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USING ENTROPIES IN EPILEPSY AN ELECTROENCEPHALOGRAFIC DATABASE REPORT

BY

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Abstract. This paper deals with the use of approximate, sample, wavelet entropies, as well as of all their possible combinations with the aim of describing the epileptic electroencephalographic (EEG) signal. In order to differentiate between seizure and non-seizure computed values of the entropies, a support vector machine classifier is used. The results obtained using the EEG signals from CHB MIT database from epileptic children prove that it is possible, for some of the entropies, to attain very good performance concerning the rate of classification, sensitivities and specificities comparable or better than those reported in literature.

Key words: electroencephalography; approximate entropy; sample entropy; wavelet entropy; support vector machine.

1. Introduction

Epilepsy is a chronic neurological disorder, characterized by abnormal electrical discharges of the brain cells and it affects more than 50 million people worldwide. Nearly 80% of these people live in developing countries and 3/4 of them do not get the required treatment.

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The diagnosis for epilepsy based on an electroencephalographic (EEG) examination is put when the person has more than two unprovoked seizures which can affect a part of the brain or all of it. Its symptoms vary from a disturbance of sensation such as taste, vision, feeling or hearing to loss of consciousness and incontrollable body movements. People experiencing these disorders have their lives considerably altered and can hardly find a working place. In some countries, people being ill with epilepsy also suffer from stigma. A way of detecting or predicting a seizure can diminish these problems and increase the quality of life (www.who.int).

Since 1980, when Gotman proposed a wavelet based method for classification between ictal and non-ictal EEG data (Gotman, 1982), detecting seizures by analysing the EEG signal has been a subject of interest in the scientific world. In order to have an algorithm that can detect ictal events, two major components are needed: suitable features that are thought to differentiate between seizure and non-seizure signals and a classifier that can enhance the accuracy and the sensitivity of the process.

For feature extraction there is a wide range of methods. Some of them use time-domain characteristics such as amplitude, duration, sharpness, skewness (Adjouadi *et al*., 2005), histograms (Runarsson & Sigurdsson, 2005), signal energy (Yoo *et al*., 2013) and discriminating statistics that include mean variance, zero crossing rate, entropy and autocorrelation with template signals (Dalton *et al*., 2012). Other methods include frequency-domain attributes like magnitude and phase of Fourier transform, phase-slope index (Rana *et al*., 2012), frequency moment signatures (Khamis *et al*., 2013) and wavelet-based methods where the wavelet coefficients are used mainly in pre-processing (Panda *et al*., 2010; Liu *et al*., 2012; Zhou *et al*., 2013; Shoaib *et al*., 2014).

More complex methods include the chaotic behavior of the EEG signal throughout Lyapunov exponent (Guler *et al*., 2005) and fractal dimension (Paramanathan *et al*., 2007), non-linear parameters such as second-order difference plot and phase space representation of intrinsic mode functions (Pachori *et al*., 2014; Sharma & Pachori, 2015).

In the field of seizure detection, the research based on the entropies include phase entropy, approximate entropy, sample entropy (Acharya *et al*., 2012), distribution entropy (Li *et al*., 2015), permutation entropy (Ferlazzo *et al*., 2014), Shanon entropy, Renyi entropy (Sharma *et al*., 2015), Fuzzy entropy (Abhinaya *et al*., 2016).

This article presents a method of discriminating between seizure and non-seizure periods in the EEG signal using three types of entropies (approximate entropy, sampling entropy and wavelet entropy) and combinations of them. For asserting the usefulness of the feature extracting methods, a support vector machine (SVM) classifier is used. The results are reported using the classification rate, the sensitivity and the specificity of the classifier. The analysis is made on EEG data from ten paediatric subjects from the CHB-MIT scalp EEG database (https://www.physionet.org).

2. Theoretical Background

In the information theory, the term of entropy stands for an intuitive characteristic of irregularity, complexity, disorder and unpredictability of a time series. The higher the entropy, the more complex and less predictable the system (Phung *et al*., 2014).

