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4 authors, including:

Maritza Mera-Gaona
Universidad del Cauca

Diego M López
Universidad del Cauca

Rubiel Vargas
Universidad del Cauca

Automatic Detection of Epileptic Spike in EEGs of Children using Matched Filter

Maritza Mera[1[0000-0001-8511-213X]], Diego M. López[1[0000-0001-9425-4375]], Rubiel Vargas[2[0000-0003-1548-942X]] and María Miño[3[0000-0001-7612-425X]]

[1] Telematics Department, University of Cauca, Popayán, Colombia
[2] Physics Department, University of Cauca, Popayán, Colombia
[3] Pediatrics Department, University of Cauca, Popayán, Colombia
{maritzag, dmlopez, rubiel,memino}@unicauca.edu.co

Abstract. The Electroencephalogram (EEG) is one of the most used tools for diagnosing Epilepsy. Analyzing EEG, neurologists can identify alterations in brain activity associated with Epilepsy. However, this task is not always easy to perform, because of the duration of the EEGs or the subjectivity of the specialist in detecting alterations. **Aim**: To present an epileptic spike detector based on matched filter for supporting diagnosis of Epilepsy through a tool able to automatically detect spikes in EEG of children. **Results**: The results of the evaluation showed that the developed detector achieved a sensitivity of 89.28 % which is within the range of what has been reported in the literature (82.68% and 94.4%), and a specificity of 99.96%, the later improving the specificity of the best reviewed work. **Conclusions**: Considering the results obtained in the evaluation, the solution becomes an alternative to support the automatic identification of epileptic spikes by neurologists.

Keywords: Matched Filter, Spike detection, Epilepsy, Seizure.

1 Introduction

Reading EEGs by specialists is a task which consumes a lot of effort and time due to the duration of EEG signal recordings. In general, EEG records have durations between 20 and 30 minutes and in some cases the records are even longer (48 or 72 hours), representing one of the main causes of the high cost of diagnosing neurological diseases such as epilepsy [1]. In the same manner, the difficulty of diagnosing this kind of disease increases in developing countries, due to the lack of medical personnel; in countries like Colombia, for example, there is a rate of one neurologist per 200,000 inhabitants [2], as a result, it is difficult to guarantee diagnosis and timely attention to patients. The situation is more worrisome in the case of patients residing in rural areas because the specialists are located in the clinical centers of main cities.

Considering the above mentioned, automatic detection of different abnormal events present in EEG signals arises as an alternative to reduce the reading times of an EEG signal and increase the opportunity of EEG reading services, because once the abnormalities on the signal are identified, the specialist would only have to confirm or denied them.

The automatic reading of EEGs is a field of research in which different approaches have been developed in order to offer tools that facilitate the reading of EEG records, especially for those which are of long duration. In [3], the authors proposed to classify epileptiform events using time-frequency analysis and a random forest-based classifier, achieving an accuracy of 83%. Likewise, in [4] features extracted from wavelet coefficients are used to classify the EEG segments with a 93% sensitivity and specificity. In [5], a tool based on neural networks for the detection of epileptic seizures was developed, accomplishing an accuracy, specificity and sensitivity of 88.67%, 90 % and 95% respectively.

Considering the above, the main challenge of the works that have been developed so far is to improve the percentages of effectiveness and reliability of the detection or classification of epileptic seizures. Due to epileptic discharges do not occur under the same pattern, thus, characterize and classify them under the same model can reduce the effectiveness of detection or classification. Consequently, some investigations have been developed for the identification of specific patterns in order to increase the reliability of the reading.

The objective of this research is to propose an epileptic spike detector based on matched filter for supporting diagnosis of Epilepsy through a tool able to automatically detect spikes in EEG of children. The automatic detection of spikes from an EEG waveform implies the identification of an epileptic spike template.

This paper has been organized as follows: section 2 describes the dataset used to support the development and evaluation of the proposal, theorical description of the Matched Filter and the development of the detector to automatically identify epileptic spikes. In section 3, the experimental evaluation of the sensitivity and specificity of the epileptic spike detector is presented. In section 4 the discussion of the results and contributions are described. Finally, section 5 describes the conclusions of the work.

