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An Entropy-based Feature in Epileptic Seizure Prediction Algorithm

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Abstract : *Epilepsy prediction is a vital demand for people suffering from epileptic onset. Prediction of seizure onsets could be very useful for drug-resistant epileptic patients. We propose an epileptic seizure prediction algorithm to predict an onset of epilepsy and discriminate between pre-seizure periods and seizure free periods. The proposed algorithm is based on entropy features of 60 (1 hour segmented into 60 periods) with free seizure periods and repeated for 24 hour, and 60 (pre-seizure periods) of the CHB-MIT Scalp EEG Database (Female less or equal 12 age). Critical values of the sample entropy and approximate entropy are estimated to locate starting of the seizure onset. These values are taken as warning to a probably seizure starts within a specific time. The prediction time in order of 1min- 49min is achieved in 60 seizure periods under study in this task. SVM is used to classify pre-seizure periods from seizure free periods for the mentioned data. The performance is evaluated and analysed.*

Keywords : *Epilepsy, Epilepsy Prediction, Sample Entropy, Approximate Entropy, Svm, Eeg Signals.*

I. Introduction

Epilepsy is among the most common neurological disorders caused by large number of small electrical discharges of nerve cells. Epileptic seizure is a complex symptom caused by a variety of pathologic processes in the brain. It may cause a variety of temporal changes in perception and behavior. Epileptic seizures may be accompanied by an impairment or loss of consciousness; psychic, autonomic, or sensory symptoms; or motor phenomena. In some patients seizures can occur several times per day; in rare instances, they occur only once per year [1]. A system able to predict seizures would allow some preventive measures to keep the risk of seizure to a minimum. Electroencephalographic (EEG) signals are the most commonly used source for Epileptic seizure prediction. Enormous efforts have been done on seizure prediction through EEG monitoring for a long time. It has been observed that the transition from the interictal state (period between seizures) to the ictal state (seizure) is not sudden and may be preceded from minutes to hours [2]. Some significant features are extracted from EEG signals, which are greatly beneficial for the diagnosis of epileptic seizure. The goal of seizure prediction problem is to predict an upcoming seizure based on the analysis of EEG signal recorded from patients. An automatic seizure prediction system could bring a fast off-line diagnosis by reviewing EEG data by neurologist and can send an online warning signal to enhance the patient's safety. It was reported that childhood epilepsy was associated with high frequency epileptic activity [3]. The development of a fully automated seizure detection / prediction system may be challenged by invincible factors namely, the possible inter-subject differences and the presence of artifacts that may lead to false positive detections. Nonetheless, even a semi-automated system with high sensitivity and specificity would be a useful aid to physicians [4]. Many researchers are available in the literature for automated detection and prediction of Epileptic seizures using EEG signals [5-7]. Several methods have been developed for handling EEG signals as the application of pattern recognition classification methods, Multi-layer Perceptron Neural Network [8-12] and Support Vector Machine (SVM) [13-15]. Most of the automatic epileptic seizure system is built by time-frequency domain based feature extraction followed by a variety of classification Model. The performance of these automatic detection systems depends on the feature extraction of the EEG signal.

Recently studies on the basis of estimating entropies have been employed for biomedical studies. In [16], a modification of E-R entropy named approximate entropy (ApEn) is suggested by the authors. Richman [17] proved that there is a bias in computing ApEn and he proposed a modified version of the ApEn, known as sample entropy (SamEn). It quantifies the degree of complexity in a time series. Approximate entropy and sample entropy methods are compared for EEG signal in [18], the authors demonstrated that sample entropy method gave more robust results, and it is less sensitive to the length of the data. The sample entropy has been used as a feature for the classification of different categories of EEG signal [19-22]

In this task, we propose an Epileptic seizure prediction algorithm to discriminate between pre-seizure period and seizure free period using entropies as features extraction, a method to estimate prediction time is suggested. SVM is used as a classifier, performance is evaluated and the results are analyzed.