The use of entropies in the analysis of EEG recordings of epilepsy patients started in the 21st century, once new formulations for entropies were developed. Some of those expressions were successfully used in detecting and predicting epileptic seizures (Alotaiby *et al*., 2014) and led to the conclusion that, during a seizure, the brain's electrical activity is more predictable than during its normal activity, conclusion pointed out by a significant drop of the value of entropy. Another conclusion was that the artefacts gave to the EEG ictal signal a behaviour of a non-ictal one (Fergus *et al*., 2015; Zaylaa *et al*., 2015).

The approximate entropy (ApEn) was developed through a series of formulas and statistic and it was proved useful in the classification of complex systems. It is a parameter that quantifies the regularity of a data sequence. Firstly used in analyzing cardiac variability and pulsatile release of endocrine hormones, the ApEn was used in the analysis of EEG data as well, where it was proved that its value significantly drops during ictal periods due to synchronic electrical discharges of a large group of neurons during the epileptic seizure (Srinivasan *et al*., 2007).

ApEn is defined by the formula (1) and can detect changes in the episodic behavior by comparing the similarities of samples, using the length of the pattern, *m*, and the coefficient of similarity or the diameter of the phase space partition (grain), *r* (Acharya *et al*., 2015)

$$\mathrm{ApEn} = \Phi^m(r) - \Phi^{m+1}(r), \tag{1}$$

where:

$$\Phi^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\ln C_i^m(r), \tag{2}$$

$$C_i^m(r) = \sum_{j=1}^{N-m+1}\theta(d(x(i)-x(j))-r), \tag{3}$$

$$\theta(u) = \begin{cases} 0, u < 0 \\ 1, u \geq 0 \end{cases} \tag{4}$$

and C^m is the correlation sum of an *m*-dimensional pattern; *N* is the length of the signal; $d(x(i)-x(j))$ represents the maximum norm in a phase space of embedded vectors; θ is the Heaviside function. For more details, see reference (Hope & Rosipal, 2001).

The most suitable value for the parameters *m* is 2 and for *r* is 0.2 times the standard deviation of the EEG signal (Pincus, 1991; Zhang *et al*., 2014).

The advantages of ApEn are: it can be computed for relatively short noisy data, it can differentiate between a large amount of systems such as periodical, chaotic and stochastic ones and it can provide a better classification rate compared to that obtained by using the Kolmogorov-Sinai entropy. ApEn also has its drawbacks and amongst them there are its dependence on the length of the data entry, so it is not suitable for long time series and it counts self-matches so that its reproducibility is absent (Acharya *et al*., 2015).

The sample entropy (SampEn) measures the regularity of a physiological system and it is defined by the formula

$$\mathrm{SampEn} = -\ln\left(\frac{A}{B}\right), \tag{5}$$

where

$$A = \left\{\left[(N-m-1)(N-m)\right]/2\right\} A^m(r), \tag{6}$$

$$B = \left\{\left[(N-m-1)(N-m)\right]/2\right\} B^m(r), \tag{7}$$

$$A^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} A_i^m(r), \tag{8}$$

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^m(r). \tag{9}$$

A represents the total number of forward matches of length *(m+1)* and *B* is the total number of template matches of length *m*. Parameters *N*, *m* and *r* are the same as defined for ApEn.

The SampEn is independent from the input data length and it is also a measure of self-similarity of the pattern. If the value of SampEn is greater than another one's, by a certain length, *m*, and a certain similarity criterion, *r*, then it remains grater for any other values for *m* and *r*. SampEn is relatively reproducible and reduces the systematical error given by ApEn. A high value of SampEn means that the signal is unpredictable and a low value that the signal is predictable and that in the input data set there is a large amount of similarities (Richman & Moorman, 2000).

SampEn has the advantages of being successfully used for very short noisy data series, for discriminating a large variety of systems and theoretically with good results in cases of random numbers as the self-matches are excluded. SampEn's drawback is that it doesn't give coherent results in case of scattered data (Acharya *et al.*, 2015).

The wavelet entropy (WEn) is based on a form of wavelet transform that can be applied to non-stationary signals and it is defined by the formula (3) (Grossmann & Morlet, 1984).

$$\mathrm{WEn} = -\sum_{i<0} p_i \ln p_i \,, \tag{10}$$

where: p_i is a probability distribution of a time series and i is the level of resolution.

