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A versatile EEG spike detector with multivariate matrix of features based on the linear discriminant analysis, combined wavelets, and descriptors

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ABSTRACT

The wavelet transform has been used together with many types of classifiers for processing and detecting epilepsy patterns (spikes) in electroencephalographic signals (EEG) in the last 2 decades. A new improved detector architecture is proposed that applies a combination of wavelets and descriptors in a multivariate matrix of features to extract and enhance discriminatory information of spikes. The number of extracted features is reduced by linear discriminant analysis (LDA) that always determines a one-dimensional matrix containing distributions of spike and non-spike samples. A simple linear classifier is used after LDA for binary classification. The area under the curve (AUC) drawn by the receiver operating characteristics (ROC) is used as index to compare performance among different classifier configurations. The result is a classifier architecture that has an AUC index of 0.9941 representing sensitivity and specificity of 97.37% and 97.21%, respectively. The proposed architecture allows different configurations to be tested without changing the classifier architecture and its training is done without iteration.

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1. Introduction

The principle of EEG exams is to record electric brain activity using scalp electrodes. During EEG exams of patients with epilepsy, specific bioelectric signals like spike and sharp wave are observable. The presence of these events in EEG signal defines a clinical diagnosis of epilepsy. The spike has a duration between 20 and 70 ms, and the sharp wave has a duration ranging from 70 to 200 ms [17].

Researchers in the last 2 decades made an effort to use the wavelet transform (WT) for processing, denoising, and detecting spikes in EEG signals. During this period, many wavelet families were proposed like Daubechies series 2 to 8, Coiflet, or Biorthogonal, being the most used by researchers to detect EEG spikes [2,5,8,11,16,18], however, there is no agreement of which wavelet is the most appropriate to enhance EEG spike detection, or how many decompositions of the WT are necessary. Experimental results are needed to assert wavelets for a specific signal [9,25].

After the signal decomposition by the WT, descriptors are used to extract discriminant features (such as maximum, minimum, mean and standard deviation values, and the approximate entropy coefficient) from the decomposed signal coefficients [2,9,12,18,25–27]. The extracted features may be interpreted as a multidimensional matrix, that represents the signature of the signal being processed [4].

The more features extracted to represent a signal, the higher the dimensionality of the matrix. The matrix of discriminant features might have its dimensionality reduced through principal component analysis (PCA), independent component analisys (ICA), or linear discriminant analysis (LDA) [1,8,18,24], and then used as input data for an EEG signal classifier, such as artificial neural networks [18,22,23], fuzzy logic [10,21], or support vector machine (SVM) [18,28].

From the studies in the literature, it is possible to see a large number of experiments involving different types of wavelets, descriptors, and architectures of classifiers. The achieved sensitivity and specificity from these studies range from 70% to 97.3%.

The novelty of this work is a new improved classifier architecture based on the linear discriminant analysis (LDA), combining wavelets and descriptors to enhance EEG spike detection. Differently from the studies in the literature, the proposed classifier does not implement a prediction phase, being able to classify spikes just after the LDA processing. The classifier was assessed comparing

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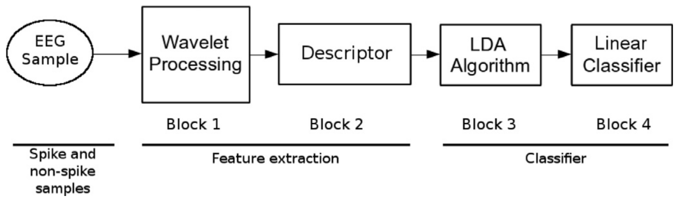

Fig. 1. The classifier block diagram divided into 4 main steps: (1) EEG signal decomposition by WT; (2) feature extraction by descriptors; (3) LDA processing; (4) selection of a spike or non-spike sample by a simple linear classifier.

performance of 98 different wavelets and 14 descriptors, finding among them the best combination, achieving a sensitivity of 97.37% and a specificity of 97.21%.

2. Methods

2.1. EEG signal

The signal was obtained using scalp EEG in international standard 10–20 electrode montage from different 24 h exams made available by the Pequeno Príncipe Hospital, Curitiba city, Brazil. The signals were sampled at 200 Hz and filtered by a notch filter at the mains power frequency and a low-pass filter with cut-off frequency of 70 Hz. The low-pass filter used is equivalent to a Butterworth filter of second order with −40 dB/decade.

A neurologist selected 494 non-correlated EEG spikes from different channels. The selected spikes were recorded in sample vectors of 2 s of duration and denoted as spike samples, S_n. The spikes varies between 60 and 200 ms (sharp-waves) and were recorded with the spike centred in the sample vector. Additionally, 1500 sample vectors of 2 s containing normal brain activity were selected and recorded from seizure free sections, being named as non-spike samples, P_m. This study was approved by the Research Ethics Committee of the Pequeno Príncipe Hospital.