The rest of this paper is split into four sections; section 2 contains the entropy. Material and methods are given in section 3. Section 4 is devoted to discuss the results. Finally, section 5 concluded this paper.

II. Entropy

2.1 APPROXIMATE ENTROPY (APEN).

Approximate entropy can be defined as a measure of the complexity or irregularity of a time series. Less value of ApEn means less complexity and irregularity of the signal and vice versa. The steps to estimate ApEn is summarized as follow [16].

Let m vectors of sequence X of data of length N are defined by:

$$X(i)=[x(i),x(i+1),\ldots,x(i+m-1)],i=1,2,\ldots,N-m+1 \quad (1)$$

Define d[X(i), X(j)], as the maximum absolute difference between X(i), X(j)

Define Crm(i) = (number of x(j) such that d[X(i), X(j)] > r) / (N-m+1), measures the frequency of patterns similar to that one given by the window of length m within a tolerance r.

Compute the natural logarithm of each Crm(i) and then average it over i.

$$\varphi^{m}(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log(C_i^m(r)) \quad (2)$$

Increase the dimension to m+1. Repeat c. and d. to obtain Crm+1(i), ϕm+1(r)

Finally, approximate entropy is computed as

$$A_p E_n(m,r,N) = \emptyset^{m}(r) - \emptyset^{m+1}(r) \quad (3)$$

2.2 SAMPLE ENTROPY (SAMPEN).

Sample entropy is a measure of complexity as approximate entropy (ApEn) but it doesn't include self-similar patterns (phi's) as ApEn does. For a given embedding dimension m, number of data points N, SampEn is the negative logarithm of the probability that if two sets of simultaneous data points of length m have distance > r then two sets of simultaneous data points of length m+1 also have distance > r and we represent it by SampEn (m,r,N)

$$\text{SampEn} = -\log(A/B) \quad (4)$$ Where,

A= no of template vector pairs having d[X(i), X(j)] > r of length m+1

B= no of template vector pairs having of d[X(i), X(j)] > r of length m

It is clear from the definition that A will always have smaller value than B, so the value of SampEn will be always positive. A lower value of SampEn also indicates more self-similarity in the time series.

III. Materials And Methods

The pediatric EEG data used for this task is contained within the CHB-MIT Scalp EEG Database, which can be downloaded from the Physionet website [23], but we include only female subjects who less or equal 12 years age. The database information is summarized in Table 1.

In most cases, the files of the mentioned subjects contains exactly one hour of digitized EEG signals. Only seizures in the first hour period are taken in the consideration in this task, so we have 60 seizures obtained from 12 different subjects. Only signals of FP1-FP7 electrodes are considered. All signals were sampled at 256 samples per second with 16-bit resolution.

Table 1: Database Information.

subjects	age	Gender	Seizures	Interictal (h)
Chb01	11	F	7	46
Chb05	7	F	5	39
Chb06	1.5	F	3	24
Chb09	10	F	1	19
Chb11	12	F	3	39
Chb12	2	F	10	24
Chb13	3	F	7	33
Chb14	9	F	7	26
Chb16	7	F	6	19
Chb20	6	F	6	29
Chb22	9	F	3	31
Chb23	6	F	2	9

3.1 Prediction Time

In order to get a reasonable prediction time (time between start of alarm to time of the actual seizure starts), the entropy (sample entropy and approximate entropy) are estimated according to (3), (4) respectively for all pre-seizures periods. We used m=2, r = 0.2 Standard deviation of EEG data for all periods containing seizures. Significant variations of entropies before starting of the seizure are noted for all seizures. Figure 1 shows for subject chb01_15 which contains seizure at 88.8 min for example.Sample entropy and approximate entropy are varied continuously but when they varied slowly at low entropies level (critical level) determined in section 3.2, we consider this as start of alarm of a probably seizure will occur. In the Figure 2 we consider start of alarm is at t= 53.8 from starting of 1hr-period of subject chb01-14 and actual seizure occurred at 28.8 from starting of 1hr-period of subject chb01_15 (contains seizure at 28.8 min.) so we can say that prediction time of this seizure is 35 min. after repeating this steps for most of seizure period in the 60 seizure periods under study, we find different prediction time between 1min. and 49min.