2 Materials and methods

This section presents a description of the main materials, methods and concepts considered for the implementation of the automatic detection of epileptic spikes in an EEG signal.

2.1 Database

For this research, 100 electroencephalograms from children with suspected epilepsy were collected. This collection was made as part of the Neuromotic project whose general objective is the development of a TeleEEG system to support the diagnosis of epilepsy in rural areas in Colombia [6]. As part of this project, the development of a component to support the reading of EEG by a neurology professional is sought.

In the construction of the dataset and in accordance with bioethics standards, an informed consent was obtained for each EEG record, the aforementioned consent was approved by the Ethics Committee of the Universidad of Cauca, Colombia. Each EEG record was acquired using the BWII EEG device and the BW Analysis software, both developed by Neurovirtual. The device has FDA certification.

Each EEG record was acquired under the electrode positioning system 10-20 [7], considering a sampling rate of 200 samples per second, and an approximate duration of 30 minutes. Some EEG records were taken in patients in the waking state (46 records) and others in sleep (54 records).

Once the records were digitized, they were evaluated by a neuropaediatrician who established the diagnosis. The EEGs diagnosed as abnormal went through an annotation process, in which segments with epileptic alterations were documented describing in detail the beginning and end of an epileptic abnormality.

2.2 Matched Filter

Matched filters are basic signal analysis tools used to extract known waveforms from a signal that has been contaminated with noise [8]. The model used for the extraction or detection of the wave can be seen in Figure 1.

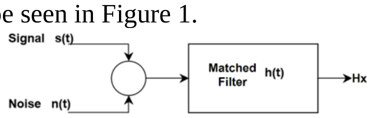


Fig. 1. Detection scheme, after [8].

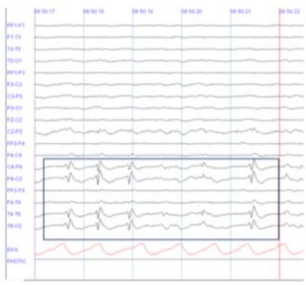
The scheme defined in figure 1 describes the implementation of a filter *h(t)* to extract the signal *s(t)* contaminated with noise *n(t)*, as a result of applying *h(t)* it is obtained the hypothesis H_x. In this scheme, the null (H_0) and alternative (H_1) hypotheses are considered in equations (1) and (2). If the waveform that is sought is present in the signal, hypothesis H_1 is confirmed, otherwise H_0 hypothesis is confirmed. In the context of the detection of epileptic spikes, *x(t)* is a function describing the EEG measured brain activity, the noise *n(t)* represents a normal brain activity of a patient (EEG base rhythm), the signal *s(t)* the epileptic spike to be found, H_0 normal activity of the patient and H_1 the presence of the epileptic spike.

$$H_0 : x(t) = n(t) \tag{1}$$

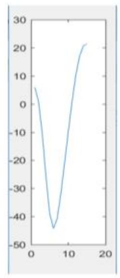
$$H_1 : x(t) = s(t) + n(t) \tag{2}$$

This mechanism works very well in practice when a known pattern or waveform is sought, because the filter allows to maximize the SNR (signal noise ratio) of the filtered signal and reduce the effect of noise on the original signal [9]. However, when waveforms are not known, the method does not work efficiently.

In this work, the development of a tool that supports the diagnosis of epilepsy through the identification of epileptiform events is sought. For this purpose, a review has been made in the literature on characteristic patterns that describe the presence of an epileptic discharge. In this sense, it could be observed that epileptic seizures generate electric shocks on some areas of the brain generating unexpected changes in the waveform of EEGs. In some cases, the appearance of waveforms is identified periodically or semiperiodically or simply the disorganization of the electrical activity of the patient. Some of the most wanted patterns by neurologists during the inspection of EEGs correspond to peaks (narrow and broad). Considering the above, a tool that allows the automatic detection of spikes from an EEG waveform that works as a template is proposed. This template was constructed by averaging 25 segments diagnosed as spikes by a neuropediatric expert in reading EEGs. Figure 2 (a) shows an example of the appearance of epileptic spikes in the base rhythm of the EEG wave on channels 17, 18, 22 and 23 of the EEG.



