Spike-and-Wave detection in epileptic signals using cross-correlation and decision trees

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***Abstract*— Identify spike-and-waves patterns in epileptic signals is a typical problem in electroencephalographic (EEG) signal processing. In this paper we propose cross-correlation coupled with decision tree model as new method in order to assess and detect spike-and-wave discharges (SWD) in long-term epileptic signals. The proposed approach is demonstrated in terms of accuracy, sensitivity and specificity classification on real EEG signals using a database developed with medical annotations.**

***Keywords*— Spike-and-waves, Pattern Recognition, EEG, Cross-Correlation, Decision Tree, Epilepsy.**

***Resumen*— Identificar patrones de pico-y-onda en señales epilépticas es un problema típico en el procesamiento de señales electroencefalográficas (EEG). En este trabajo proponemos la correlación-cruzada junto con el modelo de árbol de decisión como un nuevo método para evaluar y detectar descargas de pico-y-onda (SWD) en señales epilépticas a largo-plazo. El enfoque propuesto se demuestra en términos de precisión, sensibilidad y especificidad durante la clasificación en señales de reales EEG, utilizando una base de datos desarrollada con anotaciones médicas.**

***Palabras clave*— Pico-y-onda, Reconocimiento de Patrones, EEG, Correlación-Cruzada, Arboles de Decisión, Epilepsia.**

I. Introduction

The International League Against Epilepsy (ILAE) [1] defines epileptic seizure as a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain. Electroencephalography (EEG) is a non-invasive and widely available biomedical modality that is used to diagnose epilepsy and plan treatment; neurologists trained in EEG are able to properly determine epilepsy diagnose. They visually identify its onset and presence through the analysis characteristic waveforms, known as spikes, associated with epileptic seizures, which include: mode of onset and termination, clinical manifestations, and abnormal enhanced synchrony [2]. A spike is characterized by short bursts of high amplitude, synchronized and multi-phasic activity, in which polarity changes occur several times, which manifest themselves at or around the epileptic focus and stand out from the background EEG [3]. A spike-and-wave discharge (SWD), see Figure 1, is a regular, symmetrical, generalized EEG pattern seen particularly during absence epilepsy; its detection is a typical problem in bioengineering and it has been addressed in various research works such as [4]–[6].

Spike-and-wave detection fits into the broad framework of decisions support systems analysis: typical features into relevant information for tasks such as classification, regression, density estimation, and clustering [7]. In this study we will focus on a decision tree, it is a hierarchical data structure implementing the divide-and-conquer strategy. It is an efficient nonparametric method, which can be used for both classification and regression [8]. See [9]–[12] for some works in epileptic signals.

In this work, we create a database with 96 spike-and-waves from different EEG raws and we estimate the spike-and-wave

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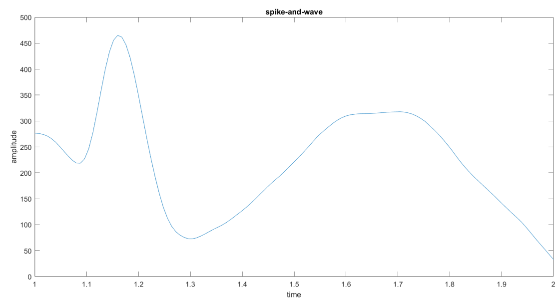

Fig. 1. Spike-and-wave waveform example from annotated database. x axis is time and y axis is amplitud in mV.

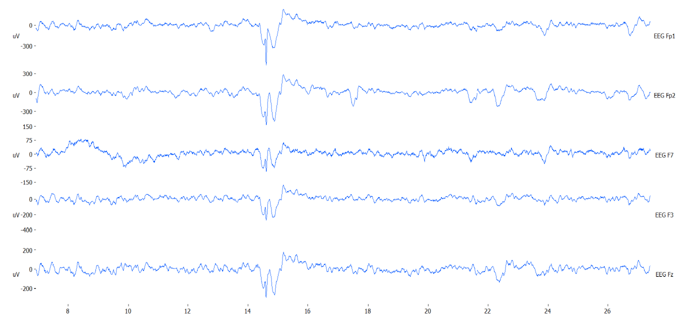

Fig. 2. Spike-and-waves in one EEG epoch, we can see the waveform occurrence at second 15 in all channels. x axis is time and y axis is amplitud in mV.

detection in two EEG long-term epileptic signals, see Figure 2. For this estimation, we compare the waveforms in all channels of EEG with each spike-and-wave of the database using a cross-correlation coefficient.