The WEn is a measure of the level of disorder associated with the multi-resolution analysis of a signal and gives information about its dynamics (Rosso *et al*., 2001). This type of entropy can be used in identifying the main component of a signal and it can offer a good result in the case of mono-frequency signals. WEn is, like any other entropies, a measure of order or disorder of a signal and, as an advantage, it can detect changes in a non-stationary signal due to the localizing characteristics of the wavelet transform. Another advantage of WEn is the short computational time because this entropy doesn't depend on any parameter and it uses the fast wavelet transform in a multi-resolution framework, cutting out noises (Kumar *et al*., 2010; Acharya *et al*., 2015).

3. Results

The set of the used EEG data is the CHB-MIT scalp EEG database from PhysioNet (www.who.int). This database consists of 664 recordings from 22 patients grouped in 23 cases (one case represents the same female patient after one year and a half away from the first recording), 129 files contain one or more seizures and 435 are seizure-free files. The records were collected at the Children's Hospital in Boston from paediatric patients with intractable seizures that were monitored after several days of withdrawal of anti-seizure medication in order to assess their candidacy for surgical intervention. Another case, case 24 related to patient 23, was added to the database later on and it is not included in the information provided for the first 23 cases.

The patients are 5 males aged between 3 and 22 years and 17 females aged between 1.5 and 19 years. The patients were continuously monitored, but due to the hardware limitations, there are gaps between consecutively-numbered record files during which the signals were not recorded and some recordings contain "dummy" signals interspersed among EEG ones in order to obtain an easy-to-read display format. With the aim of keeping the privacy of the subjects, all protected health information in the *.edf files were replaced by surrogate ones. This may be the reason why some cases lack recordings and it looks as if they are not continuously acquired. For example, this is the case of subject Chb20, who misses the following recordings: 9, 10, 18, 19, 20, 24, 32, 33, 35 to 58 and 61 to 67. Either this is the explanation, or the number of records is irrelevant in the numbering of the files and, thus, they have been randomly chosen.

Another drawback consists in that some cases should contain longer data series, two or four hours long, but all the downloaded files do not exceed one hour of recorded EEG signals. So, where the seizure is annotated to appear after three hours or so, there is no way in finding it in one hour long file. The most relevant case for this matter is subject Chb06, in whose case the information file states that some recordings are four hour long and, when checking the *.edf files associated with each recording, it states that the file is one hour long and that is exactly how long the recording is.

All signals were sampled at 256 Hz, with 16-bit resolution and most of them contain 23 EEG signals. There are some cases that contain 24 or 26 signals because there are also electrocardiographic (ECG) signals.

The EEG signals were recorded using the International 10-20 system of EEG electrode positions and nomenclature, but the arrangement of the extracted channels is sometimes changed, switched, doubled or inversed with no justified reasons. In the case of subject Chb12, for example, the montages of electrodes are changed several times with no explanation and without a stated piece of information about how it may or may not affect the recorded data.

Due to such kind of doubts concerning some files from this database, only 10 patients were chosen for analysis; two male and 8 female, aged between 2 and 14 years old. The subjects used in this study were: Chb12 as subject 1, Chb14 as subject 2, Chb16 as subject 3, Chb20 as subject 4, Chb24 as subject 5, Chb01 as subject 6, Chb02 as subject 7, Chb03 as subject 8, Chb05 as subject 9 and Chb08 as subject 10. From these cases, a number of 42 seizure and 42 non-seizure EEG signals were extracted. The seizure signals had the full length of the seizure as it was annotated in the patient information files and the non-seizure signals were extracted from the middle of seizure-free files, having the same length as that of the previous seizure. Examples of a seizure EEG signal and a seizure-free one can be seen in Figs. 1 and 2 respectively.

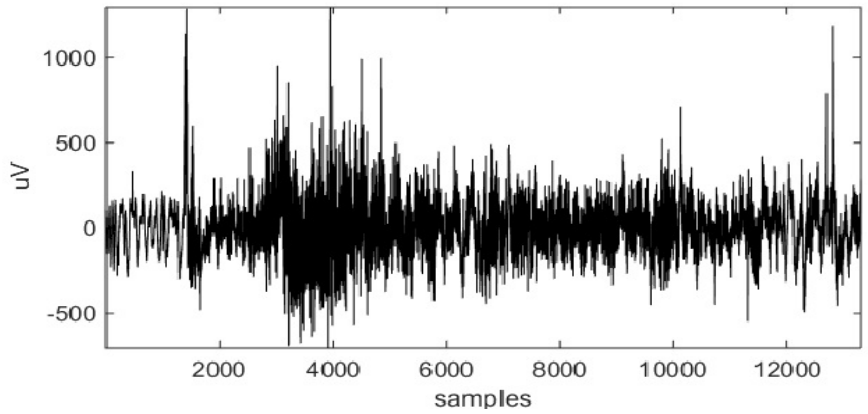


Fig. 1 − Seizure EEG signal on channel 22 of Subject 8.