(b) Epileptic Spikes in the rhythm base.



(b). Epileptic spike pattern.

Fig. 2. Epileptic Spikes in the rhythm base.

From the epileptic spikes detected, the epileptic spike pattern of Figure 2 (b) was constructed. Considering the visual analysis performed by the neurologist, it was defined that the size of the segments of epileptic spikes extracted should contain data of 15 samples, 13.33 ms, in order to capture the data from the beginning of the spike until the end of it.

2.3 Epileptic spike detector

Considering the wave pattern which describes an epileptic spike, a spike detector algorithm was constructed using matched filter and sliding windows over an EEG channel. The algorithm is defined below:

Algorithm 1. Spikes detector.

```
Void SpikesDetector (windowSize, slidingSize, pattern, EEGChannel, spikesBeginnings, spikesEnds, thresh)
    startIndex = 0
    maxIndex = Lenght (EEGChannel)
    b_matchedFilter = createMatchedFilter(pattern)
    while (startIndex< maxIndex) do
        segment = EEGChannel(:, startIndex: maxIndex + windowSize)
        matches = matchedFilter(segment,  template, thresh, b_matchedFilter)
        if (isNotEmpty(matches)) do
            spikesBegginings.Add (startIndex)
            spikesEnds.Add (startIndex+windowSize)
            startIndex = startIndex + slidingSize
        else
            startIndex = startIndex + windowSize
        end if
End SpikesDetector
```

The algorithm receives 7 as arguments, the size of window, size of sliding, pattern, EEG channel, Beginnings and ends of detected segments, and threshold. The size of the window allows determining the start and end of the segment to be analyzed, as well as the size of the sliding allows knowing how many samples move to the right of the beginning of the segment that has been analyzed. The threshold establishes the percentage of similarity between the window analyzed and the template of spikes. Figure 3 illustrates the afore mentioned process.

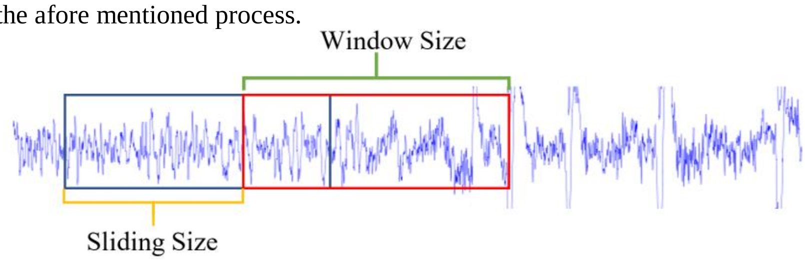


Fig. 3. Analysis scheme by window.

The *pattern* corresponds to the template constructed from the epileptic spikes, *EEGChannel* corresponds to a channel extracted from the EEG in which the pattern will be searched. *spikesBeginnings* and *spikesEnds* correspond to the arrangements where the beginnings and ends of the segments that have presence of the pattern of epileptic spikes are stored, and the function *createMatchedFilter* creates a matched filter based on the template. The algorithm analyzes the entire EEG channel while segments can be extracted through the sliding window, and for each window extracted a review is made with the Matched Filter to determine if this window has the presence of the epileptic spike pattern.

The algorithm that describes the Matched Filter is described below:

Algorithm 2. Matched Filter.

```
Var matches MatchedFilter (segment, template, thresh, b_matchedFilter)
    y = FilterSignal(b_matchedFilter, segment)
    u = template.'*template
    matches = ReviewThreshold (y,thresh,u)
    return matches
End MatchedFilter
```

Where *segment* describes segment to evaluate, *template* represents the epileptic spike pattern, *thresh* sets a detection threshold, which was established empirically in 0.9 by testing values between 0.6 and 1, *b_matchedFilter* contains the matched filter based on template, *y* contains the segment filtered with the matched filter, *u* stores the autocorrelation matrix of the template and function *ReviewThreshold* establishes if *y* exceeds the threshold. The autocorrelation matrix is used for detecting the appearance of patterns in a signal, in this case, the autocorrelation matrix was used for detecting the pattern of spikes in the brain activity.

