Epileptic Seizure Detection From EEG Signal Using Discrete Wavelet Transform and Ant Colony Classifier

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***Abstract*—Electroencephalogram (EEG) is the electrical signal of brain which contains valuable information about its activities. In this paper, we propose a new approach for the early detection of epileptic seizure in EEG. The proposed approach is based on Discrete Wavelet Transform (DWT) and Ant Colony (AC) Classifier. We started by applying DWT to decompose the EEG signal into its sub-bands to extract the energy ratio from wavelet coefficients. Beside we extract some statistical features from the original signal, and we use the extracted features as the input for the AC algorithm to derive classification rules, which are used to detect epileptic seizures in the EEG of the monitored patient. Our experimental results on real dataset show that our proposed approach achieves a high level of detection accuracy.**

***Index Terms*—Anomaly Detection, Epileptic Seizure, Ant Colony Classifier**

I. INTRODUCTION

Epilepsy is the most common neurological diseases which affects more than 40 million persons in the world. It can be caused by number of unrelated conditions, such as damage resulting from high fever, stroke, toxicity, electrolyte-imbalances which disturb the nervous system, etc. Epilepsy is a chronic nerve disorders characterized by recurrent seizures that can vary from a brief lapse of attention or muscle jerks, to severe and prolonged convulsions [1].

Epileptic seizures can be categorized as partial or general. Partial seizures are usually produced from a localized area in the brain, and may spread to other areas. Partial seizure is divided into simple and complex depending on the patient's response during a seizure [2]. Generalized epileptic seizure involves the entire brain and produces bilateral motor symptoms generally accompanied with loss of consciousness. Both types of epileptic seizures can occur at all ages. Generalized epileptic seizures can be subdivided into absence (petit mal or little illness) and tonic-clonic [3] (grand mal seizures).

The nature of seizures, timing, severity and the situations in which they occur can cause social difficulties for patient. Discrimination or rejection may also be a problem for a person with seizures. Furthermore, family and friends tend to be overprotective or impose unnecessary restrictions that can lead to isolation and social problems. Fearing is a negative response, where many try to keep their epilepsy a secret from others. People with active epilepsy cannot drive and keeping their jobs can be more difficult for them.

Epilepsy can be treated in many cases and the most important treatment today is pharmacological. The patient takes anticonvulsant drugs on a daily basis, trying to achieve a steady-state concentration in the blood, which are chosen to provide the most effective seizure control. Surgical intervention is an alternative for carefully selected cases that are refractory to medical therapy. However, in almost 25% of the total number of patients diagnosed with epilepsy, seizures cannot be controlled by any available therapy. Furthermore, side effects from both pharmacological and surgical treatments have been reported in [4].

Monitoring brain activity through the ElectroEncephaloGram (EEG) has an important role in the diagnosis of neurological diseases, especially for the early detection of epileptic seizure activity. Clinical or in hospital wired EEG system records functional and physiological changes within the brain over a short period of time, usually $20-40$ minutes. Data are recorded from multiple electrodes placed at various positions on the scalp of a patient. Elliptical seizure creates clear abnormalities in the EEG, and the early detection of seizure requires continuous and remote monitoring.

With the rapid development of Wireless Sensor Networks (WSNs), many EEG sensors and wireless EEG headset are available today in the market. Usually, invisible electrodes are placed in the head scalp and are connected to a transceiver, which transmits the acquired EEG signal to a Local Processing Unit (LPU), such as SmartPhone. These days, headset or sensors are placed in hidden and comfortable way at the head and allow monitored patient to continue their daily life activities without disruption. The LPU transmits the gathered data by sensors to healthcare providers without any processing, and our objective is to automatically detect epileptic seizure using the gathered data in the LPU.