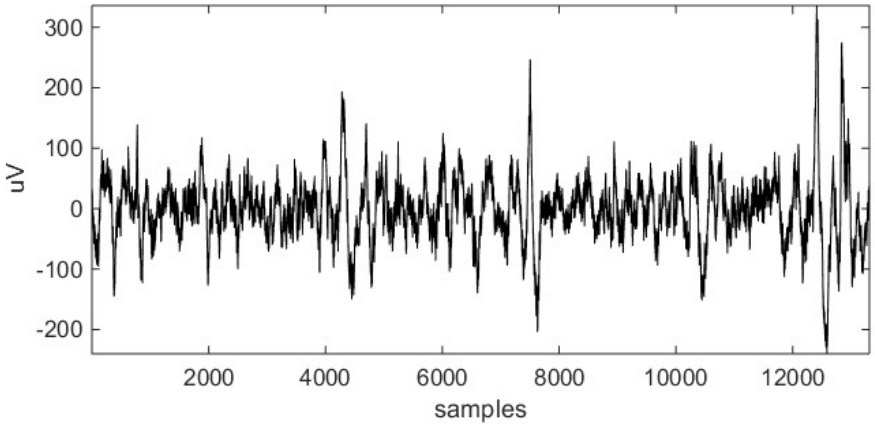


Fig. 2 − Non-seizure EEG signal on channel 22 of Subject 8.

In order to form the feature vector, for each of the 10 patients, there were considered, one by one, the three types of the mentioned entropies (ApEn, SampEn and WEn) and each of the possible combinations of them. There were computed both for EEG signals with seizure and for non-seizure free EEG signals, for all the channels. Then, the SVM classifier was applied. There were computed the classification rates, the sensitivities and the specificities for all the pointed out cases.

In what it follows, the performances of the SVM classifier are illustrated in terms of classification rates, sensitivities and specificities.

In Table 1, for all kind of proposed entropies, there are reported the numbers of channels on which there were obtained the specified classification rates.

For Subject 1, Subject 3, Subject 4, Subject 5, Subject 8 and Subject 9 there were channels where the classification rates were higher than 90%. The best results were obtained for Subject 1 and Subject 8.

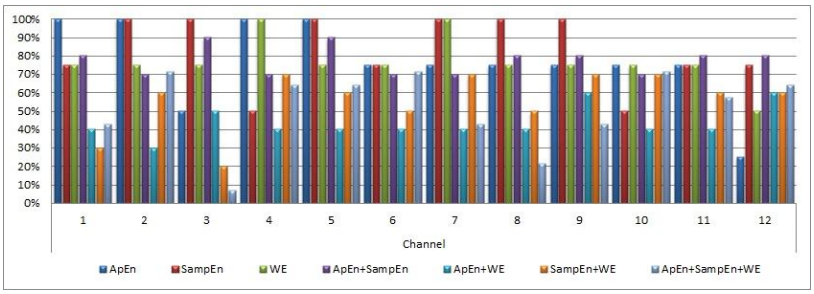
In Fig. 3 there are reported the classification rates for Subject 1.

As we can see from Fig. 3, there are classification rates above 90% both for all types of individual entropies and for merged ApEn with SampEn. For SampEn there are 11 channels with 100% classification rates.

