Optimizing EEG Energy-based Seizure Detection using Genetic Algorithms

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***Abstract*—Epilepsy is one of the most common neurological conditions, affecting 2.2 million people only in the U.S., causing seizures that can have a very serious impact in affected people's lives, including death. Because of this, there is a remarkable research interest in detecting epilepsy as it occurs, so that it effects and consequences can be mitigated immediately.**

In this paper, we describe and implement an energy-based seizure detection algorithm which runs over electroencephalography (EEG) signals. Because this technique comprises different parameters that significantly affect the detection performance, we will use genetic algorithms (GAs) to optimize these parameters in order to improve the detection accuracy. In this paper, we describe the GA setup, including the encoding and fitness function.

Finally, we evaluate the implemented algorithm with the optimized parameters over a subset of the CHB-MIT Scalp EEG Database, a public data set available in PhysioNet. Results have shown to be very diverse, attaining almost perfect accuracy for some patients with very low false positive rate, but failing to properly detect seizures in others. Thus, the limitations found for energy-based seizure detection are discussed and some actions are proposed to address these issues.

I. Introduction

Epilepsy is a neurological condition characterized by "uncontrolled excessive activity of either part or all of the central nervous system" [1]. A person suffering epilepsy has attacks, also called seizures, resulting from the disruption of the electrical communication between neurons. According to the Epilepsy Foundation [2], epilepsy is the fourth most common neurological condition, only outnumbered by migraine, stroke and Alzheimer's disease. Its incidence (i.e., people developing epilepsy each year) in the U.S. is estimated at 48 for every 100,000 people. The prevalence of epilepsy is estimated at 2.2 millions in the US, or 7.1 for every 1,000 people; and up to 16.5 per 1,000 Americans have reported to had suffered from epilepsy at some point in their lives. The work from Helmers et al. [3] also study the incidence and prevalence of epilepsy in the U.S. based on claims databases from two major health insurance companies, resulting in an estimated prevalence of 8.5 cases per 1,000 people. While these authors also compute incidence rates, they remark that these data might not be reliable. Also, they conclude that incidence shows higher rates for children under 5 years and adults over 60 years. The work from Camfield and Camfield [4] explores the incidence and prevalence of epilepsy in children from a global perspective, concluding that they are higher in underdeveloped countries, and especially in rural areas.

Also, the impact of epilepsy has been thoroughly addressed in the medical literature. The Epilepsy Foundation [5] highlight the main related conditions to be low scholar performance, cognitive or learning difficulties, depresion, anxiety or other mood changes, sleeping problems, unexplained injuries or falls, osteoporosis, reproductive problems or even death. The impact of this medical condition goes beyond the direct effect of seizures, and its consequences on quality of life have been recently addressed by Vaurio et al. [6] or Heersink et al. [7]; and include diminished social support and stigmatization, which can lead to lower employment rates and annual incomes.

While reducing the impact of epilepsy in the affected people's life is an important step, in this paper we are mostly concerned with the direct consequences of epileptic seizures. Some of these consequences are explored by Fisher et al. [8] by surveying affected people, and include major injuries resulting from seizures such as head injuries, broken bones, shoulder dislocation, burns or even a car crash; and more minor injuries such as falls, dropping objects, incontinence, scrapes or hallucinations. A very recent paper by Devinsky et al. published by The Lancet Neurology [9] explores a more serious consequence, namely sudden unexpected death taking place after a seizure.

Because of the high incidence and prevalence of epilepsy, the high negative impact it poses on affected people's lives and the forementioned potential risk during seizures occurrence, there is a high research interest on being able to detect such occurrences. Being able to detect that a seizure is taking place is useful to provide early assistance to the affected person, reducing the risk and impact of the seizure.

In this paper we present an energy-based seizure detection technique that runs over electroencephalography (EEG) signals. Because there are several parameters which are critical to the detection performance, these are optimized using genetic algorithms. Once optimized, this technique is evaluated using a subset of the CHB-MIT Scalp EEG Database, which is publicly available in PhysioNet.