3 Results

For the evaluation of the epileptic spike detector, 8 segments of EEG records extracted from the dataset of 100 patients were used. The final test used 60 minutes of recording of brain activity, these records were divided into 100 segments with 10 seconds of recording, 8 segments of these contained spikes. Considering the annotations made on the dataset, beginnings and ends of 56 segments in which epileptic discharges occur in the form of a spike are known. In this sense, the spike detector was used for each EEG segment and the correctly identified, badly identified and unidentified segments were counted to determine the sensitivity and specificity of the detection. Figure 4 describes examples of spikes (epilepsy episodes) contained in extracted segment with abnormalities.

Segment 1: 7 spikes

Segment 2: 7 spikes

Segment 3: 6 spikes

Segment 4: 8 spikes

Segment 5: 6 spikes

Segment 6: 7 spikes

Segment 7: 6 spikes

Segment 8: 8 spikes

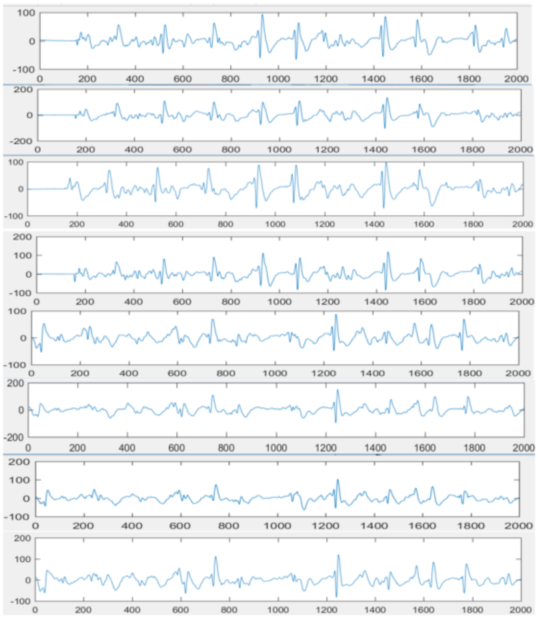


Fig. 4. Description of each segment.

Each segment described in Figure 4 was reviewed by the detector of spikes. The results can be seen in Table 1.

Table 1. Results of the evaluation.

Segment	Real spikes	Spikes detected
S1	7	9
S2	7	29
S3	6	10
S4	8	16

S5	6	6
S6	7	19
S7	6	7
S8	8	14

In the results obtained, it can be seen that the number of spikes detected in each segment is greater than the actual number of spikes. With this in mind, each spike identified by the detector was reviewed to analyze the reason for the error. It was possible to identify that in some cases, a real spike was being identified twice or three times by the detector, due to the reduced size of the sliding window and in other cases, the abrupt fall of the slow waves that occur just after the spike occurrence is also considered by the detector. It is also important to mention that slow waves are also considered an abnormality by the neurologists annotating the EEG. Thus, the spikes detected with close beginnings (difference between beginnings less than 20 samples) were considered as a single one.

Considering the above, Table 2 presents the results of the evaluation eliminating repeated spikes, the detection of slow waves and the number of spikes not detected.

Table 2. Results of the evaluation.

Segment	Real spikes	Detected Spikes	Slow waves	Spikes not detected	Wrong detected spikes
S1	7	7	1	0	0
S2	7	7	12	0	1
S3	6	5	6	1	0
S4	8	7	6	1	0
S5	6	5	1	2	0
S6	7	7	9	0	0
S7	6	4	2	2	0
S8	8	8	5	0	0
TOTAL	**56**	**50**	**42**	**6**	**1**

Considering the results obtained in Table 3, it can be concluded that the built-in epileptic spike detector achieved a sensitivity of 89.28%. To calculate the sensitivity, the size of the segments (2000 samples) and the number of windows that were generated through the sliding window implemented in the detector were considered, which generated for each segment analyzed a total of 369 windows that had to be evaluated. Considering that there were 8 segments analyzed, 2,952 windows were revised, which allows obtaining a specificity of 99.96%

4 Discussion

In this paper, the development of a new mechanism for the automatic detection of epileptic spikes based on the implementation of a matched filter and a template representing the waveform of an epileptic spike is presented. The tool developed reached a sensitivity of 89.28% and specificity of 99.96% in the identification of epileptic spikes on a dataset with EEG records of children.