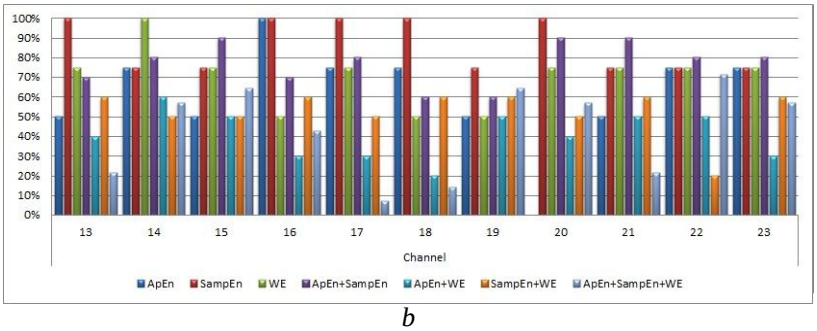
The worst results were attained for Subject 6 and Subject 7 as there were few channels where the classification rates were higher than 60% (but fewer than 70%). In Fig. 4 there are represented the classification rates for Subject 6.

Table 1
The Numbers of Channels on Which there Were Obtained the Specified Classification Rates

Entropy	Classification rate, (%)	Subject									
		1	2	3	4	5	6	7	8	9	10
ApEn	≥60	16	1	3	16	0	3	0	23	6	1
	≥70	16	1	3	16	0	0	0	21	6	1
	≥80	5	0	0	7	0	0	0	21	0	0
	≥90	5	0	0	7	0	0	0	3	0	0
SampEn	≥60	21	8	11	1	16	3	0	23	9	1
	≥70	21	8	11	1	16	0	0	17	9	1
	≥80	11	0	0	0	5	0	0	17	0	0
	≥90	11	0	0	0	5	0	0	3	0	0
WEn	≥60	19	6	17	5	15	2	0	23	18	7
	≥70	19	6	17	5	15	0	0	16	18	7
	≥80	3	0	5	0	10	0	0	16	1	0
	≥90	3	0	5	0	10	0	0	8	1	0
ApEn+SampEn	≥60	23	13	14	14	10	0	6	22	2	4
	≥70	21	4	8	5	3	0	0	20	0	0
	≥80	14	2	4	2	0	0	0	5	0	0
	≥90	5	0	1	0	0	0	0	1	0	0
ApEn+WEn	≥60	3	7	0	1	4	0	0	16	13	0
	≥70	0	2	0	0	1	0	0	9	2	0
	≥80	0	0	0	0	0	0	0	0	1	0
	≥90	0	0	0	0	0	0	0	0	0	0
SampEn+WEn	≥60	14	6	6	5	1	0	2	21	11	2
	≥70	4	1	1	2	0	0	0	17	2	0
	≥80	0	0	0	0	0	0	0	4	0	0
	≥90	0	0	0	0	0	0	0	0	0	0
ApEn+SampEn+ +WEn	≥60	9	3	6	0	1	1	3	22	3	0
	≥70	4	0	1	0	0	0	0	18	0	0
	≥80	0	0	0	0	0	0	0	7	0	0
	≥90	0	0	0	0	0	0	0	0	0	0

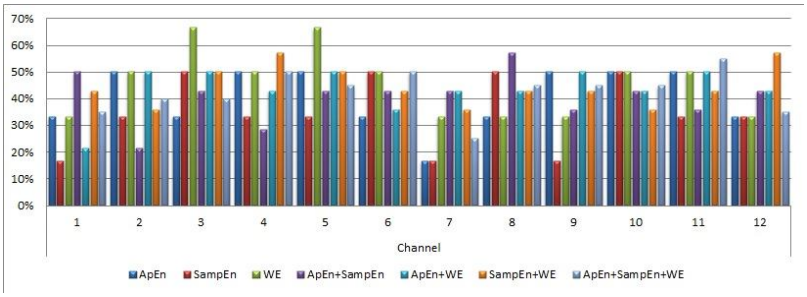


a

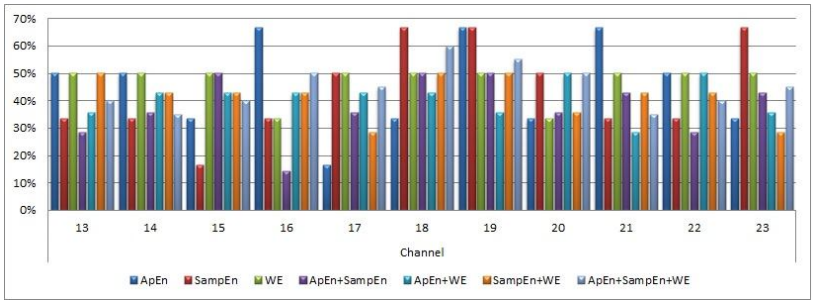


b

Fig. 3 – Classification rates for Subject 1, for all types and combination of entropies (*a* for channel 1 to 12 and *b* for channel 13 to 23)



a



b

Fig. 4 − Classification rates for Subject 6, for all types and combination of entropies (*a* for channel 1 to 12 and *b* for channel 13 to 23).