This paper is structured as follows: first, section II provides the biomedical background required to properly understand this paper's contribution, including the structure of EEG data and how it can be used to perform energy-based seizure

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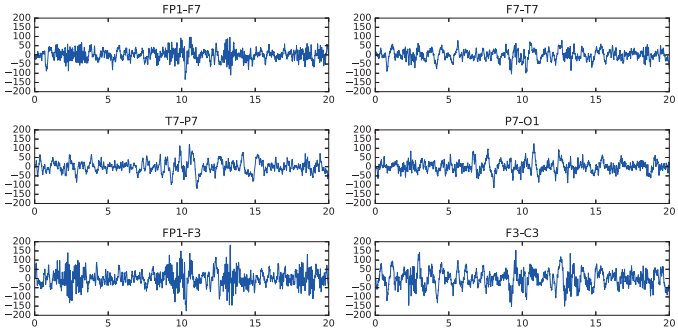


Fig. 1: 20 seconds of six different EEG channels (in μV).

detection. Later in section III, we place this paper into its context by presenting related work, including the state of the art in seizure detection. A thorough description of the energy-based seizure detection algorithm used in this work is presented in section IV, whereas in section V we explain the process for optimizing the parameters of such technique using genetic algorithms, delving into its encoding and fitness function. Since a preliminary evaluation is carried out to validate our proposal, its setup, methodology and results are described in section VI. Finally, in section VII we present some conclusive remarks to summarize the paper and highlight its main accomplishments, while at the same time proposing some future work to keep exploring this research line.

II. Biomedical Background

First of all, it is worth noting that EEG is the name given to both the collection of the waves measured in the brain and the technique used for measuring those waves. We are going to use both terms indistinctly along this paper. With respect to the acquisition technique, the EEG data used in this paper follows the international 10-20 system, which defines the location of scalp electrodes [10]. An example of EEG signals is depicted in figure 1, where the first 20 seconds of the first patient's third session from the CHB-MIT Scalp EEG Database are shown for six different channels.

Brain waves measurements come from the change in potential from neurons. However, it is impossible to record the activity of a single neuron with a surface EEG and therefore its final measurement will correspond to the depolarization and repolarization of thousands or millions of neurons. Notice that neurons must fire synchronously. Hence, the final measurement of the EEG will be the level of excitability of different parts of the brain and the intensity and form of the brain wave will be determined by the number of neurons acting together.

Between the EEG signals it is possible to distinguish different rhythmic activities depending on their frequency. EEG rhythms have been established as follows: Delta Waves (0.5–4Hz) appear during deep sleep and sometimes during some severe organic brain diseases, Theta Waves(4–8Hz) are related with some activity in children but also with emotional stress in adults and they may appear in some neurological diseases as degenerative ones, Alpha Waves (8–13Hz), which are found

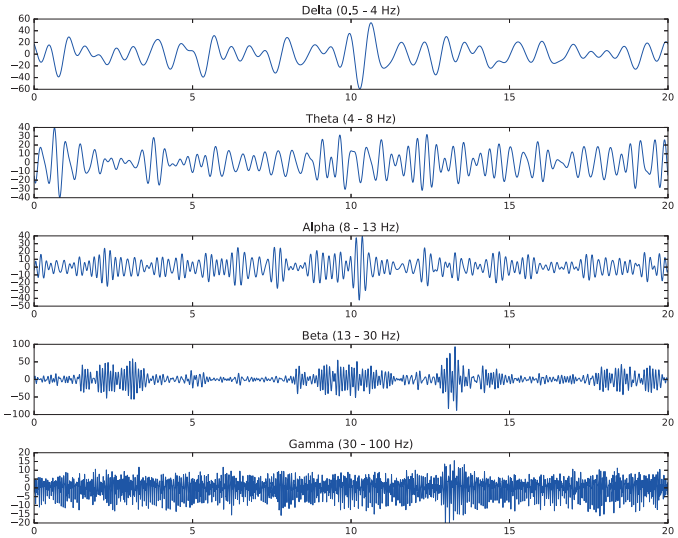


Fig. 2: EEG rhythms corresponding to an EEG channel.

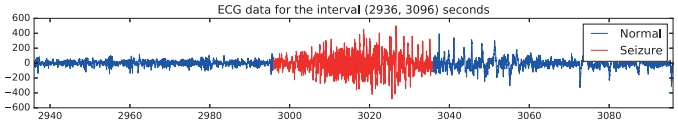


Fig. 3: Normal vs. seizure brain activity in the EEG signal.