2.2. The new proposed detector

The block diagram of the new proposed EEG spike detector is presented in Fig. 1. The EEG samples are processed by a combination of wavelets in block 1, using 5 levels of decomposition: D1, D2, D3, D4, and D5. Descriptors are calculated in block 2 for each decomposition level of each wavelet used in block 1. The result of block 2 is a multidimensional matrix of features that will be processed by LDA in block 3. LDA rotates the matrix of features, determining a one-dimensional projection where discriminant features will keep the best separability between classes. In block 4, over the distributions of the one-dimensional matrix, a linear classifier is applied, detecting spike samples from non-spike samples.

The software used for this work was entirely written in Java language. No third-party software has been used.

2.3. The wavelet selection

The WT was introduced by Mallat [14] to decompose non-periodic signals in time and frequency. Each decomposition refers to a specific range of frequencies. The WT decomposes signal frequencies in coefficients called “approximation” and “details” and put them on their respective position in time [3,15]. Discrete implementations of the wavelet transform (DWT) were programmed and assessed in a dedicated software for this work.

In our study, 98 wavelets were assessed to select the best one that enhances the EEG spike detection. The wavelets assessed

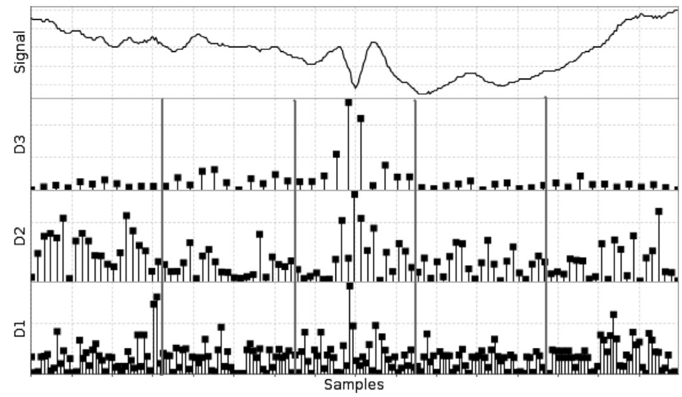

Fig. 2. The signal has a spike sample centred in window. D1, D2, and D3 are 3 detail decompositions of WT Daubechies series 3 (DB3). To calculate the **centred energy** descriptor, coefficients of a decomposition level are divided into 5 groups as shown by the vertical lines.

are (detailed explanation of those wavelets is described elsewhere [15]):

- Daubechies series 1 to 38 (38 wavelets);
- Symlets series 2 to 20 (19 wavelets);
- Biorthogonal 11, 13, 15, 22, 24, 26, 28, 31, 33, 35, 37, 39, 44, 55, and 68 (15 wavelets);
- Reverse biorthogonal 11, 13, 15, 22, 24, 26, 28, 31, 33, 35, 37, 39, 44, 55, and 68 (15 wavelets);
- Coiflet series 1 to 5 (5 wavelets);
- Legendre 2, 4, and 6 (3 wavelets); and
- Haar, Haar Orthogonal, and Dmeyer (3 wavelets).

All spike samples were decomposed by each one of those wavelets in 5 decomposition levels. A comparison of mean energy value per decomposition level was performed among the wavelets. The wavelets with higher energy values were then applied to the proposed algorithm and their performance was assessed.

2.4. The descriptor selection

Descriptors are used to extract features to distinguish between spike and non-spike samples from the decomposed EEG signal by the WT.

In this work, 13 descriptors were considered for the proposed architecture: Approximate Entropy (ApEn) [20,27], Energy, Standard Deviation, Max Value, Min Value, Mean, Variation, Median, Mode, Norm, Range, Average Power, Root Mean Square, and a new developed descriptor named Centred Energy.

About the centred energy, Fig. 2 presents an EEG spike sample centered in the sampling vector. D1, D2, and D3 are the 3 decomposed detail coefficients obtained by WT using Daubechies series 3 (DB3). It is possible to observe high coefficient values in the same region of the spike sample. To determine the centred energy, each decomposition level is divided into 5 groups, denoted by the vertical lines in Fig. 2. The ratio between the energy of the central group of a decomposition level and the entire energy of the same decomposition level is calculated.

Eq. (1) determines the centred energy of a vector S_i with N samples where $i = 1, 2, \ldots, N$. S_i is any decomposition level of the signal processed by WT. The idea of this descriptor is to highlight samples whose coefficients showed a higher value compared with neighboring coefficients, thus identifying samples that were probably identified by wavelet transform compared with the

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