It is obvious that for subject 6, classification rates between 60% and 70% are achieved for ApEn, SampEn, WEn and for combination of all the three entropies, but only for three, two or one channels.

In Table 2, for all kind of proposed entropies, there are reported the numbers of channels on which there were obtained the specified sensitivities.

In Table 3, for all kind of proposed entropies, there are enclosed the numbers of channels on which there were attained the listed specificities.

Table 2
Numbers of Channels on Which there Were Obtained the Specified Sensitivities

Entropy	Sensitivitity (%)	Subject									
		1	2	3	4	5	6	7	8	9	10
ApEn	≥60	11	11	2	14	0	11	1	21	0	2
	≥70	11	11	2	14	0	1	1	7	0	2
	≥80	11	11	2	14	0	1	1	7	0	2
	≥90	11	11	2	14	0	1	1	7	0	2
SampEn	≥60	11	16	4	0	14	3	0	18	0	3
	≥70	11	16	4	0	14	0	0	5	0	3
	≥80	11	16	4	0	14	0	0	5	0	3
	≥90	11	16	4	0	14	0	0	5	0	3
WEn	≥60	7	22	15	1	20	8	4	22	19	3
	≥70	7	22	15	1	20	1	4	14	19	3
	≥80	7	22	15	1	20	1	4	14	19	3
	≥90	7	22	15	1	20	1	4	14	19	3
ApEn+SampEn	≥60	18	18	16	11	11	3	7	15	3	7
	≥70	9	15	10	9	3	3	0	15	0	1
	≥80	9	15	10	9	3	0	0	7	0	1
	≥90	5	10	1	1	1	0	0	2	0	0
ApEn+WEn	≥60	10	11	8	9	6	1	9	18	14	3
	≥70	3	3	0	1	2	1	2	18	8	0
	≥80	3	3	0	1	2	0	2	14	8	0
	≥90	0	1	0	0	0	0	2	5	2	0
SampEn+WEn	≥60	17	7	7	5	5	1	5	20	10	5
	≥70	12	4	2	1	0	1	0	20	8	0
	≥80	12	4	2	1	0	0	0	16	8	0
	≥90	0	0	2	0	0	0	0	4	0	0
ApEn+SampEn+ +WEn	≥60	5	7	2	1	3	5	3	23	10	0
	≥70	5	7	2	1	3	1	3	23	10	0
	≥80	1	2	1	0	1	0	0	16	4	0
	≥90	0	0	1	0	0	0	0	9	0	0

The CHB-MIT database has been used in several studies, starting with Shoeb's work on epileptic seizure detection using machine learning application. Using this approach, 96% of seizures were detected, but the specificity depends on the patient (Shoeb, 2009). As it can be seen from Table 3, even very high

specificities (grater then 90%) are attained by all the subjects if the ApEn values represent the feature vector. Regarding specificities between 80% – 90% also the combination between ApEn and SampEn attests to be a good choice for all 10 subjects.

Table 3
Numbers of Channels on Which there Were Obtained the Specified Specificities