The greater cross-correlation coefficient absolute number, more similar the waveforms are, so only the ones with the higher coefficients are spike-and-waves candidates. These are then ordered in a matrix, such that the similarity with the waveforms found in the database is greater than 40% of the total, with at least one-second distance between the candidates. Next, a spike-and-wave classification using k-fold cross-validation through the decision tree is estimated in terms of accuracy, sensitivity and specificity values.

The preliminary test suggests that this methodology is potentially useful for effectively detecting spike-and-wave discharges in epileptic seizures with an accuracy of 97% with 86% and 98% values on sensibility and specificity respectively. The remain of this document is structured as follows. Spike-and-wave is introduced in section II, then the proposed methodology is explained in Section III, next in Section IV the decision tree is introduced, in Section V the methodology is demonstrated on real EEG epileptic signals. Discussions and conclusions are finally reported in Section VI.

II. Spike-and-wave discharge

The spike-and-wave pattern seen during an absence seizure is the result of a bilateral synchronous firing of neurons ranging from the neocortex to the thalamus, along the thalamocortical network [13]. Absence Seizures are more common in children. It causes lapses in awareness, sometimes with staring and it can be so brief they sometimes are mistaken for daydreaming and may not be detected for months. Children between the ages of three and seven exhibit continuous spike-and-wave discharges during slow-sleep. This disorder is found in 0.2%-0.5% of all child epilepsy cases. Spike-and-wave activity occupies about 85% of the non-rapid eye movement sleep [14]. This continuous pattern during sleep, like other aspects of the spike-and-wave activity, are not completely understood either. However, what is hypothesized is that corticothalamic neuronal network that is involved in oscillating sleep patterns may begin to function as a pathologic discharging source [5]. Since marking the spike-and-wave seizures in long-term EEG recordings manually is a time consuming task, especially if one is interested in the number of occurrences and the duration of each absence seizure, an automatic absence seizure detection method is highly desired. A spike-and-wave discharge detection algorithms can be classified in the following three categories [4]:

1) Algorithms that use the information extracted from changes in the amplitude (magnitude) of the EEG signal when SWD occurs.
2) Detection based on monitoring the energy power in the frequency bands which SWD occupied.
3) Combination of the first two methods together into labeling the SWD activities in the EEG recordings. The threshold, overlapping window technique and band pass filter are commonly used for enhancing the performance of the detection algorithm.

III. Methodology

Let $\widehat{\boldsymbol{X}} \in \mathbb{R}^{N\times M}$ be an EEG raw signal, measured simultaneously on N different channels with 256 Hz of sample rate and $\widehat{\boldsymbol{SW}} \in \mathbb{R}^{1\times P}$ a spike-and-wave pattern database gathered from different EEG signals $\widehat{\boldsymbol{X}}$, given by

$$\widehat{\boldsymbol{X}} = [x_1, x_2, ..., x_m, ..., x_N]^T \quad with \quad 1 \leq m \leq N \quad (1)$$
$$\widehat{\boldsymbol{SW}} = [sw_1, sw_2, ..., sw_p, ..., sw_P] \quad with \quad 1 \leq p \leq P \quad (2)$$

where $N = 23$ and $P = 96$. The proposed methodology is composed in four stages.
The first stage is the filtering of $\widehat{\boldsymbol{X}}$ and $\widehat{\boldsymbol{SW}}$ using two cascade Butterworth IIR filters in $\mathbb{Z}$ domain with empirical design based on physicians experience, a 2-order lowpass filter with cutoff frequency of 100 Hz and 1-order highpass filter with cutoff frequency of 30 Hz, see eq. 3-4 respectively

$$\boldsymbol{W_{lp}}(z) = \frac{b}{(1-az^{-1})^2} \quad (3)$$
$$\boldsymbol{W_{hp}}(z) = \frac{b(1-z^{-1})}{(1-az^{-1})} \quad (4)$$