So we take a 1min-presizure period as a minimum prediction time in this task to extract its entropy features.

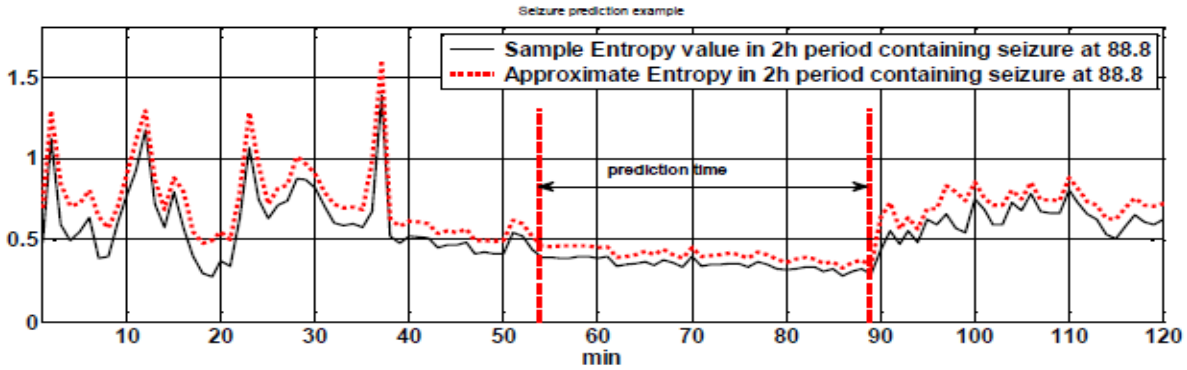

Figure 1: Entropy variation for subject chb1_01 containing seizure at 88.8 min.

The signal of the chb01_15 as an example of 1min-presizure period is depicted in Figure 2 and the signal of the subject chb01_1 as an example of seizure free period is depicted in the Figure 3. The entropy (sample entropy (S1) and approximate entropy (S2)) are estimated for both signals. S1=0.33, 0.38 & S2=0.72, 0.98 for signal of Figure 2 and Figure 3 respectively.

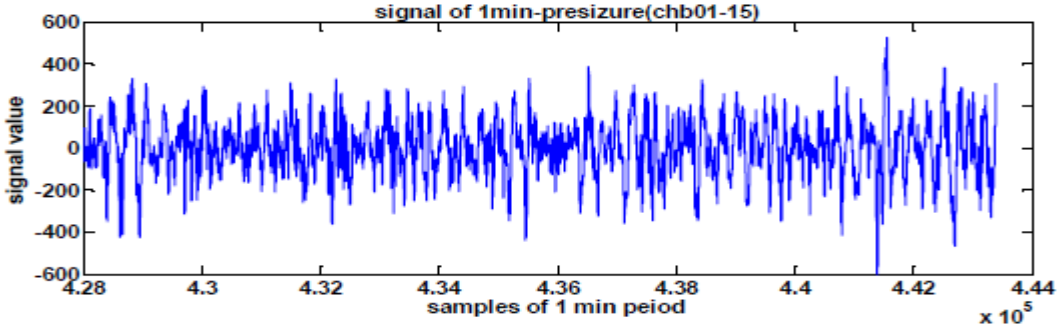

Figure 2: signal of the subject chb01_15 (1min- pre-seizure)

