An approach to absence epileptic seizures detection using Approximate Entropy

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Abstract— **Epilepsy is one of the most common chronic neurological diseases and the most common neurological chronic disease of childhood. The electroencephalogram (EEG) signal provides significant information neurologists take into consideration in the investigation and analysis of epileptic seizures. The Approximate Entropy (ApEn) is a formulated statistical parameter commonly used to quantify the regularity of a time series data of physiological signals. In this paper ApEn is used in order to detect the onset of epileptic seizures. The results show that the method provides promising results towards efficient detection of onset and ending of seizures, based on analyzing the corresponding EEG signals. ApEn parameters affect the method's behavior, suggesting that a more detailed study and a consistent methodology of their determination should be established. A preliminary analysis for the proper determination of these parameters is performed towards improving the results.**

I. INTRODUCTION

Epilepsy is one of the most common disorders of the brain. The estimated number of children and adolescents in Europe with active epilepsy is 0.9 million (prevalence 4.5-5.0 per 1000) [1]. Diagnosis of this disorder is a challenging task, which is based on the experience of the neurologist and is prone to subjective or biased judgment of the latter or a caring person. The need for a higher diagnostic precision is obvious, for which electroencephalogram (EEG) analysis methods prove helpful. Neuronal systems have been shown to exhibit some kind of nonlinear or chaotic behavior. This makes it reasonable to apply methods from the theory of non-linear dynamics, such as the entropy [2], when analyzing signals describing neuronal activity, such as the EEG. High entropy values indicate a high level of disorder in a system, whereas low values describe a more ordered system. Approximate entropy (ApEn) is a statistical parameter proposed by Pincus [3] to quantify the regularity

of a time series data of physiological signals. It has already been used in many applications such as analysis of heart rate variability [4]-[7], detection of epilepsy [8]-[9] and analysis of the endocrine hormone release pulsatility [10].

Our dataset contains EEG signals from either normal periods or from periods where an absence seizure takes place. Typical absences are brief, generalized epileptic seizures of sudden onset of motor arrest and staring, and sudden termination as well. Transient impairment of consciousness is an essential component of typical absences [11]. When it comes to seizure detection, these characteristics form a particular challenge in contrast to other types of seizures with longer durations and more pronounced clinical manifestations. Related work in this field reports the application of ApEn on spike-wave discharges associated with absence seizures is presented in [12], where EEG signals of Long Evans rats are analyzed. This study reports average accuracies of up to 97% when combining ApEn and multi-band EEG power spectra as features.

This paper presents an investigation on the application of ApEn towards the detection of epileptic absence seizures in EEG signals. It is admitted that parameters involved in this algorithm have considerable influence on the results. Therefore a preliminary analysis is performed in order to identify the effects of these parameters in ApEn behavior. Subsequently, the selected parameters' values are used in the algorithm along with a threshold and a seizure detection rule. Finally, the calculated ApEn is used to classify EEG signals between seizure and no seizure states. Performance measures are presented giving promising results which can improve with a further optimization of the parameters. Combining these, a methodology is proposed in order to use ApEn for the detection of absence seizures.

II. MATERIALS AND METHODS

A. Subjects and procedures for data acquisition

The study consisted of 8 patients with epilepsy, 4 males and 4 females, aged between 2 and 10 years. Surface EEG was recorded from all patients during routine long-term Video-EEG monitoring sessions at the University General Hospital of Heraklion. Informed consent for usage of the EEG for research purposes was obtained from the patient's parents. Epileptic seizures were identified by a neurologist expert and all of them were classified as absence like

generalized seizures.

EEG signals were recorded at 21 scalp loci of the international 10–20 system (channels Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, A1, A2, O1, O2), with all electrodes referenced to the earlobe. An electrode placed in the middle of distance between Fp1 and Fp2 on the subject's forehead served as ground. EEG data were sampled at 256Hz. For this study, only artifact free EEG time series (without eye blinks, spikes, head movements, chewing, general discharges) were selected, similar to other related studies [13]. The final dataset consisted of long-term recorded EEG segments containing 75 seizures.

B. Approximate Entropy

ApEn was introduced as a quantification of regularity in sequences and time series data, initially motivated by applications to relatively short, noisy data sets [3]. Approximate entropy represents the predictability of future values in a time series on the basis of previous values, with larger values corresponding to more complexity or irregularity in the data. Given N data points from a time series $X(n)=\{x(n)\}=\{x(1),\ x(2),..,\ x(N)\}$, the ApEn value is calculated through the following steps:

1. The vector sequences $X_v(1),\ X_v(2),...,\ X_v(N-m+1)$, are formed as $X_v(i)=\{x(i),\ x(i+1)...,\ x(i+m-1)\}$, which represent m consecutive values, commencing with the ith point.