Let $\boldsymbol{X}$ and $\boldsymbol{SW}$ be the filtered original signals. Then in the second stage the filtered signal $\boldsymbol{X}$ is splitted into set of non-overlapping 1 seconds segments using a rectangular sliding window so that

$$\boldsymbol{X}^{(i)} = \boldsymbol{\Omega}^{(i)}\boldsymbol{X} \quad (5)$$
$$\boldsymbol{\Omega}^{(i)} = \left[\boldsymbol{0}^{L\times iL}, \boldsymbol{I}^{L\times L}, \boldsymbol{0}^{L\times N-iL-L}\right] \quad (6)$$

where $\boldsymbol{0}^{N\times M} \in \mathbb{R}^{N\times M}$ is the null matrix, $\boldsymbol{I}^{N\times N} \in \mathbb{R}^{N\times N}$ is the identity matrix and L is the number of measurement obtained in 1 seconds.
In the third stage, a cross-correlation is used to find the best match between the two signals $\boldsymbol{X}^{(i)}$ and $\boldsymbol{SW}_p$. Cross-correlation measures the similarity between $\boldsymbol{SW}_p$ and shifted (lagged) copies of $\boldsymbol{X}^{(i)}$ as a function of the lag. Note that $\boldsymbol{X}^{(i)}$ is an EEG $\mathbb{R}^{N\times M}$ matrix and $\boldsymbol{SW}_p$ is a $\mathbb{R}^{1\times P}$ vector which contains all the spike-and-wave to be analyzed, assuming that $i = p = n$ then a cross-correlation $r_{\boldsymbol{X},\boldsymbol{SW}}$ for the displacement in time of each EEG channel with respect to each spike-and-wave is given by

$$r_{\boldsymbol{X},\boldsymbol{SW}}[\tau] = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{X}^{[\tau-n]}\boldsymbol{SW}[n] \quad (7)$$

Then waveforms similarity are classified by the local peaks of the absolute value of $r_{\boldsymbol{X},\boldsymbol{SW}}$. Of which, only the peaks greater than a certain threshold given by eq. 8, are considered similar enough. Besides, a minimum distance of 1 second is established between peaks, which means that for this algorithm there could not be more than one SWD per second.

$$\max_{[\boldsymbol{X},\boldsymbol{SW}]^T} \left|r_{\boldsymbol{X},\boldsymbol{SW}[\tau]}\right| - \sigma\left(r_{\boldsymbol{X},\boldsymbol{SW}}[\tau]\right) \quad (8)$$

where $|.|$ is the absolute value and σ is the standard deviation.
Finally in fourth stage, a spike-and-wave candidates are ordered in a $\boldsymbol{C} \in \mathbb{R}^{N\times P}$ matrix, where $N = 23$ channels and $P = 96$ spike-and-waves. Only the candidates which are

similar to at least the 40% of the waveforms found in the database, are kept.

$$P * 40\% \leq [C_{1,1} \leq C_{1,2} \leq ... \leq C_{n,p} \leq ... \leq C_{N,P}] \leq P \tag{9}$$

Last two stages are using as a D-dimensional input vector for decision trees classifier in two regions namely spike-and-wave and non-spike-and-wave. The proposed methodology can be summarized by using the next algorithm:

Data: EEG raw
Result: SWD detection
for *each SWD* **do**
  for *each $\boldsymbol{X}^{(i)}$ for each channel* **do**
    1. Cross-correlation estimation between each SWD and $\boldsymbol{X}^{(i)}$, see eq. (7);
    2. SWDs candidates selection: based-on the waveform similarity and the distance between peaks of 1 second greater than a threshold given by eq. (8);
    3. SWDs: Only the SWDs greater than 40% of the total of coincidences are chosen, see eq. (8) and Figure 4;
    4. Steps 2. and 3. are using as a D-dimensional input vector r for decision trees classifier in two regions namely spike-and-wave and non-spike-and-wave, see Figure 3;
  end
end

Algorithm 1: SWD detection by using cross-correlation and decision trees.

IV. Decision Tree

A decision tree is a hierarchical model for supervised learning whereby the local region is identified in a sequence of recursive splits in a smaller number of steps. A decision tree is composed of internal decision nodes and terminal leaves, see Figure 3. It is defined in a way that there is a single node, called the root, which has no parents, and all other nodes only have one parent. When a node receives an input a specific test, designed for that particular node, is applied to it and one of the branches is taken depending on the outcome. This process starts at the root and is repeated recursively until a leaf node is hit, at which point the leaf's value constitutes the output. Each specific test is a simple function which defines a discriminant in the input space dividing it into smaller regions that are further subdivided as we take a path from the root down. In this manner a complex function is broken into a series of simple decisions by simply writing the tests down as a tree.

