Typical Absence Epilepsy Identification on EEG

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Abstract—This paper describes the methodology and results obtained from the classification of EEG signals in two groups: 1) Patients with typical absence seizure; 2) Patients with other kind of epilepsy or healthy. Three main techniques were applied to identify the morphological features from EEG signals in order to evaluate recordings without having to train a model using a database: Continuous Wavelet Transform, Competitive Neural Networks and Correlation. An interface was developed to include clinical information in order to create an auxiliary system for the identification of absence epilepsy. Data from 24 patients, with different types of epilepsy and non-epileptic, were analyzed, and all of them were correctly classified. The system can be used as auxiliary in the identification of typical absence epilepsy either in clinic or in education.

Keywords—Continous wavelet transform, neural network, automated diagnosis, EEG signal processing, Spike-slow wave complex, absence epileptic seizures

I. INTRODUCTION

Epilepsy is a public health problem. It is a central nervous system disorder in which brain activity becomes abnormal, causing seizures, or periods of unusual behavior, sensations or loss of awareness.

Typical absence epilepsy is a type of epilepsy that causes a short period of awareness, with immediate recovery. It does not cause muscle movements. During the seizure, patient is unable to be aware of its surrounding. This kind of epilepsy is more common in children and adolescents. It is called “petit mal” as it does not cause severe injuries in patients such as myoclonic seizures. However, 40% of patients that do not receive treatment, develop epilepsy with convulsions [1].

Typical absence seizure (TAS) can be identified on EEG by the spike-slow wave complex. It is formed by a spike followed by a slow wave. The frequency of the complex is between 3 and 4 Hz [2] [3] [4]. It is a generalized onset seizure: it starts in both sides of the brain at the same time.

EEG is commonly used for epilepsy diagnosis as it is a non-invasive method that allows us to analyze the electrical cerebral activity [4]. The standard international system to obtain EEG clinical recordings is the 10-20, which consists of 19 channels and a referential point. These recordings typically have a duration between 20 and 40 minutes.

Neurologists commonly analyze, visually, 19 channels at the same time in intervals of 10 seconds, which demands too much attention and time. Furthermore, there are some cases in which patients need to be monitored for 24 hours or even weeks [5]. During the analysis, neurologists need to observe signal features at the same time, paying attention to signal amplitude and the main frequency components.

Neurologists need to learn and get familiar with EEG waves to be able to identify patterns. This ability is acquired by experience [6]. According to a research, complexity to identify epilepsy is variable depending on the kind of epilepsy, getting better results for epilepsy with convulsions, and intermediate for absence epilepsy. Neurologists might give an inaccurately diagnosis due to a lack of experience and fatigue can also lead into signals misclassification [7].

An accurately diagnosis in an early stage is important as it is necessary that patients receive an appropriate treatment.

In order to classify correctly a seizure, it is necessary to know the differences with the rest of the seizures, concentrating in the search of those features that allow the automatic detection employing signal processing and artificial intelligence techniques. Therefore, a complete classification of epileptic seizures was made as depicted in Figs. 1, 2 and 3.

Each epileptic seizure is related to different wave forms. Table I shows different abnormal patterns that can be found in an EEG recording that have similar morphology.

Inside the EEG recordings, it is possible to find similar patterns of typical absence seizure but with a different clinical diagnostic. Table II presents a comparison between some of them and their characteristics.

Fig. 1. Epileptic seizures classification according to its cortical distribution.
The objective of the presented work is to describe a methodology to identify TAS in EEG using Continuous Wavelet Transform (CWT) and Competitive neural networks. 

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**TABLE I.** ABNORMAL EEG PATTERNS (MODIFIED FROM [8]).