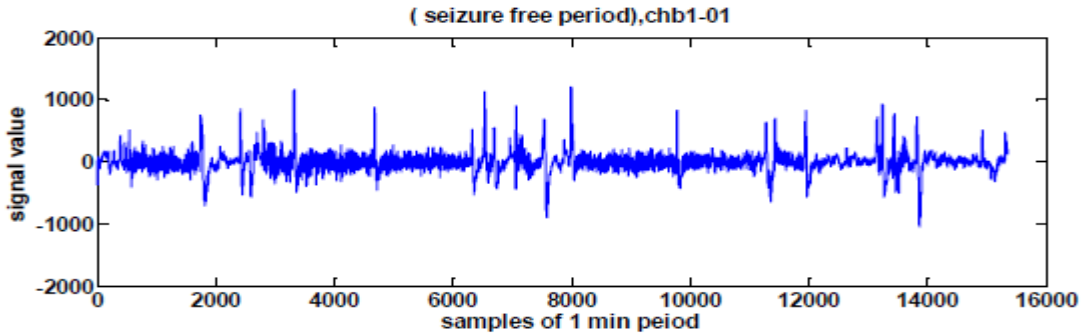

Figure 3: Signal of the subject chb01_01 (free seizure period)

3.2 Estimated Entropy Critical Value

We have 60 seizures period in this database as they detailed in Table 1, 60 (1min-preseizure period) are extracted from the mentioned database to get their entropy features, and we segmented every 1h-period of the interictal period of the subject chb01 (seizure free period) into 60 periods for all 24 hr of subject chbo1 which are assigned as seizure free period. A long period of non-seizure EEG is used to ensure that awake, sleep, abnormal, and artifact-contaminated EEG are included [24].

In order to get distinct values of entropy to discriminate between pre-seizure periods and seizure free period, we calculate the entropy values of the 60 (1-min-pre-seizure) periods for 1min. duration and also we calculate the entropies of 60 seizure free periods of 1hr-period of the subject chb01_1 for example. The sample entropy and the approximate entropy values for all periods are shown in Figure 4 and Figure 5 respectively

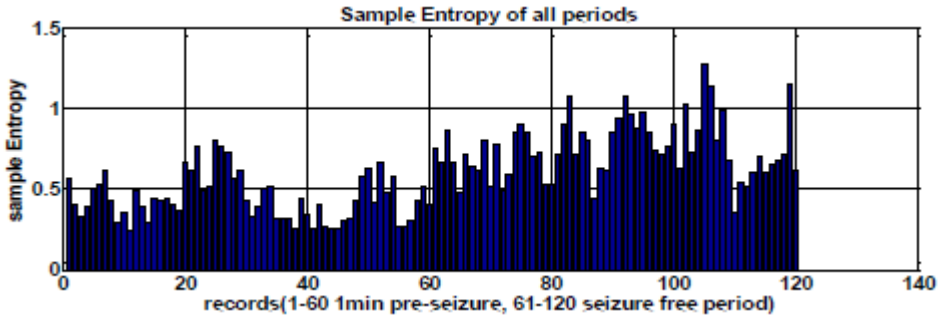

Figure 4: Sample entropy for all periods

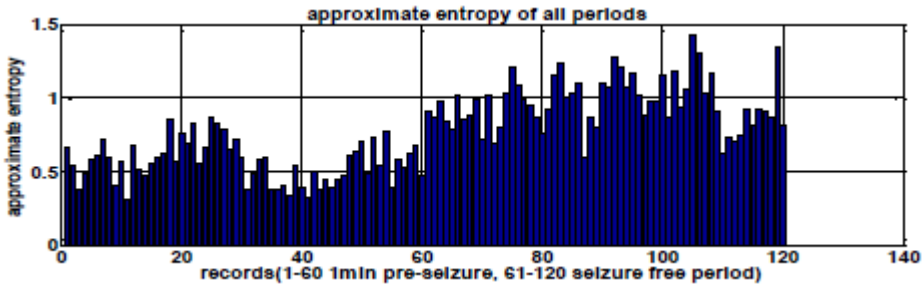

Figure 5: Approximate entropy for all periods

There are a significant difference in the entropy values of the 1min-presizure period (1-60) and the values of the seizure free periods (61-120). Higher values of entropy always related to less system order and more randomness [19].

