: Firstly, the clear presence of HFOs among the chosen channels was decided visually by a clinician, and, secondly, channels with different noise levels were selected and taken into account in order to evaluate the performance of the various methods on a solid basis.

B. Support Vector Machines (SVM)

SVMs are popular supervised learning models that associate essentially two successive steps, (i) training phase and (ii) testing phase [19]. In our context of HFOs detection, the objective of SVM learning technique is to distinctly classify data into two binary classes: HFO and background. The optimal setting parameters of SVM structure were obtained based on relevant marked clinical HFOs, which have been considered as a ground truth for both training and testing stages.

C. Features

SVM is related to mathematical rules inspired from information theory, where the decision or the classification of patterns is based on successive features and class labels well organized in the structure of SVM technique [19]. In our context, the EEG cerebral data is composed of two binary classes: background activities and HFO activities. The implementation of the SVM based approach is done using the following six features ranged respectively from Feature 1 up to Feature 6, which are computed from the band-pass filtered version and also from the time-frequency map in the [80-500] Hz frequency range. These features are detailed hereafter:

- Feature 1 (F1) is computed from the mean $\bar{x}$ of the EEG signal x and its standard deviation $\sigma(x)$

$$\mathrm{F1} = \bar{x} + \sigma(x) \quad (1)$$

- Feature 2 (F2) consists in the difference between the maximum value and the minimum value of the time frequency matrix map, which is computed using the complex CMOR2-1.114 wavelet

$$\mathrm{F2} = \max \sum_{t,f} \mathrm{C}(t,f) - \min \sum_{t,f} \mathrm{C}\,(t,f) \quad (2)$$

- Feature 3 (F3) is calculated from the mean $\overline{\mathrm{TEO}}$ and the standard deviation $\sigma(\mathrm{TEO})$ of Teager Energy Operator (TEO)

$$\mathrm{F3} = \overline{\mathrm{TEO}} + \sigma(\mathrm{TEO}) \quad (3)$$

where $\mathrm{TEO} = x(n)^2 - x(n+1).x(n-1)$, and $x(n)$ is the EEG signal. TEO is one of the most popular operators that has been used in the estimation of both instantaneous amplitude and instantaneous frequency curves.

- Feature 4 (F4) is the number of zero crossings computed according to the following equation:

$$\mathrm{F4} = \sum \mathrm{abs}[\mathrm{diff}\left(\frac{1+\mathrm{sgn}(x)}{2}\right)]/N \quad (4)$$

where N is the length of the EEG signal taken into consideration, abs is the absolute value, diff calculates differences between adjacent elements of x and sgn is the function that extracts the sign.

- Feature 5 (F5) is the maximum value (maximum coefficient) of the autocorrelation $\mathrm{R}_{xx}(t)$ of the signal x.

$$\mathrm{F5} = \max[\mathrm{R}_{xx}\,(t)] \quad (5)$$

- Feature 6 (F6) is the maximum coefficient of the Power Spectrum Density (PSD) of the signal x, which is computed as follows:

$$\mathrm{F6} = \max\,[\mathrm{PSD}(x)] \quad (6)$$

In order to train our SVM classifier, 200 events were selected from the database, and divided respectively into 100 events of cerebral background and 100 events of cerebral HFOs. Then, the six features were computed for each event. The matrix containing the labeled classes as well as the values of features is used in the training phase to produce the optimized structure of SVM, which will be used in the automatic recognition (testing phase).

Once the training phase is completed, the automatic recognition of HFOs using the optimized structure of SVM can be done. Fig. 1 summarizes the difference between the training and testing phases using SVM technique.

Based on the six features F1-F6 and the optimized SVM structure, a 50 ms sliding window scans the entire EEG signal. In fact, the window length (50 ms) is chosen so as to approximate the average duration of all HFOs events used in the training phase. The sliding window moves only by one sample in order to determine if it matches the HFO class or the background class. Once the scanning of the entire database is finished, all the windows corresponding to HFO class are set to 1 and the remaining segments are set to 0. In the next step, the segments with value 1 are delimited in time. Each portion of the rectified-filtered signals confused with level 1 above the threshold ($\delta_{\text{rectified}}$) is detected as a candidate HFO, if it consists of at least six peaks (i.e. 3 cycles).