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Description</th>
<th>Cortical distribution</th>
<th>Symptoms</th>
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<tr>
<td>Myoclonic</td>
<td>Bilateral muscle jerks. Without loss of consciousness.</td>
<td>Bilateral</td>
<td>Sleepless or sleepy</td>
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<tr>
<td>Clonic</td>
<td>Rhythmic movements.</td>
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<td>Tonic</td>
<td>Body stiffness.</td>
<td>Bilateral</td>
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</tr>
<tr>
<td>Tonic-clonic</td>
<td>Loss of consciousness. Gradual recovery.</td>
<td>Bilateral</td>
<td>Sleepless or sleepy</td>
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<tr>
<td>Atonic</td>
<td>Loss of muscle tone. Loss of consciousness. Immediate recovery.</td>
<td>Bilateral</td>
<td>Sleepless or sleepy</td>
</tr>
<tr>
<td>Absence</td>
<td>Loss of consciousness. Immediate recovery.</td>
<td>Bilateral</td>
<td>Sleepless or sleepy</td>
</tr>
</tbody>
</table>

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**TABLE II.** EEG PATTERNS WITH FEATURES SIMILAR TO TYPICAL ABSENCE SEIZURE [9] [10] [11] [12] [13] [14].

<table>
<thead>
<tr>
<th>Wave</th>
<th>Clinic description</th>
<th>Freq. (Hz)</th>
<th>Detonating</th>
<th>Age of highest prevalence (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bilateral Hyper-synchronous slow waves</td>
<td>Hyper-synchronization of slow waves caused by hyperventilation</td>
<td>1.5-4</td>
<td>Hyperventilation</td>
<td>8 - 12</td>
</tr>
<tr>
<td>Generalized</td>
<td>Lennox-Gastaut syndrome</td>
<td>2.5</td>
<td>Photostimulation</td>
<td>3 - 19</td>
</tr>
<tr>
<td>Typical absence crisis</td>
<td></td>
<td>3 - 4</td>
<td>Hyperventilation</td>
<td>4 - 14</td>
</tr>
<tr>
<td>Atypical absence crisis</td>
<td></td>
<td>2 &gt;3</td>
<td>Hyperventilation</td>
<td>4 - 14</td>
</tr>
<tr>
<td>Generalized interictal epileptic discharge</td>
<td></td>
<td>3 - 4</td>
<td>Present during sleep</td>
<td>0.3 - 2</td>
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A. Related work

Some authors proposed different methodologies to detect seizures in EEG based on Discrete Wavelet Transform (DWT), combined with neural networks (NN) [15] [16]. Authors in [17] presented a real-time absence seizure prediction algorithm based on Wavelets. The system presented false-positives due to slow-wave-sleep.

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II. Methodology

A. Subjects and data

EEG and medical history of 24 children and adolescents between 3 and 18 years were analyzed. They were obtained according to the tenets of the Declaration of Helsinki by the neuropediatrician Martin Arturo Silva Ramirez, using a Comet-PLUS® Portable EEG recording and Review System from Grass Technologies®, with a 200 Hz sampling rate. The distribution of the electrodes was according to the 10–20 standard under an average assembly. Each recording contains 19 channels and has an average duration of 30 minutes. They were classified in four categories: 1) 4 Patients with Typical Absence Epilepsy; 2) 5 Patients with Atypical Absence epilepsy; 3) 10 Patients with any other kind of epilepsy; 4) 5 Patients nonrelated to any kind of epilepsy.

The specialist inspected and evaluated each recording to score signals and identify seizures. In order to double-check the score, different seizures were randomly shown to the specialist individually. Finally, the specialist reviewed each recording entirely to find epileptic seizures that had been...
In this work the mother wavelet Daubechies 4, shown in Fig. 4 has been frequently used in EEG diagnosis [20] [21] [22] [23]. Distinguished because of its multi-resolution capability, and it identify signal frequencies along the time. This technique is them has a specific frequency range and a variable amplitude. Spike and the slow wave were found separately, as each of them would be at least one channel of each group with a seizure at the same time. These groups are defined as follows:

Group 1= Parietal 1 + Parietal 2
Group 2= Temporal 1 + Temporal 2
Group 3= Frontal 1 + Frontal 2
Group 4= Parietal 1 + Temporal 1 + Frontal
Group 5= Parietal 2 + Temporal 2 + Frontal

C. Continuous Wavelet Transform parameters

In order to identify the spike-slow wave complex, the spike and the slow wave were found separately, as each of them has a specific frequency range and a variable amplitude.