The construction of the dataset arose as a need to have a set of training data which describes in detail the beginning and end of an epileptic abnormality, due to in the literature there are different datasets that only describe periods of time in which the appearance of an abnormality can be observed and then disorganization or new appearances of the abnormality. One example is the Physionet EEG database [10], which is one of the most widely used pediatric EEG databases. This database does not describe the exact segments of the start and end of specific abnormalities.

The main contribution of this work for the field of neurology is the implementation of a method that automatically detects epileptic spikes with high reliability with respect to the values found in the literature. This could decrease the reading time of EEGs and facilitate the diagnosis of Epilepsy by neurologists. Additionally, the proposed method was tested using real data from a Dataset built by the authors and annotated with the help of a neuropediatrician to document the exact segments where the epileptic abnormalities occur in electroencephalograms.

In previous investigations, many tools have been designed to detect points in EEG signals. The main objective of these in the majority is to reduce the reading time of the specialists, since normally they face large volumes of data [11]. In [12] the authors describe the development of a tool for the detection of epileptic spikes using neural networks, in which a PPV (positive prediction value) of 72.67% and a sensitivity of 82.68% were obtained. In [13], an approach is proposed to analyze the EEG record following a Markov paradigm in order to increase the sensitivity of the detection, however, the result becomes a solution with high computational complexity. In [14] a spike detector developed using analysis of energy and frequency changes is described, for this a SNEO (smoothed nonlinear energy operator) is used for testing different window functions, however, the results were performed using a dataset with animal records and the objective of the tool is to support real-time evaluation of EEGs. In [15] a detector of single spikes and spikes with slow waves is proposed. The results of the evaluation show that the built model improves the accuracy of the classification when the single spikes and spikes with slow waves are considered as different classes, however, the detection is performed in two stages, the first to detect a possible spike and the second one to extract features of the window and classify it as a spike, a spike with a slow wave or not spike, this could imply a greater computational load. In this study, the authors performed several configurations, obtaining a sensitivity between 87.9% and 94.4%, as well as a specificity between 86.7% and 92.3%.

Considering the works reviewed, the solution developed in this study obtained a sensitivity (89.28 %) within the range of what has been reported in the literature (82.68% and 94.4%) and improving with 99.96% the specificity of 93% of the best reviewed work. This as consequence of the good template built for spikes in brain activity of the children and the threshold used for comparing the autocorrelation matrix of the window with the template, which was obtained empirically. Furthermore, it is expected that this proposal reduces the computational load due to it perform fewer stages compared with other approaches.

As future work the characterization of the greatest number of abnormalities associated with epilepsy in order to develop an epileptic event detector that includes abnormalities other than epileptic spikes is proposed. Considering that not all the abnormalities associated with epilepsy can be easily represented in a wave pattern, it is also recommended to include a classification process based on a process of feature extraction through signal processing to support the classification of the segments that cannot be represented through a wave pattern. Finally, the spike detector implemented in this project was tested using EEG records of children, however, this mechanism could be used to detect epileptic spikes in adult patients, since the waveform does not change.

5 Conclusion

This paper described the implementation of an epileptic spike detector through the development of a sliding windowing mechanism that allows to screen an EEG signal window by window and determine whether these correspond to epileptic spikes by comparing a template with each window using a matched filter. The template was constructed from the calculation of the average of 25 segments corresponding to 25 epileptic spikes and the Matched Filter method implemented achieved a sensitivity of 89.28% and a specificity of 99.96%. The main contribution of this work for the field of neurology is the implementation of a method that automatically detects epileptic spikes with high reliability with respect to the values found in the literature. This could potentially decrease the reading time of EEGs and facilitate the diagnosis of Epilepsy by neurologists.

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