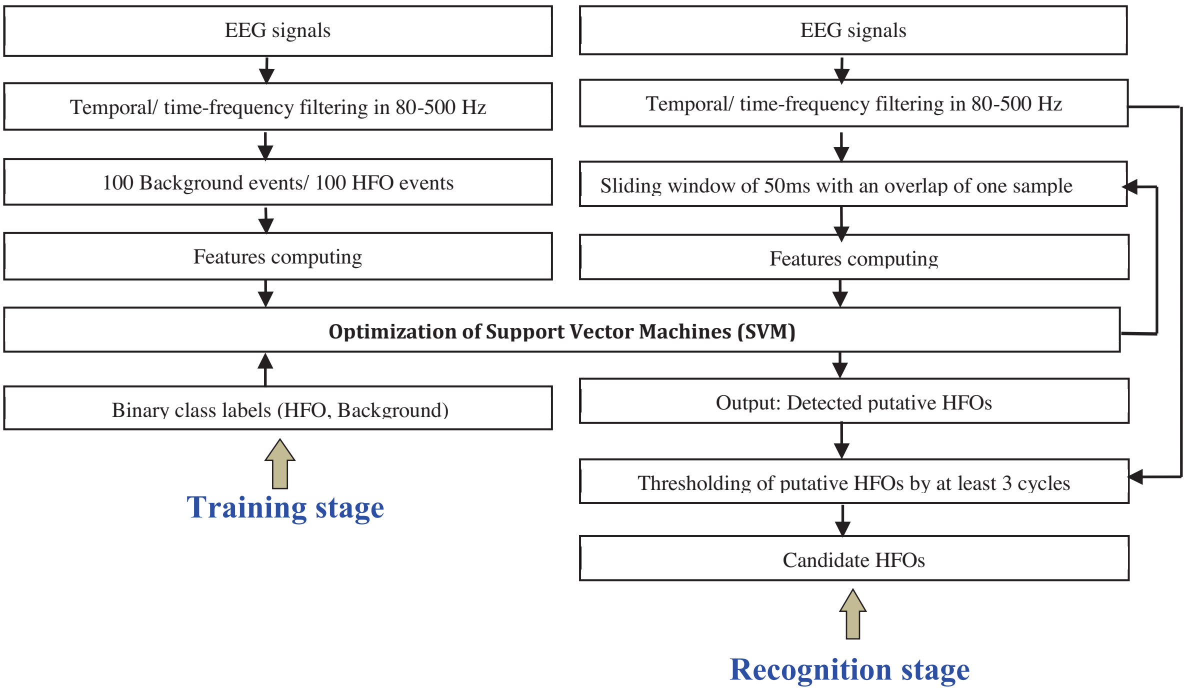

Fig. 1. Flowchart of HFOs detection using SVM.

The threshold level $\delta_{\text{rectified}}$ is computed according to the following equation:

$$\delta_{\text{rectified}} = \beta.\sigma \tag{7}$$

σ represents the standard deviation of the rectified-filtered version of all background segments, which are selected manually from the database. β is defined as the input training parameter that should be optimized as much as possible.

III. Visual Marking and Performance Assessment

HFOs patterns were visually marked by two independent experienced-reviewers well trained in HFOs analysis. In fact, an event can be identified as a relevant or consistent HFO if it consists of at least three consecutive periods in the frequency range of [80-500] Hz, and it should be also clearly distinguished from the average value of background.

Only HFOs events detected by the two experts were considered as relevant HFOs bursts and considered as a gold standard. The remaining segments were discarded and considered as "background activities". We note the terms of background activities here as an indicator of the absence of HFO oscillations.

The commonly metrics used in our framework are respectively: Sensitivity, False Discovery Rate (FDR), Area Under the ROC (Receiver Operating Characteristic) Curve (AUC) and the required Execution Time (ET). They are defined as follows:

$$\text{Sensitivity} = 100\,\frac{\text{DP}}{\text{POS}} \tag{8}$$

$$\text{FDR} = 100\,\frac{\text{FP}}{\text{TP+FP}} \tag{9}$$

$$AUC = \sum_i (FDR_i - FDR_{i-1}) * (\frac{Sens_i + Sens_{i-1}}{2}) \quad (10)$$

Generally, HFOs detection algorithm produces a list of candidate HFOs, with their position in time and their duration. As shown in Table 1, in the context of binary classification, a visually identified HFO corresponds to a positive and a visually identified background corresponds to a negative.

Table 1. Confusion matrix of HFOs classification.

		Predicted class	
		HFO	Background
Real class	HFO (Positive)	TP	FN
	Background (Negative)	FP	TN

In particular, if the confusion matrix is diagonal, the classifier is perfect. So, according to Table 1, candidate (detected) HFOs may correspond to either true positives (TP) or false positives (FP). POS (positives) is the number of HFOs events visually identified. DP (detected positives) is the number of positives which overlap with candidate HFOs. TP is the number of candidate HFOs, which overlap with positive events. FP is the number of candidate HFOs which do not overlap with positive events. AUC is the area under the ROC. As shown in Fig. 2, AUC surface is computed from measuring the area under points $Sens_i$ vs. FDR_i. Finally, in our case, the execution time is computed using Dell i3 computer (4GB RAM, Processor speed of 2.3 MHz).

IV. Results and Discussion

The measure of performance in terms of both sensitivity, FDR, AUC and ET for the proposed SVM algorithm is done by modifiying the input parameter β. Fig. 2 shows the ROC curve that characterizes the variation of mean Sensitivity vs. FDR. As shown in Fig. 3, the optimal point of input threshold β is indicated by the dashed-yellow arrow, and corresponds to β = 10. The values of both sensitivity and FDR corresponding to this point are 71.06% and 6.36% respectively. The AUC of the ROC curve is equal to 0.8219. The ET for processing 4s EEG signal using the proposed method is approximately equal to 38.76 seconds.

To compare our method with other studies is not a simple task. There is a changing variability between various studies, which can generate some difficulties when comparing their performance.