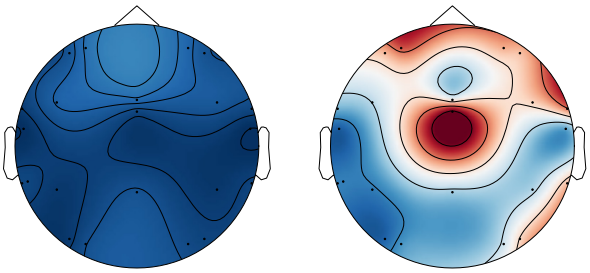
in normal adults when they are awake but relaxed and Beta Waves (13–30Hz), related with any type of mental activity. Gamma Waves (over 30Hz) have been traditionally included in the range of Beta Waves but still now there is no an agreement about their function. These frequency bands are not arbitrary, but rather arose from some specific distribution over the scalp. Figure 2 shows the different rhythms for the first channel shown in figure 1 (FP1-F7) during 20 seconds.

When a seizure occurs, it is often reflected in the EEG signal with a higher electric activity. An example of this effect is shown in figure 3, which plots a portion of an EEG channel where a seizure occurs. The seizure onset and ending is depicted in red, and it is visible how brain activity is much higher during the seizure.

A simple yet effective way of detecting a seizure given the EEG is to compare the energy of a small window (called foreground) with the energy of a much larger window (background). Seizures often last a few seconds, and in most cases they last less than two or three minutes. If the foreground's energy is significantly larger than the background's, then it is likely that the foreground window is part of a seizure. The background window should be long enough to ensure that a seizure is not taking place during all the window's duration.

The energy of a window can be computed as described in Equation 1, where L is the window length, t is the time in the middle of the window and $x(i)$ is the signal value at time i.

$$E(t) = \frac{1}{L} \sum_{i=t-L/2}^{i=t+L/2} x^2(i) \tag{1}$$



(a) Normal activity (b) Seizure

Fig. 4: Topographic map plotting EEG signal energy in two different scenarios for the same patient. Blue means lower energy values; red means higher.

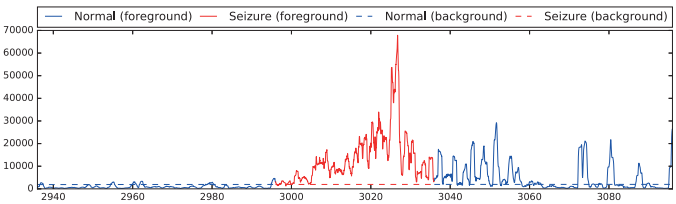


Fig. 5: Energy of foreground (1 sec) and background (10 min) EEG windows.

The topographic map in figure 4 plots the energy during normal brain activity (figure 4a) and during a seizure (figure 4b) over the scalp surface. The difference of energy during normal brain activity and during a seizure can be easily observed in the color code.

Finally, figure 5 compares the energy of a 1-second foreground window and a 10-minutes background window. It can be seen that the background window is unaffected by the seizure, as it comprises a much larger timeframe than the seizure itself, which is declared to last 40 seconds. It is for this reason that comparing the ratio between the two windows is an effective procedure for seizure detection.

However, it can be seen that the end of the seizure is not that clear just looking at the energy values. This is because immediately after the seizure there is often a short period called “postictal period” in which the patient may experiment confusion, before the normal brain activity is recovered. This is not a significant handicap for this work, since it is not an issue if the detection algorithm considers the seizure to be longer than it actually is.

III. Related Work

Due to the impact of epilepsy seizures in society, many studies have been developed in an attempt to perform automatic seizure detection or even more, to predict them. Some of the earliest approaches go back to the 90s with Gotman [11] describing improvements to previous seizure detection algorithms. These improvements considered a larger temporal context and enhanced specificity.