Two categories of abnormal activities could be found in EEG recordings of patients suffering from epilepsy: interictal which consists of abnormal signals recorded between epileptic seizures and ictal which is defined as the activity recorded during an epileptic seizure. The EEG signature of an inter-ictal activity is occasional transient waveforms, as either isolated spikes, spike trains, sharp waves or spike-waves. EEG signature of an epileptic seizure (ictal period) is composed of a continuous discharge of polymorphic waveforms with variable amplitude and frequency, continuous spikes observed

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over a duration longer than the average duration of inter-ictal abnormalities [5].

With the huge amounts of EEG recordings data, the early detection of ictal phase in automatic manner is required for early intervention by taking the appropriate actions. However, the complex nature of EEG signal and the similarity between epileptic seizure features and some of the background noise such as (eye blinks, stress, sleep deprivation, muscle activity, etc.) make challenging the automatic solutions to detect epileptic seizures in an efficient manner [3]. Existing approaches suffer from high ratio of false alarms.

In this paper, we propose a new scheme for the early and efficient detection of epileptic seizures in Electroencephalogram (EEG) signal. Our proposed approach is based on extracting and analyzing features from EEG signal, instead of directly analyzing the signal itself. We first extract statistical features from EEG signal and we decompose the signal into four decomposition levels to extract the Energy ratio of wavelet coefficients. We apply machine learning algorithm on the extracted features to distinguish between normal brain activities and epileptic seizures on the LPU. The LPU raises alarm for healthcare professionals upon detection of seizure.

We use DWT to decompose the EEG signal into its subbands, and we extract the energy ratio from wavelet coefficients as one feature. Afterward, we extract some statistical features from the original EEG signal, and we use all those features as input for Ant Colony (AC) classifier to derive the set of classification rules, which will be used to detect epileptic seizure in EEG.

The remaining of this paper is organized as follows. Section II reviews related work for detection of epilepsy in EEG. Section III briefly reviews related techniques used in our proposed approach. Section IV presents our proposed approach. In section V, we present our results from experimental evaluation. Section VI concludes this paper.

II. Related work

Authors in [3] classify the EEG signal of patients suffering from epilepsy in two categories of abnormal activity: the first category is inter-ictal and the second is ictal. They found that the entire process of all suggested signal processing's methods which conducted to detect epilepsy seizures can be generally subdivided into two main stages: (i) feature extraction and (ii) classification. Once a set of features has been obtained to characterize a section of EEG, a classification algorithm is used to decide whether this section of EEG is associated with an epileptic seizure or not.

Authors in [6] proposed an approach for EEG signal classification based on feature extraction using Wavelet Transform (WT) and classification scheme using Neural Network (NN). Their proposed approach able to distinguish between normal and epileptic EEG signal over a reasonable duration of 24 seconds. They notice that the selection of suitable wavelet and the choice of decomposition level are have a large impact on the detection accuracy. As the EEG signal does not have any useful frequency component above 30 Hz, they use 4 decomposition level for the detection of abnormal activities in EEG.

Authors in [7] briefly present the commonly used classification algorithms to design Brain Computer Interface (BCI) system based on EEG such as: linear classifiers, Neural Networks, Nonlinear Bayesian classifiers and Nearest Neighbor classifiers. They also provide guidelines to help reader chose a classifier adapted to a given context.

Authors in [3] compared several methods for time-frequency analysis of EEGs to calculate the Power Spectrum Density (PSD) of each segment. They extracted some features and use artificial NN to identify existing anomalies in EEG signal.

Authors in [8] proposed a method for the detection of epileptic seizure based on multichannel EEG signals (unipolar and bipolar). First, 16-channel scalp EEG data were collected from 3 patients with epilepsy. Then approximate Entropy was applied on the data to extract different kinds of dynamic EEG rhythms. After that, they extract some features from all channel (standard deviation and energy). Finally, they classified data using Support Vector Machine (SVM) with different kernels to test the classification accuracy.