The mean value of the sample entropy in 1min-presizure period is 0.4416
The mean value of the sample entropy in seizure free period is 0.7529
The mean value of the approximate entropy in 1min-presizure period is 0.5658
The mean value of the approximate entropy seizure free period is 0.9702
We can consider the mean values of the sample entropy and approximate entropy of the 1min-presizure as critical values to alarm that an expected seizure may occur within a specific time, and this will depend on values and characters of the entropy

3.3 Support Vector Machine (Svm) Classifier

The SVM is a distinguishing classifier defined by a separating hyperplane (the plane with maximum margins) between the two classes of the training samples within the feature space by focusing on the training cases placed at the edge of the class descriptors so not only an optimal hyperplane is fitted, but also training samples are effectively used. In that way high classification accuracy is achieved with small training sets. A good separation between data points with different features is achieved by the hyperplane where the nearest training data points of any class, have the largest distance. The details of SVM algorithm can be reviewed in [15]. In this task, we used a quadratic Kernel function to suit nonlinear classification of EEG data. We selected the parameter C equal 1, which can be viewed as a way to control over fitting.

3.4 Epileptic Seizure Prediction Algorithm

The flowchart of the proposed algorithm for Epileptic Seizure Prediction is illustrated in Figure 6

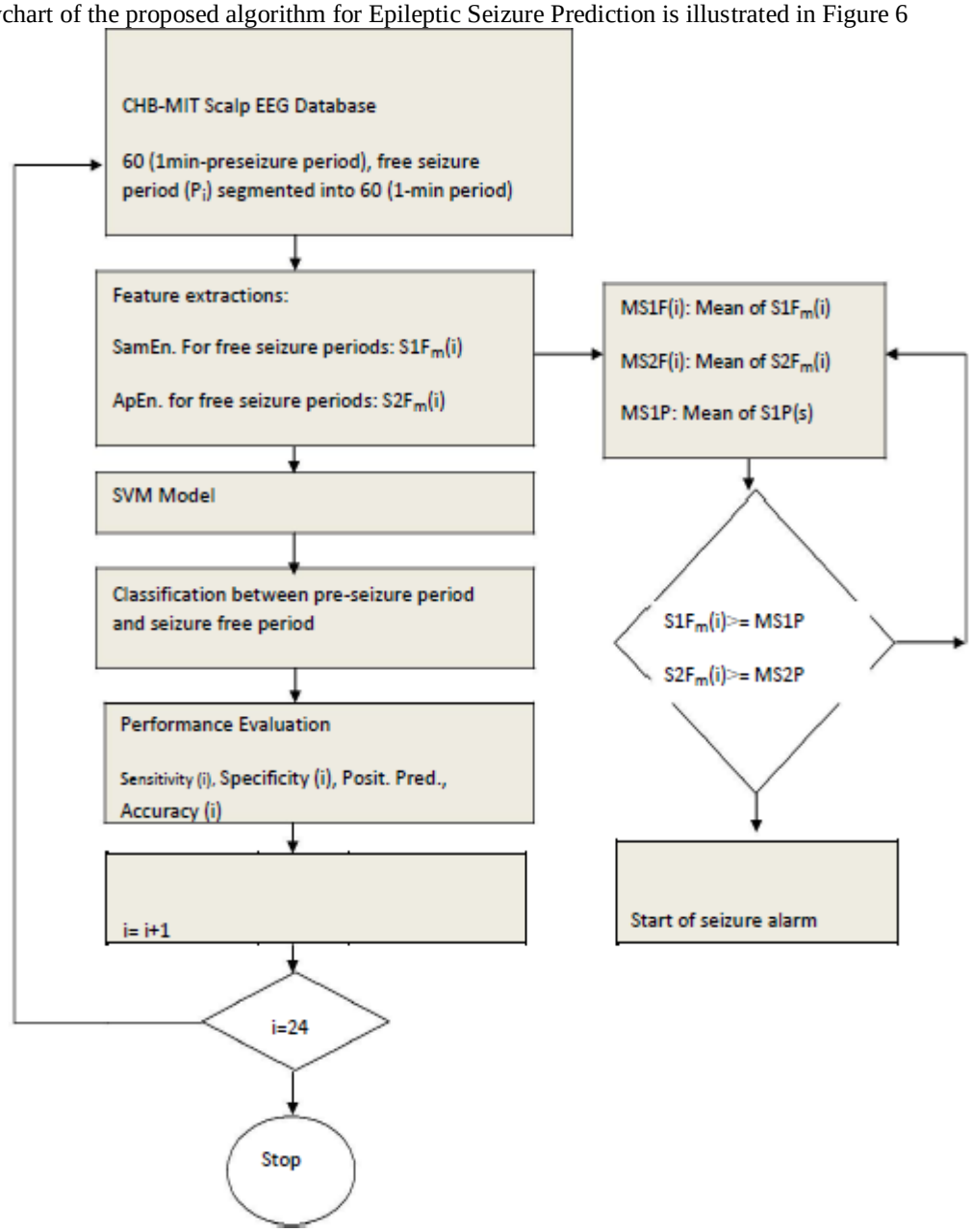

Figure 6: The flowchart algorithm for Epileptic Seizure Prediction.

3.5 Performance Evaluation