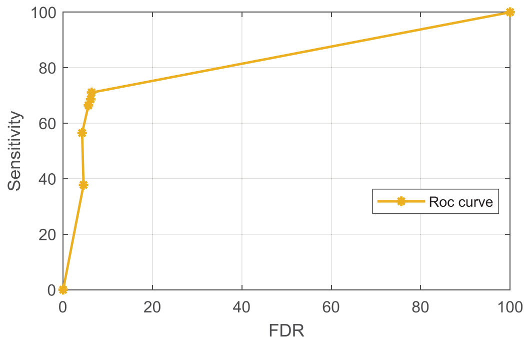

Fig.2. ROC curve of SVM algorithm obtained by varying the input parameter β.

As a matter of fact, in the literature, different techniques of acquisition of EEG recordings have been reported. Different types of electrodes (macro-electrodes, microelectrodes, grid…) have been used in the recordings of EEG signals. Moreover, there is no systematically common brain region used in the different studies. The definition of the frequency band of the High Frequency Oscillations varies with the studies. Finally, there is no gold standard and no common database available for researchers working on HFOs analysis. So, for relevant comparison between different HFOs detection methods existing in the literature, it is necessary to test methods using the same database and the same "Gold Standard". As a result, we propose in this paper a comparative study between our SVM algorithm and six other methods that have been previously implemented, namely RMS, CMOR, BUMP, MP, HHT and DECISION TREE.

The RMS algorithm is based essentially on finite impulse response (FIR) filter and the root mean square RMS operator. All details about the description and the varying input parameters for this algorithm are provided in [18]. The second detector for HFOs detection is based on the complex Morlet wavelet (CMOR) for which implementation details are provided in [2], [18]. The next method is based on bumps modeling. Then, the fourth method used as basis the matching pursuit technique. The 5th method we compared with our proposed algorithm is the Hilbert Huang Transform (HHT) (see [1] for more details and a formal description). Lastly, the 6th approach is based on decision tree [18]. The results of performance comparison through different methods are plotted in Fig. 3 and listed in Tab. 2. With the EEG data used in the present study, the most robust method in terms of best tradeoff between sensitivity and FDR is the HHT-based method, yielding the highest difference between sensitivity and FDR. On the other hand, the CMOR method is the one that provides the highest AUC surface.

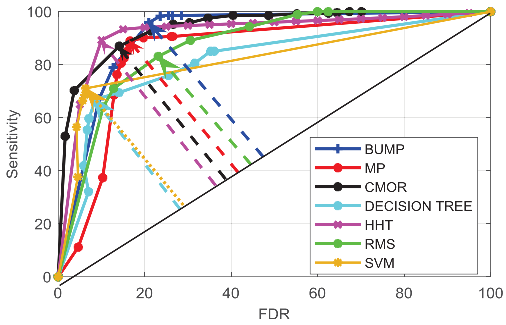

Fig. 3. ROC curves of different HFOs-detection techniques.

Another finding in this study is that the BUMP method achieves a high sensitivity (near to 98%) with a FDR around 23%. One advantage of the proposed SVM method compared to other techniques is that it provides the lowest false detection rate (FDR = 6.36**%**) when considering the point of tradeoff. However, the main limitation of the current implementation of SVM method concerns its sensitivity (71.06%), which is particularly lower than that of RMS, CMOR, BUMP, HHT and MP methods even if it is higher than that provided by the DECISION TREE algorithm. As a final finding, the fastest approach in terms of execution time is the RMS method and the slowest one is the BUMP based method.

V. Conclusion

HFOs are an accurate functional indicator for delineating the epileptogenic tissue in the case of patients suffering from drug resistant epilepsy. In addition, HFOs have provided effective information and become a relevant biomarker to understand some fundamental mechanisms related to epileptogenicity and seizures. Therefore, in recent past years studying HFOs has gained an increasing interest. In the literature, some studies have focused on the understanding of epileptic phenomena, whereas other ones have dealt with methodological and technical detection of HFOs. Highly variable performance has been noted among various studies. The optimal method should meet the following conditions (i) high sensitivity is required in order to detect correctly all true HFOs events, (ii) false detection should be reduced, (iii) running time should be fast enough and (iv) the approach should not be sensitive to transient activities without oscillations (spurious HFOs) [20]. These requirements are difficult to fulfill simultaneously, and a tradeoff between sensitivity and FDR is usually unavoidable. All tested methods in our framework present a tradeoff between sensitivity and FDR which can change from one method to another. The best method that performs well is HHT based method with an acceptable execution time.

Table 2. Performance of the seven tested methods

Technique	Sensitivity (%)	FDR (%)	AUC	ET (s) for processing 4s EEG signal
RMS	83.14	23.13	0.8723	0.3682
CMOR	87.00	14.12	0.9406	0.7081
BUMP	95.86	20.96	0.9116	8612.1305
MP	88.93	16.62	0.8496	378.1382
HHT	92.56	10.57	0.9220	4.6248
DECISION TREE	66.96	8.62	0.8208	37.8542
SVM	**71.06**	**6.36**	**0.8219**	**38.7676**

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