The authors in [9] provide PyEEG, an open source platform based on Python module for EEG feature extraction which can also be used to analyze other physiological signals that can be treated as a time series. Authors in [10] propose a hybrid technique based on DWT with approximate entropy (IApE) to measure irregularities in EEG signal. These irregularities measures are used as input for Artificial Neural Network (ANN) classifier for early detection of epileptic seizure.

The authors in [11] proposed an algorithm based on DWT and SVM. First, they decompose the signal into its subbands, and for each sub-band, the energy and covariance were extracted and used as input for the SVM classifier to discriminate between seizure and non-epileptic seizure.

In this paper, we propose a new approach for the early detection of epileptic seizures in EEG signal. Our proposed approach is based on machine learning algorithm and numerical analysis to detect epileptic seizures. First, we use DWT to decompose the EEG signal into four sub-bands, then we extract the energy percentage of wavelet coefficients and some statistical features from the original signal. Then we use extracted features as input for Ant Colony (AC) which will discover the set of classification rules used to detect epileptic seizure in EEG signal.

III. Background

In this section, we briefly survey the Discrete Wavelet Transform (DWT) and Ant Colony Optimization (ACO) classifier used in our proposed approach. For detailed information about these algorithms, reader may refer to [12]–[14].

A. Discrete Wavelet Transform

DWT converts a signal into a series of small waves through multi-stage decomposition. It is used to find the instant at which an abrupt change takes place. The basic idea behind the wavelet analysis consists of decomposing the signal S

into a set of wavelet coefficients, where the signal can be reconstructed as a linear combination of the wavelet functions weighted by the wavelet coefficients.

The wavelet transformation analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into approximation and detail coefficients [15]. The approximation coefficients are then further decomposed using the same wavelet decomposition step. This is achieved by successive highpass and lowpass filtering of the time domain signal using the following equations:

$$HP(S) = A_{1j} = \sum_k S(k)h(2j-k) \tag{1}$$

$$LP(S) = D_{1j} = \sum_k S(k)g(2j-k) \tag{2}$$

The procedure of multi-resolution decomposition of a signal S is schematically shown in figure 1. Each stage of this scheme consists of two digital filters and two down-samplers by 2 (squeezes the signal to half of its size). The first filter, HP is the High Pass filter and the second, LP is Low Pass filter. The outputs of HP and LP filters in the first stage HP are the details coefficients $D1$ and the approximation coefficients $A1$ respectively. The first approximation coefficients $A1$ are further decomposed and this process is continued up to the desired decomposition level as shown in figure 1.

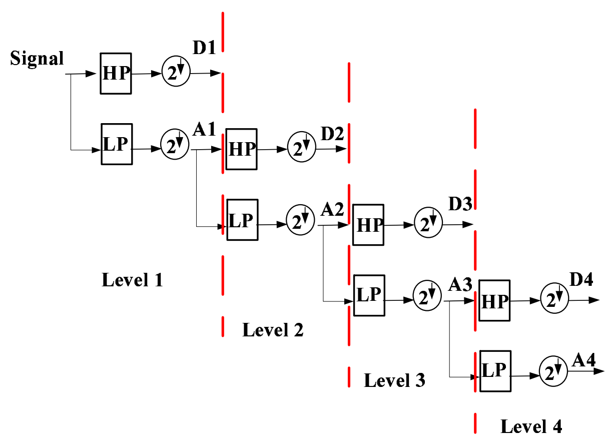

Fig. 1. Four level wavelet decomposition

The number of decomposition levels and the selection of suitable wavelet is important for the analysis accuracy of DWT. In this work, we choose the widely used DWT, Daubechies of order 4 (Daub4) and the EEG signals were decomposed into four levels. This four-level wavelet decomposition process will produce a total of five groups of wavelet coefficients, each corresponds to the frequency band of brain electrical activity: $D1$ ($43.4 - 86.8$ Hz), $D2$ ($21.7 - 43.4$ Hz), $D3$ ($10.8 - 21.7$ Hz), $D4$ ($5.4 - 10.8$ Hz), and $A4$ ($0 - 5.4$ Hz), which correlate with the EEG spectrum that falls within four frequency bands of: delta ($1 - 4$ Hz), theta ($4 - 8$ Hz), alpha ($8 - 13$ Hz) and beta ($13 - 22$ Hz) [16].