In the recent years, due to the high interest in this research field and the medical advantages it poses, the number of works in automatic seizure detection has grown significantly. When reviewing the literature, it is found that most works use wavelets transforms to carry out this task. Some relevant examples are those by Guo et al., where an artificial neural network is used with entropy features [12] or line length features [13] derived from multiwavelet transforms of the EEG signal; Zandi et al. [14], where wavelet packet transform is computed to quantify the separation of seizure and non-seizure states; Faust et al. [15], where wavelets, non-linear dynamics and neural networks are combined for seizure detection; Chen [16] and [17], where dual-tree complex wavelet transform with Fourier features is explored; Chen et al. [18], where the magnitud of Fourier coefficient with different wavelet scales are used as features and different classification algorithms are tested; Ahammad et al. [19], were wavelet-based features are used for both event and onset detection using a linear classifier; or Abbasi and Esmaeilpour [20], where multi-layer perceptron is used for seizure detection from statistical characteristics obtained from the discrete wavelet transform of the EEG signal.

In other cases, classical machine learning techniques have been used to face the problem of seizure detection. For example, Fergus et al. [21] extract different statistical features from the EEG signal and evaluate their convenience using different rank methods (e.g. principal components analysis or linear discriminant analysis) and classifiers. Shoeb and Guttag [22] have also worked in this problem using spectral, spatial and temporal features. They eventually proposed an application for a vagus nerve stimulation device [23] and an approach to classification using support vector machines (SVM). Also, Temko et al. [24] and Mathieson et al. [25] used SVM to perform onset detection on neonatal patients with features extracted from the power spectrum density of the EEG Fourier transform. Also, Bogaarts et al. [26] used this technique with median decaying memory for EEG dynamic normalization. Finally, Baldassano et al. [27] have proposed the use of hidden Markov models with data from intracranial EEG and tested it in dogs.

Some works have also described approaches where signal energy is key for seizure detection. For example, Correa et al. [28] used a sliding window to compute some energy-based features of the signal. Meanwhile, Fu et al. [29] used Hilbert marginal spectrum analysis to obtain, among others, energy features which are later fed to a support vector machine.

While most of the research works perform seizure detection using EEG signals, some authors have worked in seizure detection using other signals or sources. For example, Lockman et al. [30] propose the use of a wristband with an accelerometer for detecting rhythmic movements, obtaining good accuracy but many false positives. Arends et al. [31] propose a system for detecting seizures using audio recordings, which worked in half of the patients with an intellectual disability. Moreover, Andel et al. [32] compare different non-EEG-based devices for seizure detection, concluding that two of them provide a good tradeoff with high accuracy and low positive rate: a mattress-based detector and a wrist-based detector. A review

of both research and commercial systems for non-EEG seizure detection is provided by Vel et al. [33].

Finally, while seizure detection is a highly interesting research field, there is a much higher interest, yet less advances, in seizure prediction. In 2006, Mormann et al. [34] described the state-of-the-art in the field, pointing out that most promising works up to that moment yielded non-reproducible results, remarking the unpredictable nature of seizures. Ten years later, Mormann and Andrzejak [35] commented on the advances over that decade and Freestone et al. [36] provided some hints for the future. Prior to 2016, Gadhoumi et al. [37] provided a survey of different seizure prediction works in the last decade. Recently, Namazi et al. [38] studied the Hurst exponent and fractal dimension for seizure forecasting, Parvez and Paul [39] proposed a seizure prediction method using undulated features from intracranial EEG signals and Yoo [40] worked on prediction using power spectral densities as features and support vector machines as classifiers.

Despite of the many successful attempts of performing seizure detection, after an extensive review of the state of the art we have found a lack of proposals using EEG energy. This is why in this paper we will focus in a different method for tackling this problem using EEG energy and evaluate its performance.

IV. Methodology

This section describes the seizure detection algorithm, which performs a sequence of stages given an EEG channel. It should be noted that, except for the *channel aggregation* stage, this process is repeated for each channel. The pseudocode for the seizure detection system is shown in algorithm 1.

A. Filtering

The first step involves filtering the signal. A low-pass filter of f_{lo} Hz and a high-pass filter of f_{hi} are applied to the signal. By doing this, only a subset of the signal frequencies are considered. Depending on the values of f_{lo} and f_{hi}, this could leave one or several frequency bands such as those shown in figure 2 (delta, theta, alpha, etc).