The CWT analyzes signals in time intervals, so we can identify signal frequencies along the time. This technique is distinguished because of its multi-resolution capability, and it has been frequently used in EEG diagnosis [20] [21] [22] [23]. In this work the mother wavelet Daubechies 4, shown in Fig. 5, is proposed to identify spike-slow wave complex, because its morphology has similarity with TAS pattern, shown in Fig. 6, and after testing with other mother wavelets and getting the best correlation. Daubechies 4 has shown good results for EEG analysis in previous works [22] [24] [25] [26].

Based on clinical guidelines, patients who present convulsions are not candidates for typical absence epilepsy, therefore the system sends an alert and does not continue with the analysis for patients that present this symptom.

B. Generalized seizures

The first step consists on extracting all seizures along the whole EEG recording. It was used the “BFEENEEG–Buscador de foco epiléptico en electroencefalograma” software, developed by Ramírez-Fuentes C. A. et al., [18]. It analyzes the complete EEG recording and identifies segments of signals where seizures occur. It generates a matrix where positions of found seizures are marked for each channel.

The next step consists on identifying generalized seizures. The cerebral cortex was sectioned into six regions, and they were labeled to identify which of them were or were not active. Regions are defined in Table III.

To determine if an event is generalized or not, five groups were defined, based on generalized seizure definition [19], there would be at least one channel of each group with a seizure at the same time. These groups are defined as follows:

Group 1= Parietal 1 + Parietal 2
Group 2= Temporal 1 + Temporal 2
Group 3= Frontal 1 + Frontal 2
Group 4= Parietal 1 + Temporal 1 + Frontal
Group 5= Parietal 2 + Temporal 2 + Frontal

TABLE III. SIX CEREBRAL CORTEX REGIONS CONSIDERED FOR GENERALIZED SEIZURES CLASSIFICATION.

<table>
<thead>
<tr>
<th>Region</th>
<th>Label</th>
<th>Positions</th>
</tr>
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<tbody>
<tr>
<td>1 Left parietal lobe</td>
<td>Parietal 1</td>
<td>Fp1, F3</td>
</tr>
<tr>
<td>2 Right parietal lobe</td>
<td>Parietal 2</td>
<td>Fp2, P4</td>
</tr>
<tr>
<td>3 Left temporal lobe</td>
<td>Temporal 1</td>
<td>T3, T5</td>
</tr>
<tr>
<td>4 Right temporal lobe</td>
<td>Temporal 2</td>
<td>T4, T6</td>
</tr>
<tr>
<td>5 Left frontal lobe</td>
<td>Frontal 1</td>
<td>Fp1, F3, F7</td>
</tr>
<tr>
<td>6 Right frontal lobe</td>
<td>Frontal 2</td>
<td>Fp2, F4, F8</td>
</tr>
</tbody>
</table>

We needed to find the optimal number of scales and voices that allows us to discriminate interest frequencies for spikes and slow waves from the rest, considering that a bigger number of voices leads to increased consumption of computational resources and longer processing time. We selected scales from 2 to 6 that corresponds to a range of frequency approximately between 1.56 and 44.64 Hz, calculated from the sample frequency. To choose the number of voices, we generated sinusoidal signals with frequencies between 0.5 and 5 Hz every 0.5 Hz, and evaluate the values obtained from CWT for interest frequencies versus non-interesting frequencies. We chose 6 voices as the optimal number of voices providing the enough resolution to find the patterns without compromising the computational work. We set two frequency ranges: one from 2.4 Hz to 4.9 Hz for slow waves, and another from 15.7 Hz to 25 Hz for spikes.