The energy of the details and approximations signals at different resolution levels is calculated as follows:

$$ED_i = \sum_{j=1}^{N} |D_{ij}|^2 \quad i = 1, 2, \ldots, l \tag{3}$$

$$EA_i = \sum_{j=1}^{N} |A_{ij}|^2 \quad i = 1, 2, \ldots, l \tag{4}$$

where l is decomposition level, and N is the number of detail or approximation coefficients in each level. ED_i is the energy of the detail at decomposition level i and EA_l is the energy of the approximate at the last decomposition level l.

B. Ant Colony Classifier

Ant Colony (AC) classifier is a machine learning algorithm, inspired from the collective behavior of the real ants which communicate together in an indirect manner by depositing a substance called pheromone [12]. In fact, ants go out from their colony looking for food (as shown in figure 2), with their colony as start point and their destination (the food) as their stop point. Initially, the ants start searching for the food in a random manner, and they might face some obstacles and barriers which make them take a decision to search for alternative paths. Furthermore there will be a disparity between the lengths of paths. So the goal of ants is not limited to reach the destination (food), but to reach the destination using the shortest path. Let denote the shortest path between Nest and Food by S, after some amount of time the amount of pheromone in path S will be reinforced, which attracts other ants to pass through path S, which caused that all ants converge to path S as the shortest path between Nest and Food.

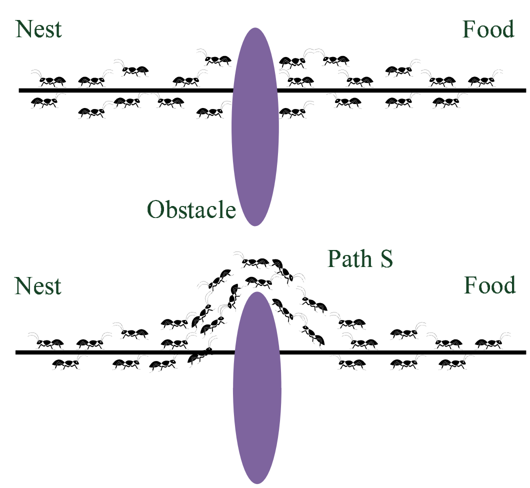

Fig. 2. Ants behaviour

In machine learning, AC is applied over labeled training to discover the classification rules, such that each path discovered by the artificial ants represents one candidate classification rule. These rules are of the form: *if "rule antecedent" then "rule consequent"*. The condition "*rule antecedent*" stands for a conjunction of terms (Y_1 & Y_2 & $\ldots$ & Y_n), where each term is a condition (Y_i, operator, value). For clarification, an example of a term when extracting the energy ratio from details coefficients of a decomposed EEG signal , the term is: $(EG < 1.6)$. The "rule consequent" is the discovered class where their attributes satisfy all the terms in the "*antecedent rule*". In our proposed approach we use the extracted features of signal as input for ant colony classifier to define the rules of normal EEG features. An example of rules:

if $(LB_j < Y_j < UB_j)$
then
$class = normal$
else
$class = abnormal$

Where Y_j represents the j^{th} extracted feature from windows j. If an extracted feature of a patient fall outside the defined interval by ant colony classifier then an alarm associated with epileptic seizure is triggered to take the appropriate actions. For detailed information about Ant colony classifier reader may refer to [17].

IV. Proposed approach

We consider a real deployment scenario where many electrodes are attached to the scalp of the monitored patient. Each of them collects EEG reading from different area as shown in figure 3. In the other side, these electrodes are connected to a transceiver (wireless mote) which in turn transfer the measurements to the LPU for real time processing. The LPU sends the collected data to the monitoring center for storage or for further analysis (long term analysis). The LPU processes the gathered data before their transmission, in order to detect epileptic seizure in monitored EEG signal, and raise a medical alarm for healthcare professionals upon detection of seizure.