Algorithm 1 Pseudocode for the seizure detection system.

procedure DETECT($\mathcal{S}, f_{lo}, f_{hi}, W_{fg}, W_{bg}, \tau_e, d, l_{min}, \tau_c$)
  $seizures \leftarrow$ EMPTYSET()
  for each $ch \in \mathcal{S}$ **do**
    $ch \leftarrow$ LOWPASSFILTER(ch, f_{lo})
    $ch \leftarrow$ HIGHPASSFILTER(ch, f_{hi})
    $fg \leftarrow$ SEGMENT(ch, W_{fg})
    $bg \leftarrow$ SEGMENT(ch, W_{bg})
    $er \leftarrow$ ENERGY(fg)/ENERGY(bg)
    $ss \leftarrow$ GETSEIZURESBYTHRESHOLDING(er, τ_e)
    $ss \leftarrow$ GROUPSEIZURES(ss, d)
    $ss \leftarrow$ FILTEROUTSHORTSEIZURES(ss, l_{min})
    $seizures$.ADDTOSET(ss)
  end for
  $seizures \leftarrow$ AGGREGATECHANNELS($seizures, \tau_c$)
  return $seizures$
end procedure

B. Segmentation

The second steps involves segmenting the EEG signal into windows. As described in section II, in this segmentation process we will obtain windows of two different sizes. The foreground comprises smaller windows will have length W_{fg}, while the background is composed of larger windows with length W_{bg}, where $W_{bg} \gg W_{fg}$.

C. Energy Computation

In this step, the energy is computed in every foreground and background window following Equation 1. Then, the energy ratio is obtained by dividing the foreground energy by the corresponding background window energy.

D. Thresholding

After energy computation, we end up with a time series of energy ratios resulting from the division of the foreground and the background. This time series can be treated as a distribution, where some values are much higher than the average or the median. In this case, we will consider that all ratios that are higher than the $\tau_e\%$ of the values (i.e., those ratios over the τ_e-th percentile) are part of a seizure.

E. Grouping

After thresholding, we have identified ratios in the time series that are part of a seizure. The next step involves grouping all those parts of the time series that are part of a seizure and are closer than d seconds among them. This process is basically building seizures from the different windows, considering that two windows are part of the same seizure if they are located less than d seconds apart one from the other.

Once the windows are grouped, we will remove those seizures that are shorter than l_{min} seconds. This filter is applied in order to remove noise or artifacts virtually increasing the energy, thus leading to false positives.

F. Channel Aggregation

The previous steps are performed for each channel individually. Upon completion, the algorithm has detected a set of seizures for each channel. The final set of detected seizures will result as an agreement between the different channels. To do so, a seizure will only be considered for the final set it has been detected in at least τ_c channels. In that case, if the boundaries of the seizure are different in each channel, then the median boundaries (onset and ending) are chosen.

V. Genetic Optimization

In the previous section we have described the different stages for seizure detection, which comprise different parameters whose values are not known in advance. In this section, we will explain how the different parameters affect the detection performance and describe a genetic algorithm for optimizing their values. The pseudocode for the genetic algorithm is

Algorithm 2 Pseudocode for the genetic algorithm.

```
procedure GeneticAlgorithm(P, t, r_m)
    p ← GenerateRandomPopulation(P)
    while stopCondition = false do
        ComputeFitness(p)
        p_n ← EmptySet
        while size(p_n) < P do
            p_1 ← SelectByTournament(p, t)
            p_2 ← SelectByTournament(p, t)
            os_1, os_2 ← Reproduce(i_1, i_2)
            os_1 ← Mutate(os_1, r_m)
            os_2 ← Mutate(os_2, r_m)
            p_n.AddToSet(os_1, os_2)
        end while
        p ← p_n
    end while
    return GetBestIndividual(p)
end procedure
```

shown in algorithm 2, and the values for its parameters are described in the experimental setup in the next section.