To evaluate the performance of the proposed algorithm, four criterias are used as follows:

$$\text{Sensitivity}(\%) = \frac{TP}{TP+FN} 100 \quad (5)$$

$$\text{Specificity}(\%) = \frac{TN}{TN+FP} 100 \quad (6)$$

$$\text{PositivePredicitivity}(\%) = \frac{TP}{TP+FP} 100 \quad (7)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} 100 \quad (8)$$

Where:

TP: True Positive, when a period having pre-seizure is classified correctly. TN: True Negative when a free seizure period is classified correctly.
FN: False Negative when a period having pre-seizure is classified as a free seizure period incorrectly FP: False Positive when a free seizure period is classified as a pre-seizure period incorrectly.

IV. Results and Discussion

The mean values of the 60 (free seizure periods) during 24 hours and the entropy critical values are calculated, shown in Figure 7. The SVM is used to discriminate between 60 free seizure periods and 60 pre-seizure periods (60% for training and 40% for testing). The performance evaluation during 24 hr periods is shown in Figure 8.

It is clear that the performance depends on which hour from 60 (free seizure periods are classified) with 60 (pre-seizure periods). At hour: 1,5,6,8,9,10,11,24 gives perfect results (100% sensitivity, 100% Specificity, 100% Positive Predicitivity, 100% Accuracy), at hours:3,4,7,17,18,19,20,21,22,23 gives excellent result (95.65% sensitivity, 100% Specificity, 100% Positive Predicitivity, 97.67% Accuracy). But there is a degradation in the results at hours: 12, 13, 14,15,16,17 with mean (73.1% sensitivity, 75.66% Specificity, 86.66% Positive Predicitivity, 86.11% Accuracy) .

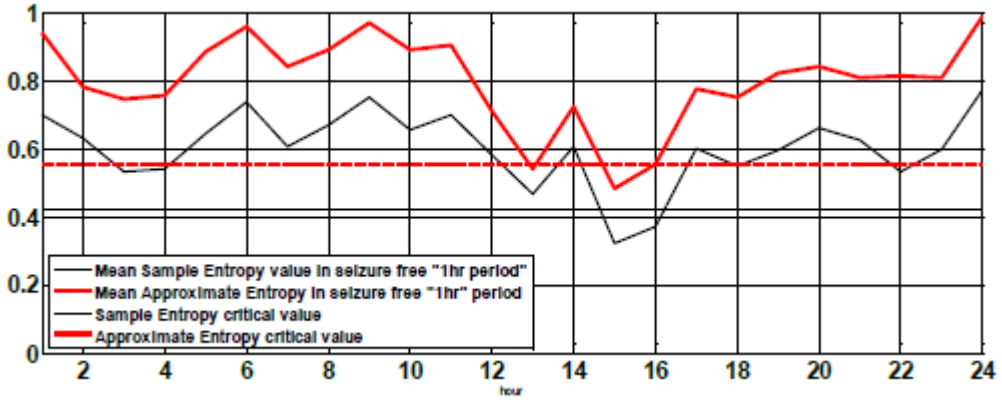

Figure 7: Mean entropy values for free seizure periods during 24 hours comparing to entropy critical values.