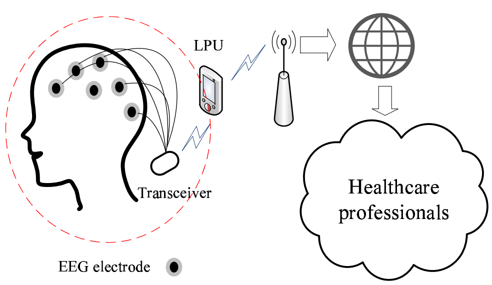

Fig. 3. WSN in medical deployment scenario

We seek to detect abnormal values on the portable device (LPU) and to reduce false alarms by distinguishing between normal EEG and abnormal EEG with epileptic seizure. Our proposed approach to detect abnormal values is based on the following 3 stages: (i) signal decomposition, (ii) features extraction and (iii) features classification. First, the signal is decomposed using DWT into four levels which will produce four levels of details coefficients ($D1 - D4$) and one final approximation coefficient $A4$.

In the second stage two groups of features will be extracted (i) from the original signal (MAX, MIN, STD and MEAN) and (ii) the energy ratio of details and approximation coefficients. Finally, we use extracted features as input for Ant Colony classifier in order to derive the classification rules for normal and abnormal EEG. The complete procedure is presented in the block diagram in figure 4 and described in algorithm 1.

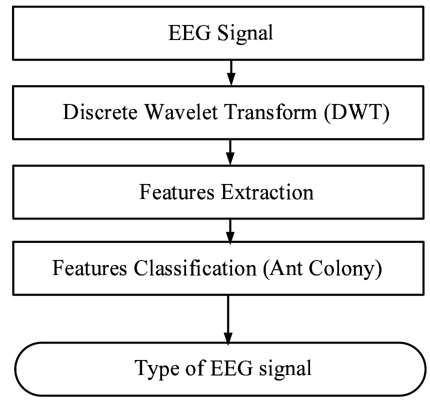

Fig. 4. EEG signal processing and features extraction

Algorithm 1 Epileptic seizure detection

$i = 0$
Set the window size w;
for $i \leq$ length of signal - w **do**
  Calculate statistical features of the sliding window
  Decompose the signal into 4 levels
  Calculate energy ratio
end for
Derive Classification rules by Ant Colony
$j = 0$
for $j \leq n$ **do**
  Calculate the Lower Bound (LB_j)
  Calculate the Upper bound (UB_j)
end for
if $(((LB_1 \leq y_{j,1} \leq UB_1)\ \&\ldots\ \&(LB_n \leq y_{j,n} \leq UB_n))$ **then**
  $Class = normal\ EEG$
else
  $Class = Epeliptic\ EEG$
end if

The rules generated by AC are applied on signal's extracted features to detect epileptic seizure. The proposed algorithm raises an alarm for healthcare professionals when at least K extracted features are outside the dynamically established interval $[LB_i, UB_i]$ by AC classifier.

V. Experimental results

In this section, we present the experimental results of the proposed approach for epileptic seizure detection from EEG signal. Afterward, we conduct performance analysis experiments to analyze the impact of window size on the detection accuracy and false alarm ratio. In our experiments, we use a publicly available benchmark dataset [18]. This dataset is divided into five sets labeled set A until E. Each subset consists