Let $\boldsymbol{C}$ be a matrix of input variables. Training data consist of inputs vectors or channels from EEG signal $\boldsymbol{X}$, see section III, along with the corresponding continuous labels $\{t_1, ..., t_N\}$. It begins with a single root node, corresponding to the whole input matrix $\boldsymbol{C}$, then growing the tree by adding nodes one at a time with respect to the threshold $P*40\%$ where the optimal choice of predictive variable is given by the local average of $\boldsymbol{C}$. This is repeated for all possible choices of variable to be split, i.e. all database values from threshold $P * 40\%$ to total

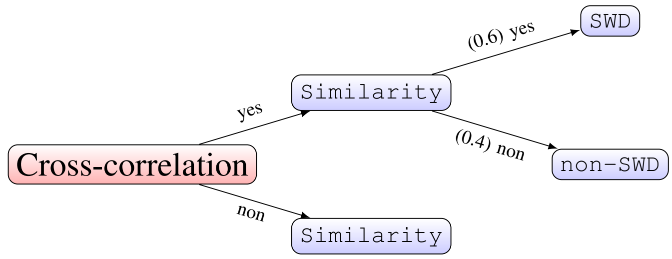

Fig. 3. A decision tree example. Consider the decision problem as to whether or not to go ahead with a cross-correlation similarity. If we go ahead with the similarity and meets the threshold (0.6), then we have a spike-and-wave candidate; on the other hand, if we don't go ahead with the similarity (0.4) then the threshold is not met and therefore we don't have a spike-and-wave candidate. Note that, this tree has only two regions given by the similarity threshold for SWD or non-SWD.

P-candidates; and the one that gives the smallest residual sum-of-squares error is retained.

We now introduce the detection trees in general form using the methodology from [16]. The goal is to predict a single target variable t from a D-dimensional vector $r = (r_1, ..., r_D)^T$ of input variables related to the cross-correlation in our study. The training data consists of input vectors $\{r_1, \cdots, r_N\}$ along with the corresponding continuous labels $\{t_1, ..., t_N\}$. If the partitioning of the input space is given, and we minimize the sum-of-squares error function, then the optimal value of the predictive variable within any given region is just given by the average of the values of t_n for those data points that fall in that region, two regions or classes in our case spike-and-wave or non-spike-and-wave, see Figure 4. To determine the structure of the decision tree, the first step is start with a single root node, corresponding to the whole input space, and then growing the tree by adding nodes one at a time. At each step there will be some number of candidate regions in input space that can be split, corresponding to the addition of a pair of leaf nodes to the existing tree. For each of these, there is a choice of which of the D input variables to split, as well as the value of the threshold. For a given choice of split variable and threshold, the optimal choice of predictive variable is given by the local average of the data. This is repeated for all possible choices of the variable to be split, and the one that gives the smallest residual sum-of-squares error is retained. The stopping of the addition of nodes, is related to the number of data points associated with the leaf nodes, to then prune back the resulting tree. The pruning is based on a criterion that balances residual error against a measure of model complexity. For example, if we denote the starting tree for pruning by T_0, then we define $T \subset T_0$ to be a subtree of T_0 if it can be obtained by pruning nodes from T_0. Suppose the leaf nodes are indexed by $\tau = 1, \cdots, |T|$, with leaf node τ representing a region $\mathcal{R}_\tau$ of input space having N_τ datapoints, and $|T|$ denoting the total number of leaf nodes. The optimal prediction for region $\mathcal{R}_\tau$ is then given by

$$y_\tau = \frac{1}{N_\tau} \sum_{r_n \in \mathcal{R}_T} t_n \tag{10}$$

and the corresponding contribution to the residual sum-of-squares is given by

$$Q_\tau(T) = \sum_{r_n \in \mathcal{R}_T} \{t_n - y_\tau\}^2. \tag{11}$$

The pruning criterion is then given by

$$C(T) = \sum_{\tau=1}^{|T|} Q_\tau(T) + \lambda|T| \tag{12}$$

The regularization parameter λ determines the trade-off between the overall residual sum-of-squares error and the complexity of the model as measured by the number $|T|$ of leaf nodes, and its value is chosen by cross-validation. For classification problems, the process of growing and pruning the tree is similar, except that the sum-of-squares error is replaced by a more appropriate measure of performance of the Gini index for a binary classifier, defining $p_{\tau k}$ to be the proportion of data points in region $\mathcal{R}\mathcal{T}$ assigned to class k, where $k = 1, \cdots, K$, in our case we have two classes spike-and-wave and non-spike-and-wave, see eq. (13).

$$Q_\tau(T) = \sum_{k=1}^{K} p_{\tau k}(1 - p_{\tau k}). \tag{13}$$

For a detailed explanation on decision tree, we refer the reader to [8], [15], [16].