A. Parameters Sensitivity

The parameters that will be optimized using a genetic algorithm are the following:

- f_{lo}: the cutoff frequency of the low-pass filter. Some low frequencies might be irrelevant for seizure detection, but we will work under the assumption that the impact of this value regarding the detection performance is unknown in advance.
- f_{hi}: the cutoff frequency of the high-pass filter. Again, we will not make any prior assumptions on how this parameter affects detection performance.
- W_{fg}: the length of the foreground window. There is not a rule of thumb for estimating the best value for this parameter.
- W_{bg}: the length of the background window. Again, there is not a general rule to know the best value for this parameter, yet it should be much larger than W_{fg}, as small values lead to windows very sensitive to the existence of seizures.
- τ_e: the threshold for considering an energy ratio to be part of a seizure. Very large values will decrease the number of detected seizures (thus increasing the number of false negatives), whereas small values will lead to an increase of false positives. In an extreme case, a value of 0 would consider the whole channel to be a seizure.
- d: the maximum distance (in seconds) for two energy ratios in the time series to be part of the same seizures. Large values might consider two different seizures to be the same. However, small values might have the opposite effect: to consider one seizure to be more than one. This last scenario can cause an additional issue, as if these *sub-seizures* are not as long as l_{min}, then the seizure will not be considered.
- l_{min}: the minimum seizure duration. When this value grows, smaller seizures will not be detected, leading to false negatives. On the other hand, smaller values may cause false positives by considering short artifacts as seizures.
- τ_c: the number of channels in which a seizure must be present in order to be considered a seizure. Increasing this value will reduce the number of detected seizures, with the risk of incurring in false negatives.

Many of these parameters establish a tradeoff between false positives and false negatives. For this reason, it is interesting to search for a combination which increase the detection accuracy, for which we will use genetic algorithms.

B. Encoding

The genetic algorithm's chromosome comprises a binary string with Gray encoding [41], which is convenient as small changes in the genotype are translated into small changes in the phenotype. The chromosome has 41 bits, which encodes the seizure detection parameters as follows:

- f_{lo} is represented using 6 bits, thus $f_{lo} \in [0, 63]$ Hz.
- f_{hi} is represented using 6 bits and the resulting value is subtracted from 256 (which is the frequency of the EEG signals in this work), thus $f_{hi} \in [193, 256]$ Hz.
- W_{fg} is represented using 4 bits, and the parameter value is computed as $0.5 + x/2$, where x is the decimal translation of the 4-bit Gray string; thus $W_{fg} \in [0.5, 8]$ s with a step of 0.5 s.
- W_{bg} is represented using 5 bits, and the parameter value is computed as $60 * (1 + x)$, thus $W_{bg} \in [1, 32]$ min with a step of 1 min.
- τ_e is represented using 6 bits, and the parameter value is computed as $100 - x/10$, thus $\tau_e \in [93.7, 100]$ % with a step of 0.1 %. In a preliminary analysis, we realized that values lower than ~ 94 % significantly increased the number of false positives.
- d is represented using 5 bits, and the parameter value is computed as $1 + x$, thus $d \in [1, 32]$ s with a step of 1 s.
- l_{min} is represented using 5 bits, and the parameter value is computed as $1 + x$, thus $l_{min} \in [1, 32]$ s with a step of 1 s.
- τ_c is represented using 4 bits, and the parameter value is computed as $(1 + x)/16$, thus $\tau_c \in [1/16, 1]$ % with a step of $1/16$ %.

C. Genetic Operators

The implemented genetic algorithm evolves a population of P individual, and carries out a tournament of size t as the selection operator, single-point crossover using a random point as the reproduction operator and random bit flipping as the mutation operator with a probability of r_m. Elitism of 1 individual is introduced to keep the best individual found at each generation in the next population.

D. Fitness Function

When describing the fitness function, it is important to first explain which is the goal to be optimized. It is clear that we want to improve the detection accuracy, but this accuracy can be explained with two different objectives.

In the first place, we want to reduce as much as possible the false positives (FP) and the false negatives (FN). In this work, we have not prioritized false positives over false negatives, as in that case we could end up with many false positives resulting from detecting noise or artifacts as seizures.

In the second place, given the same number of $FP+FN$ we want to increase the boundaries accuracy, i.e., that the detected seizure onset and ending are as accurate as possible compared with the actual seizure.

To compute the fitness function, we need two sets: the set of real seizures and the set of detected seizures. We will establish a mapping between those, where two seizures will match if they overlap. Then, unmatched seizures will be counted as false positives (if they are detected but not real) or false negatives (if they are real but not detected).

For matched seizures, the boundaries error is computed as $e = \sum (|r_o - d_o| + |r_e - d_e|)$, where r_o, d_o, r_e and d_e are the real and detected onsets and endings respectively.