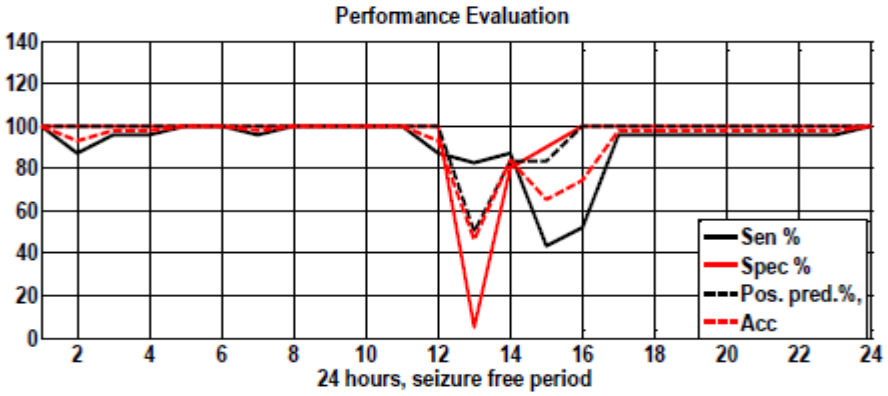

Figure 8: Performance evaluation of the proposed epileptic prediction algorithm during 24 hours

To analyze the reasons of the degradation of the results at 13th hour (chb01_17) in Figure 8, the

approximate entropy of this period (1hr) is shown in Figure 9, and comparing with the approximate entropy of 1min-preseizure period of the subject chbo1_15 (for example), in Figure 10, we note that the entropy values in spite of they are less than the entropy critical values, but they approximately constant, but in case of pre-seizure one they decreased gradually till seizure occurs. Thus we can discriminate between the pre-seizure period and those periods which resemble pre-seizure in values but not in behavior.

The result of SVM training and classifying in case of perfect result obtained at 9th hour (chb01_11) for example is shown in Figure 11.

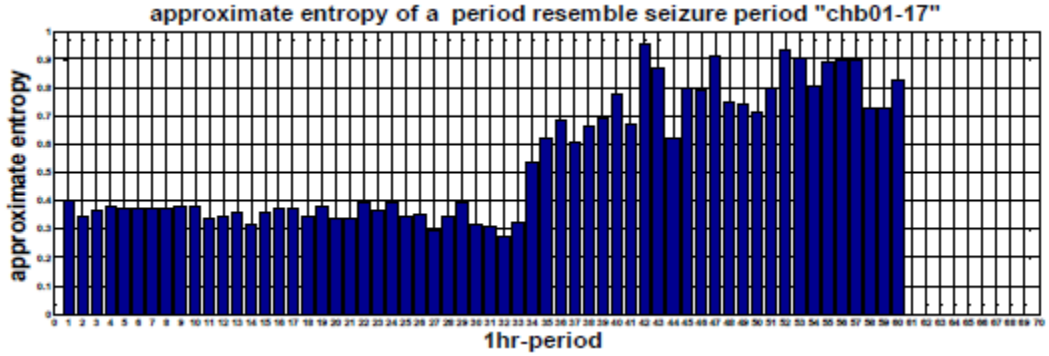

Figure 9: Approximate Entropy of the subject chb01_17 (free seizure period)