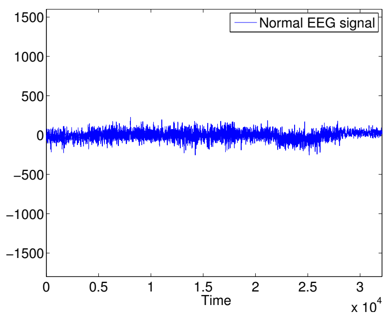

Fig. 5. Normal EEG

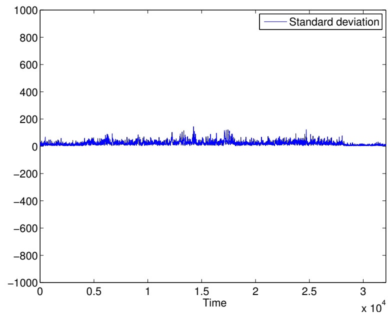

Fig. 6. STD of normal EEG

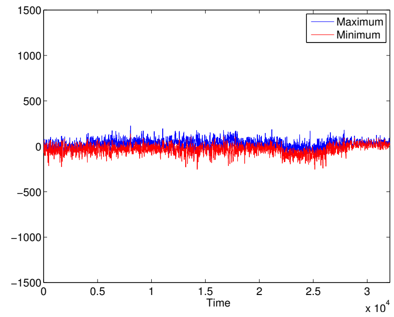

Fig. 7. Min & Max of normal EEG

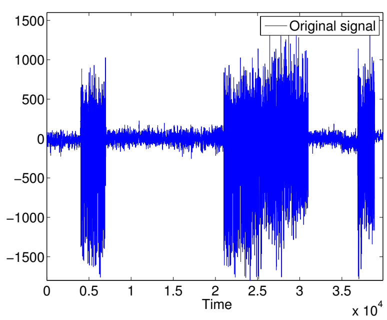

Fig. 8. EEG with Epileptic seizure

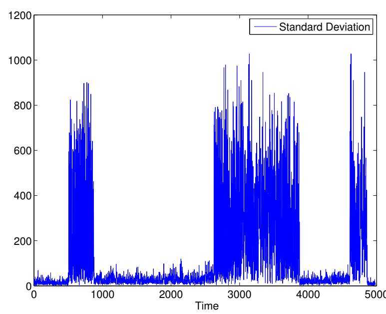

Fig. 9. STD of abnormal EEG

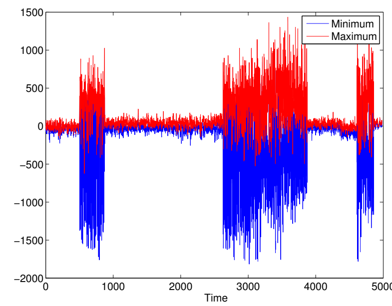

Fig. 10. MIN & MAX of abnormal EEG

of 100 segments of 23.6 sec duration, with each segment being a time series with 4097 data points and each sampled at 173.61 Hz. Each of the five sets was recorded under different circumstances.

Both sets A and B were recorded from healthy subjects, with set A recorded with their eyes open whereas set B with their eyes closed. On the other hand, sets C until E were obtained from epileptic patients. Set C and D were recorded during seizure free period, where set C was recorded from the hippocampal formation of the opposite hemisphere of the brain, whereas set D was obtained from within the epileptogenic zone. The last data set, set E, contains ictal data that were recorded when the patients were experiencing seizure. In other words, the first four sets of data, sets A until D, are normal EEG signals, while set E represents epileptic EEG signals. Figures 5 and 8 show the variation for normal and abnormal EEG respectively.

The proposed method was applied on both dataset of EEG (normal and abnormal). To reduce the volume of data, the data segment of 4097 values was partitioned using a sliding window of length = 32. First, we extract window's statistical features (MAX, MIN, STD and MEAN) then we apply the DWT at each window to derive the details coefficients ($D1 - D4$) and Approximation $A4$ coefficient. We tested different types of wavelets family and Daubechies (daubb4) gives maximum efficiency. After that we extract the energy ratio from each signal coefficients and we used both the energy ratio and the statistical features as input for ant colony classifier in order to conduct the classification. Figures 6 and 7 show the variation of extracted mean, minimum and maximum values for normal EEG, and figures 9 and 10 show the variation of STD, Maximum and Minimum values for abnormal EEG signal.