Finally, the fitness function for the genetic algorithm, which must be minimized, is described in Equation 2. The multiplier 10^4 is defined as a large constant factor in order to give more importance to the false positives and false negatives over the boundaries error.

$$f = 10^4 \times (FP + FN) + e \tag{2}$$

A perfect fitness score would be that of $f = 0$, meaning that there are no false positives or false negatives and the matching between the detected seizures and real ones is perfect.

VI. Evaluation

After implementing the seizure detection algorithm and optimizing its parameters, we have carried out experiments to evaluate the detection accuracy obtained by using it. In this section we describe the data set used, the experimental setup and the results obtained, discussing and comparing them with other works in the literature.

A. Data

In this paper we have used the CHB-MIT Scalp EEG Database [42] available for free in PhysioNet [43]. This database comprises EEG recordings from 22 pediatric subjects (5 males aged from 3 to 22 and 17 females aged 1.5 to 19) suffering from intractable seizures, collected at the Children's Hospital of Boston. These recordings were performed days after subjects stopped the intake of anti-seizure medication, in order to check their adequacy for surgical intervention.

There is a total of 24 cases, comprising a total of 664 recordings stored as EDF (European Data Format) files, from which 129 contain at least one seizure. Most of them contain 23 EEG signals, yet some might have a few more. Recording was performed with a sample frequency of 256 Hz and with 16-bit resolution.

TABLE I: Results of the seizure detection algorithm: true positives, false negatives and false positives for each patient, along with total records duration per patient

Patient	TP	FN	FP	Hours	Patient	TP	FN	FP	Hours
chb_01	7	0	0	40.55	**chb_13**	0	9	0	33.00
chb_02	1	1	1	35.27	**chb_14**	0	7	0	26.00
chb_03	4	3	0	38.00	**chb_15**	2	18	1	40.01
chb_04	4	3	0	38.00	**chb_16**	0	10	2	19.00
chb_05	5	0	1	39.00	**chb_17**	2	1	1	21.01
chb_06	0	9	7	66.74	**chb_18**	2	3	4	35.63
chb_07	2	0	2	67.05	**chb_19**	1	1	0	29.93
chb_08	2	3	0	20.01	**chb_20**	2	6	2	27.60
chb_09	3	0	8	67.87	**chb_21**	0	4	0	32.83
chb_10	4	2	2	50.02	**chb_22**	0	3	0	31.00
chb_11	0	2	0	34.79	**chb_23**	4	3	0	26.56
chb_12	0	33	1	23.69	**chb_24**	1	14	0	22.00

Since we want to learn a suitable set of parameters for the proposed energy-based seizure detection algorithm, in this evaluation we will use the first three cases as the training set. The recordings belonging to these cases will be used for fitness computation. The seizure detection performance will be evaluated over the remaining 21 cases. Testing the performance over a test set different from the training set is a common approach for solving machine learning problems, in order to avoid biased results from overfitting the training data.

B. Experimental Setup

The genetic algorithm was run with the next setup: the population size was $P = 100$, the tournament size was $t = 3$ and the mutation rate was set to $r_m = 2\%$. The stop condition was set when the GA best individual did not change over 50 generations.

To speedup the fitness computation, Apache Spark [44] was used. The process was parallelized to run in one physical server with 8 CPU cores, with the recording being the unit of parallelism.

C. Results and Discussion

After evolving the parameters, the genetic algorithm has found the next best combination: $f_{lo} = 5$ Hz, $f_{hi} = 201$ Hz, $W_{fg} = 3$ s, $W_{bg} = 12$ min, $\tau_e = 95.1$ %, $d = 6$ s, $l_{min} = 22$ s, and $\tau_c = 50$ %.

Some of these parameters are quite interesting. For instance, by removing the frequency band under 5 Hz (delta rhythm), we are ignoring those frequencies; which is consistent with the medical knowledge in the literature stating that seizures rarely occur during deep sleep. Also, we will be considering only seizures longer than 22 seconds: while there are some seizures shorter than this threshold, most conform to this condition.