D. Continuous Wavelet Transform

We aimed to build an intelligent system that didn’t need a data base to set the parameters to classify EEG signals. This means that the system will be able to determine if a patient has or not TAS pattern even if there is not an EEG recording with this seizure in the database. To achieve this, we used a competitive neural network that allows us to discriminate the spike-slow wave complex. The input data to the neural network was the CWT coefficients. This provides information about the dominant frequencies of the analyzed signal.

CWT was calculated for all generalized seizures, the result is shown in Fig. 7: at the top it is shown a segment of a seizure, and the graph at the bottom is the result of CWT. Colors represent the cross-correlation between mother wavelet and the analyzed segment among different frequencies; red means a high correlation and deep blue means the absence of that frequency in the signal in that specific scale/voice.

Obtained values from CWT were normalized by dividing all values by the greatest. Then, spike frequencies and slow
wave frequencies were extracted. The result are two vectors, joined per channel, each one composed from the average of each range, as shown in Fig. 8.

E. Competitive neural network

To discriminate segments with spike-slow wave complex, spikes and slow waves were analyzed separately, by setting two competitive neural networks, each of them with two classes: one class that indicates the presence of the frequency, and another to indicate the absence of that frequency.

As frequencies were normalized, it can be assumed that a value close to zero means the absence of that frequency, while a value close to one means that the frequency is representative for the signal. Based on this assumption, the initial value for a present frequency was set at 0.5, and 0 to the absence of that frequency:

$$C_{\text{Spike}} = \begin{bmatrix} \text{spike} \\ \text{no spike} \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix} \quad (1)$$

$$C_{\text{slow wave}} = \begin{bmatrix} \text{slow wave} \\ \text{no slow wave} \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0 \end{bmatrix} \quad (2)$$

A competitive neural network calculates the similarity measure between the input data $x_i = (x_1, \ldots, x_n)$ and the center $c_i = (c_1, \ldots, c_n)$. In order to measure similarity, we used Euclidean distance $\|x - c_i\|$. The minimum distance $d_{\text{min}}$, represents the highest similarity.

Following the Kohonen rule, we update the index of the closest center using Equation 3

$$C_{\text{new}} = C_{\text{d_{min}}} \cdot (0.1 \times d_{\text{min}}) \quad (3)$$

Given that it is not enough to do it for only one channel because each electrode may have a different amplitude of signal, and this will vary for each patient and each recording., the procedure was repeated along the 19 channels. The result are two new centers, that allows the system to classify regions with spikes and slow waves from the rest.

Using calculated centers, the system classifies seizures and generate a new binary vector for spikes and slow waves, where one means that interest frequencies had been found and zero means that they are not part of the pattern. Using these vectors, we generate the vector of Fig. 9, that is the result of segments of the signal with spikes and slow waves.

F. Distribution of CWT principal components

In the previous section we proved that spike and slow wave frequencies are present in EEG signal. However, it could happen that other frequencies compose the signal.

In this section, the CWT morphology was analyzed to determine if there are other frequencies that compose signals. As we’re looking for spike-slow wave complex, we expect to have only two components.

By using Daubechies 4 as mother wavelet of a CWT, the obtained spectrum is a Gaussian bell-shaped graph, as shown in Fig. 10. In order to verify that seizures have as maximum two principal components, we calculated the correlation between two gaussian bells and the CWT.

To build Gaussian bells, the system looks for the peaks of the curve, Fig. 11. If it finds two or more peaks, it takes the minimum points and chose the one that is closest to the center, to maintain equal Gaussian bells (red circle in Fig. 11). This information is used to generate the “base” of the bell. Then, it takes the maximum peak in each side to use it as mu (red triangles in Fig. 11).