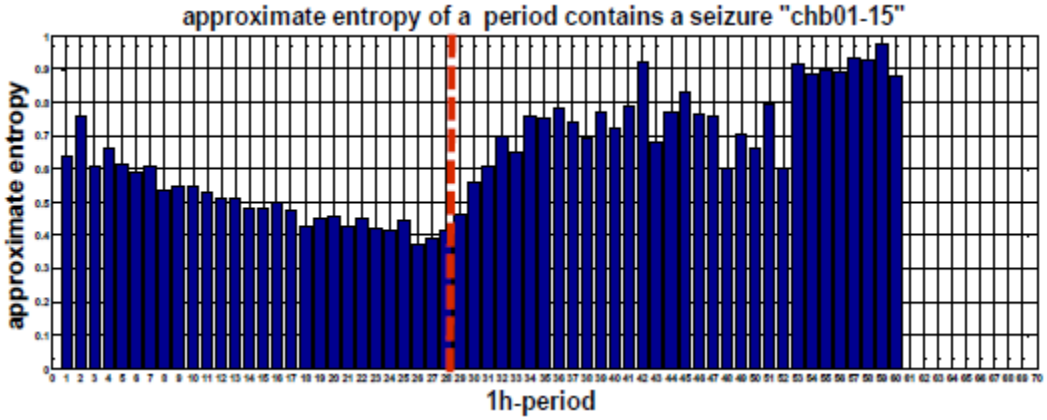

Figure 10: Approximate Entropy of the subject chb01_15 (has a seizure at 28.8min)

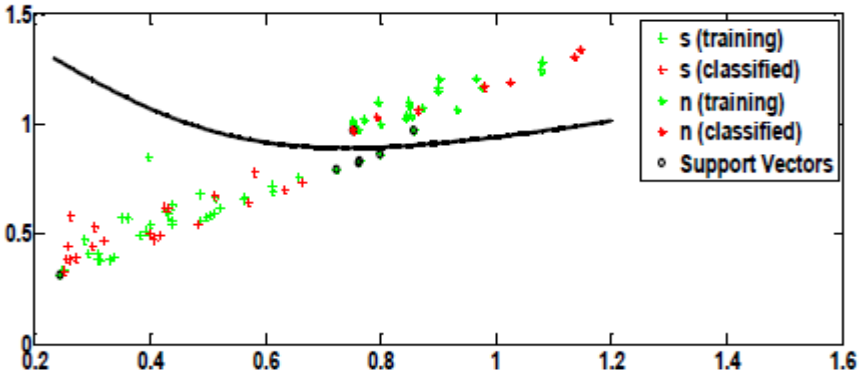

Figure 11: SVM training and classification when perfect results

V. Conclusion

An Epileptic Seizure Prediction Algorithm is achieved in this task. Entropy features are extracted from 60 (1 hour segmented into 60 periods) with free seizure periods and repeated for 24 hour, and 60 (pre-seizure periods) of the CHB-MIT Scalp EEG Database (Female less or equal 12 age). A critical value of the sample entropy (SamEn= 0.4416) and approximate entropy (ApEn= 0.5658) is estimated. These values are taken as warning to a probably seizure starts within a specific time. The prediction time in order of 1min- 49min is achieved in 60 seizure periods under study in this task. SVM is used to classify pre-seizure periods from seizure

free periods for the mentioned data. The performance results were: (100% sensitivity, 100% Specificity, 100% Positive Predicitivity, 100% Accuracy) in 8 hours different periods, and (95.65% sensitivity, 100% Specificity, 100% Positive Predicitivity, 97.67% Accuracy) in another 10 hour different periods, and mean performance values in another 6 hours different periods (73.1% sensitivity, 75.66% Specificity, 86.66% Positive Predicitivity, 86.11% Accuracy). The analysis of this degradation in the results during this periods lead to a very important contribution, we note that entropies during the seizure free period in spite of they are less than the critical value but they approximately constant, but in case of pre-seizure one they decreased gradually till seizure occurs. Thus we can discriminate between the pre-seizure period and those periods which resemble pre-seizure in values but not in behavior.

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