V. Results

We evaluate the performance of the proposed seizure detector in two epochs of 40 and 60 seconds, see Figure 4, which correspond to sleep long-term epileptic signals recordings of one patient at Fundación contra las Enfermedades Neurológicas Infantiles (FLENI). The recordings have 23 channels and were made in a routine clinical environment, so non-seizure activity and artifacts such as head/body movement, chewing, blinking, early stages of sleep, and electrode pops/movement are present in the data.

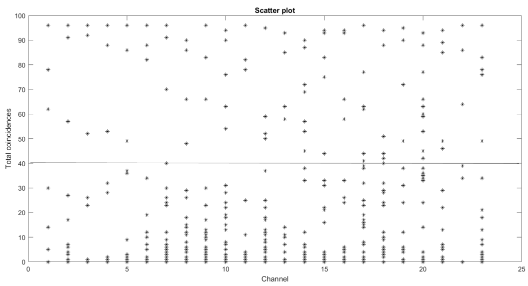

Fig. 4. Scatter plot example between all 23 channels (x axis) and the total coincidences (y axis) into database, the line in 40 is the threshold used.

We compare the medical annotate data with our cross-correlation classifier, and using 10 and 20 empirical K-fold cross-validation through decision tree to evaluate how our results can be generalize to an independent data set. We found an accuracy of 97% in 874 predictors corresponding to all database candidates from two EEG epochs with 23 channels, with 86% sensitivity and 98% specificity for spike-and-waves detection in long-term epileptic signals, see classifier performance in ROC Figure 5.

VI. Discussion and conclusions

This paper presented a new method to detect spikes-and-waves events in EEG signals. The method is based on cross-correlation coupled with decision trees. The performance was evaluated on real data in two epochs of long-term EEG signals using a database containing 96 spike-and-wave signals from different patients. Detection has 97% of accuracy, with 86% of sensitivity and 86% of specificity for spike-and-wave detection. Preliminary results reported in this work suggest that the proposed methodology is potentially useful for spike-and-wave detection in EEG long-term signals in epilepsy.

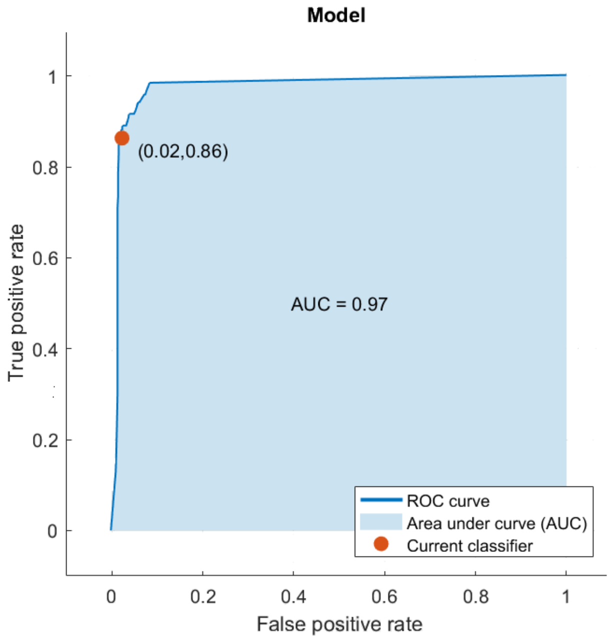

Fig. 5. Receiver operating characteristic curve (ROC) in 874 predictors

Perspective for future work includes an extensive evaluation of the proposed methodology, Implement other regularization parameter algorithms to improve sensitivity and/or specificity, as well as performing comparisons with other detection methods from the state of the art, statistical measures performance, and spectral, Time-frequency and wavelet analysis.

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