To fit the generated Gaussian bells, the system also calculates the standard deviation of each side of each peak. In Fig. 12 it is presented an example of a CWT obtained from TAS, where spike and slow wave are present at the same time (blue). Generated Gaussian bells (pink and cyan) fit in CWT.
The example shown in Fig. 13 was extracted from a CWT obtained from other kind of epileptic seizures where spikes and slow waves are components of the signal, but they are not the only two principal components. In this case, Gaussian bells do not fit in CWT, so the correlation between them is low. The result of analyzing a segment of this non-TAS signal, is shown in Fig. 14. In this case, the binary classification shows that spike-slow wave complex was not found. We classify signals as spike-slow wave if the correlation between CWT and Gaussian bells are close to one (>85%).

In order to reduce data, in this step the system analyzes only 5 channels, corresponding to the highest value obtained from generated centers in Section E. We expect these channels to have a better-defined Gaussian bell.

G. 3 Hz Frequency

The last TAS characteristic to verify is that spike-slow wave complex has a frequency between 3 and 4 Hz. We looked for spikes in segments where spikes were found with CWT, we measured the time between them, and calculated frequency using the Equation (4), where $T$ represent the time between consecutive spikes:

$$f = \frac{1}{T}$$  (4)

III. RESULTS

The methodology proposed in this paper was tested in the 24 patients, obtaining 100% of correct identification of patients with TAS and all those that do not have TAS, even if they present other types of epilepsy, including atypical absence epilepsy, which is very similar.

The proposed method identifies the presence of spikes and slow waves. Additionally, after analyzing the distribution of principal components in CWT, seizures that have more components than just spikes and slow waves, are classified accurately as not presenting TAS, as in the example shown in Fig. 13, where spike-slow wave complex is not present.

Based on neurological clinic guides and the experience of a neuropediatrician, all seizures from the 24 EEG recordings were analyzed to evaluate the sensitivity and specificity of the system for spike-slow wave pattern. Results are provided in Table IV.

IV. DISCUSSION AND CONCLUSIONS

In this paper we presented 3 techniques to identify features of an EEG signal: CWT, a competitive neural network and correlation. Working together, they allow the identification of the spike-slow wave pattern that characterizes the TAS. The correct identification of the type of seizures depends on the analysis of the EEG signal as well as the clinical information found in the clinical records.

This work goes further than some other related works as it is able to identify not only the presence of a seizure, but to identify a specific kind of seizure. Furthermore, the techniques presented could be used to identify different seizures composed of spikes and slow waves.

The methodology proposed uses unsupervised learning to find the most suitable parameters to classify signals. It presents two principal advantages: 1) it do not need a data base that contains all type of seizures, 2) it increases the accuracy of classification for different patients and even in one same patient, as it adjust parameters to the amplitude of the signals. Comparing with [17], this algorithm was able to discriminate slow waves that are not part of spike-slow wave complex.

The first crucial information was the clear understanding of the classification of the different types of seizures since they share features in the EEG signal, this is the reason of showing Figures 1 and 2 and Tables I and II. It is observed that TAS are generalized type seizures, and among these are found the absence seizures. In turn these have 4 different types.

It is shown in the results that even when other seizures might present the spike-slow wave complex, they cannot be misclassified since the condition of being one after the other, and not overlapped, is verified. Besides, the frequency between 3 and 4 Hz is another condition that will discard the confusion.
Results obtained from 24 patients with different types of epilepsy show that they were correctly identified even when the features are similar. It is also shown in TABLE IV that the system is able to identify them correctly, discarding those that are not from typical absence epilepsy.

The system can be very useful as auxiliary tool for neurologist to have a first glance of the complete recording and also for neurology students, in the practice of identification of these types of seizures.

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REFERENCES


TABLE IV. RESULTS OF EPILEPTIC SEIZURES CLASSIFICATION.

<table>
<thead>
<tr>
<th>Patient</th>
<th>Number of Seizures</th>
<th>Typical absence seizures</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
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