The results of the seizure detection algorithm for each patient are shown in table I. In order to compute the false positive and false negative rates per hour, the table also displays the total patient's recording duration of the EEG signal. It can be seen how the detection algorithm performance largely depends on the patient. For instance, in some patients

the detection accuracy is perfect, having few or none false positives, such as for patients 1, 5 or 7. In contrast, some patients are yielding very low performance: it is remarkable how for patients 6, 12, 15 or 16 no seizures are detected at all, despite the patient suffering from more that 10 seizures in all cases. Besides, the method is detecting very few false positives, with an average of 0.39 per 24 hours, which is better than most of the works in the state of the art.

A closer look at these results may shed some light towards finding the issue: energy-based seizure detection is not a good approach when the patient is having many seizures in a short period of time. This would happen because, given that seizures are the norm rather than the exception in theses cases (with up to 33 episodes in less than 24 hours), the background window is affected by this high energy, blurring the distinction between background and foreground.

There are different potential solutions for tackling this problem. First, the training patients did not have this problem, as seizures occur less often than in most of the problematic patients. Then, incorporating a more diverse set of patients to the training set might lead to a more refined configuration of parameters, better fitting all patients with less extreme cases. This makes sense as, because of how the background and foreground windows are affected when seizures occur with high likelihood, a different value for some parameters such as the energy threshold may have a big impact in the results.

Another possible solution would be to change the fitness function to give more importance to false negatives than false positives. This way, we would increase sensitivity at the cost of decreasing specificity. This is an acceptable tradeoff, as increasing the detection accuracy shall be the first concern.

Finally, another solution could be to learn different parameters for different 'types of patients'. In this approach, we can first cluster patients so that similar ones are grouped together, obtaining different groups. Then, a training set is defined as a random subset within each of these groups, and the genetic algorithm is used to optimize the parameters for each of these groups. This, however, imposes an additional requirement since a metric for establishing the similarity of patients must be defined, this being a critical step for success.

VII. Conclusions and Future Work

In this paper we have presented an approach for energy-based seizure detection using EEG signals, whose parameters have been optimized using genetic algorithms.

To start with, we have explored how seizures affect the energy of EEG signals, showing that a significantly higher energy is achieved during a seizure, which contrasts with a long-term window of the signal, which we identify as the background. This fact suggests that energy can be used for automatic seizure detection, and an algorithm has been developed which compares two windows, a short foreground with a much larger background, in order to detect a seizure in the foreground based on the difference of energy between both windows.

However, this algorithm has eight parameters whose values are difficult to estimate by hand, and there are no medical rule-of-thumb for assigning a value to all of them. For this reason, we have decided to encode all these parameters in a binary chromosome with Gray encoding so that genetic algorithms can evolve the individuals, eventually achieving a parameters setup which is suitable for proper seizure detection.

After evolving the seizure detection parameters, the algorithm is evaluated over the CHB-MIT Scalp EEG Database, a public data set available in PhysioNet comprising 24 pediatric patients. Results show that the algorithm performance is very diverse, ranging from perfect accuracies in some patients to no seizures detected at all for others. In some cases, poor results can be explained as a result of seizures being the norm rather than the exception, blurring the energy boundaries between 'normal' state and seizures. On the other hand, the number of false positives is very small, around 0.39 per 24 hours in average, less than most state-of-the-art works.

These results suggest that energy-based seizure detection may not be adequate for certain patients. Still, some potential solutions are described in the paper, which are left for future work. These include including a more diverse set of patients in the training set, learning different parameters for different groups of patients (after a preliminary clustering stage) or giving a higher weight to false negatives over false positives in the fitness function.

Additional future work to extend this research would be to use evolutionary strategies to evolve the algorithm parameters, encoding them directly as a vector of real values. More interestingly, multiobjective evolutionary algorithms could be used to optimize different objectives. These objectives could be, in order of importance: increasing the accuracy (thus reducing false negatives), reducing false positives and reducing onset errors. Exploring the Pareto front could enable to decide on a tradeoff between the first two objectives. In either case, the fitness function used for computing these metrics could be affected by the suggestions proposed before to improve the performance of energy-based seizure detection.

Finally, as stated in the paper, there is a significant research interest in the prediction of seizures before they occur, with few advances as it turns out to be a difficult medical problem. Once reliable seizure detection algorithms are achieved, most research efforts should be aimed towards addressing this problem, thus making possible prevention and adequate assistance of seizures that are known to occur some minutes ahead.

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