Entropy	Specificity (%)	Subject									
		1	2	3	4	5	6	7	8	9	10
ApEn	≥60	14	2	3	11	4	10	16	23	9	3
	≥70	14	2	3	11	4	1	16	19	9	3
	≥80	14	2	3	11	4	1	16	19	9	3
	≥90	14	2	3	11	4	1	16	19	9	3
SampEn	≥60	23	1	10	1	10	15	19	22	14	3
	≥70	23	1	10	1	10	4	19	21	14	3
	≥80	23	1	10	1	10	4	19	21	14	3
	≥90	23	1	10	1	10	4	19	21	14	3
WEn	≥60	18	0	13	12	13	15	10	22	5	6
	≥70	18	0	13	12	13	5	10	12	5	6
	≥80	18	0	13	12	13	5	10	12	5	6
	≥90	18	0	13	12	13	5	10	12	5	6
ApEn+SampEn	≥60	21	9	15	16	14	7	14	19	10	10
	≥70	19	2	9	8	5	7	7	19	3	3
	≥80	19	2	9	8	5	3	7	16	3	3
	≥90	15	0	1	1	0	1	7	7	0	1
ApEn+WEn	≥60	4	13	7	5	11	1	8	4	9	6
	≥70	0	4	0	1	5	1	1	4	2	0
	≥80	0	4	0	1	5	0	1	0	2	0
	≥90	0	0	0	0	0	0	1	0	0	0
SampEn+WEn	≥60	7	14	10	12	8	4	11	12	14	6
	≥70	3	4	3	5	4	4	1	12	8	2
	≥80	3	4	3	5	4	0	1	8	8	2
	≥90	1	0	0	3	0	0	1	2	3	0
ApEn+SampEn+ +WEn	≥60	10	7	8	2	4	4	8	20	2	1
	≥70	10	7	8	2	4	1	8	13	2	1
	≥80	0	3	0	0	3	0	0	4	1	0
	≥90	0	1	0	0	0	0	0	0	0	0

Chiang *et al*., using a seizure prediction method based on an online retraining method using filtering, wavelet coherence with complex Gaussian wavelet and linear SVM, got a 52.2% sensitivity. This outcome was obtained after post-processing, using 22 channels in case of patients 1, 6, and 8 (Chiang *et al*., 2011). For some of the subjects, in our proposed method, a much better sensitivity was attained. So, for Subject 1 and Subject 8 sensitivities better than 90% are accomplished by means of ApEn, SampEn, WEn and of the

combination between ApEn and SampEn. Even for subject 6 who did not attained so good rates of classification, for ApEn and WEn sensitivities grater then 90% were obtained (but only for one channel).

Chang *et al*. used continuous wavelet transform, filtering, coherence, SVM training and testing on data from six patients from the CHB-MIT database. As results, a successful rate of 60% was achieved for 5 patients with a 22 channel model, a successful rate of 70% for a 3 channel model and, after using adaptive channel selection of three to six channels, a successful rate of 85% for 5 patients was attained. Using a small number of channels decreased the computational rate, but it was not suitable for all patients (Chang *et al*., 2012). From Table 1, it is very easy to conclude that for five subjects, for some entropies we accomplished successful rates better than 90%.

Xiang et al. approached the problem with sample and Fuzzy entropy, features later classified with the Kolmogorov-Sinai test and SVM, respectively. The accuracy, specificity and sensitivity were: 97.16%, 97.34% and 97.01% respectively, in the case of sample entropy and 98.31%, 98.36% and 98.27% respectively in the case of Fuzzy entropy (Xiang *et al*., 2015). From Table 2, it is obviously that there were achieved better results in our study. So, for ten subjects, using WEn, sensitivities better than 90% were reached. For all the subjects, there are channels on which the sensitivity is 100%.

3. Conclusions

For all the subjects, specificities higher than 90% are achieved when using ApEn and SampEn of EEG signals and sensitivities higher than 90% when using the WEn. In the all the mentioned cases a SVM classifier was applied.

The results using the epileptic children' EEG signals from CHB MIT database prove that for some kind of entropies it is possible to attain very good performance of classification, especially concerning the sensitivity and specificity. There are comparable or better than those identified in other papers when the same database was handled.

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UTILIZAREA ENTROPIILOR ÎN EPILEPSIE
Studiu pe bază de date cu semnale electroencefalografice

(Rezumat)

Pentru descrierea semnalului electroencefalografic din timpul crizelor unor pacienți ce suferă de epilepsie, s-au folosit entropia aproximată, entropia eşantion şi cea de tip wavelet, precum şi combinații ale acestora. Pentru discriminarea entropiilor din timpul crizelor şi a celor din perioada fără criză s-a utilizat clasificatorul de tip SVM. Rezultatele obținute atunci când a fost folosită o bază de dat ce conține înregistrări de semnale EEG de la copii ce suferă de epilepsie pun în evidență faptul că, pentru unele tipuri de entropii, se obțin rate de clasificare, sezitivități şi specificități comparabile sau mai bune decât cele raportate în literatura de specialitate.