In the classification phase, we used a dataset containing 56837 records (extracted features) as input for Ant Colony Classifier. This input dataset were divided into 3 subsets. The first subset is used as training data to train the classifier and to derive the classification rules. In our experiment we used 2225 samples as training set. The second subset is the validation set, in our experiment the validation set contains 1292 samples. The last subset is the testing set, we used a testing subset with 52962 samples.

The classification rules obtained by Ant Colony classifier define the range of normal EEG using its extracted features. Any features fall outside the range of normal EEG signal will be considered as abnormal. Table I shows the range of normal EEG.

TABLE I
RANGE OF NORMAL EEG

Extracted Features	Lower Bound	Upper Bound
Energy ratio	0	0.4
STD	0	130
MAX	-100	230
MIN	-260	150
MEAN	-200	200

Figure 12 shows the 3 raised alarms by our proposed approach. We obtained three alarms resulted from the deviations in both MAX, Mean, STD, energy ratio & MIN. In fact, a visual inspection in the variation of EEG signal in figures 8

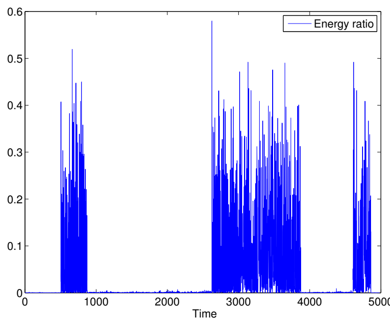

Fig. 11. Energy ratio

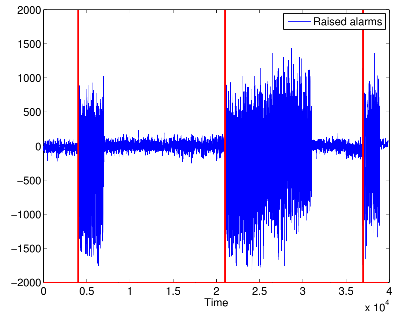

Fig. 12. Raised Alarms

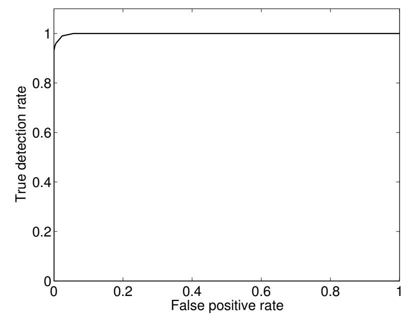

Fig. 13. ROC

confirms the utility of these alarms.

To evaluate the performance of our proposed approach, we used a dataset of a patient suffering from epileptic seizure to dervice the Receiver Operating Characteristic (ROC) curve. We analyzed the impact of the window size on the true detection and false alarm ratio. The ROC curve presented in figure 13 shows the relationship between the detection rate (equation 5) and the false alarm rate (equation 6).

$$\text{Detection Rate} = \frac{TP}{TP + FN} \tag{5}$$

Where TP is the number of True Positives, and FP is the number of False Positives. The False Positive Rate (FPR) is defined as:

$$\text{False alarm rate} = \frac{FP}{FP + TN} \tag{6}$$

A good detection mechanism must achieve a high detection ratio with the lowest false alarm rate. Figure 13 shows that our proposed approach can achieve a $DR = 100\%$ with a $FAR = 9\%$.

VI. Conclusion

In this paper, we proposed a new framework to detect epileptic seizure in medical WSNs. The proposed approach is based on Discrete Wavelet Transform and Ant Colony classifier. First we decompose EEG signal into 4 levels using DWT and we extract some features from the original signal, as well as the energy ratio of the coefficients. In the second step, we used extracted features as input to Ant Colony classifier to derive the classification rules. The rules are used to detect epileptic seizure. We applied our proposed approach on real medical dataset. Our experimental results prove the effectiveness of our approach which can achieve a high detection ratio with low false classification ratio.

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