2. The distance between $X_v(i)$ and $X_v(j)$ is calculated, defined by

$$d\left[X_v(i), X_v(j)\right] = \max_{k=1,2,...,m}\left\{\left|x(i+k-1)-x(j+k-1)\right|\right\} \quad (1)$$

3. For each $X_v(i)$ the number $N_i^m(r)$ of vectors is calculated such that

$$d\left[X_v(i), X_v(j)\right] \le r \quad (2)$$

with r representing the noise filter level.
Then, we estimate the parameters C_i^m as

$$C_i^m(r) = \frac{N_i^m(r)}{N-m+1} \quad (3)$$

4. We define $\phi^m(r)$ as the mean value of the parameters C_i^m:

$$\phi^m(r) = \frac{\sum_{i=1}^{N=m+1} \ln C_i^m(r)}{N-m+1} \quad (4)$$

5. $ApEn(m,r,N)$ is calculated using $\phi^m(r)$ and $\phi^{m+1}(r)$ as

$$ApEn\left(m,r,N\right) = \phi^m(r) - \phi^{m+1}(r) \quad (5)$$

ApEn measures the logarithmic likelihood that runs of patterns, which are close (within r) for m contiguous observations, remain close (within the same tolerance width) on subsequent incremental comparisons.

C. Approximate entropy parameters

Various parameters are involved in the calculation of ApEn that can significantly modify the results. Except embedding dimension (m), noise filter level (r), and data length (N), there is the choice whether the standard deviation used in noise filter level would be calculated from the original data series or from the individual selected EEG segments. Additional parameters include the actual threshold, as well as the number of required samples under the threshold in order for a segment to be identified as a seizure.

Even though these parameters are critical in calculating ApEn, there is no specific way for their optimal determination. Most of research work related to ApEn uses the parameters described in [3] as a rule of thumb. However, as signals of different source and pathologies can have quite different properties, these parameters should be determined, based on the specific use.

As ApEn is a statistic measure, the length of data N in which it is applied should be large enough $N>100$ in order to provide meaningful results [19]. Moreover, small values of N leads to instability and increased variation of the measure obstructing the discrimination ability between signal states. ApEn values calculated for various data lengths for a set of 60 data segments are presented in Fig. 1, as well as their standard error of mean (SEM) for both normal and epileptic signals, which are presented in Fig. 2.
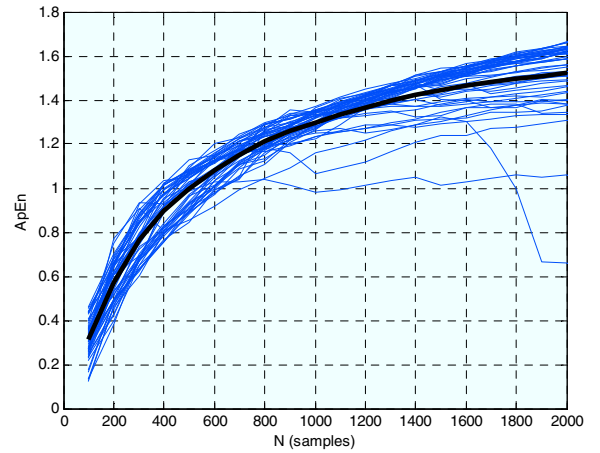

Figure 1. Effect of data lengths on ApEn values. The blue lines depict the ApEn values for various data lengths and the black thick line their average.

Improved stability appears for $N>500$, as shown in Fig. 2, where the plateau starts, so a value of $N=512$ was selected as a good trade-off between ApEn stability and computational time. For the selection of the embedding dimension, the dominant method used is the false nearest neighbors (FNN) [17]. Most segments examined by the FNN algorithm resulted in an embedding dimension of 2 or 3, so the value of 2 was selected for this study for giving better accuracy results.
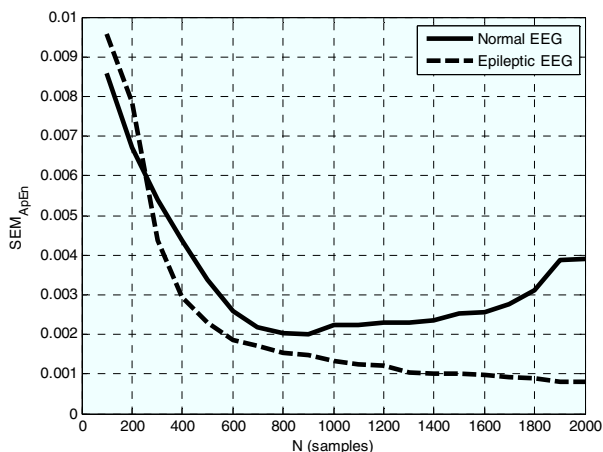
Figure 2. Standard Error Mean (SEM) of ApEn for both normal (straight line) and epileptic (dashed line) signal for various data lengths ranging from 50 to 2000 samples.

Fig. 3 presents the application of this algorithm in normal EEG segments. Analogue behavior is presented and in other EEG segments.
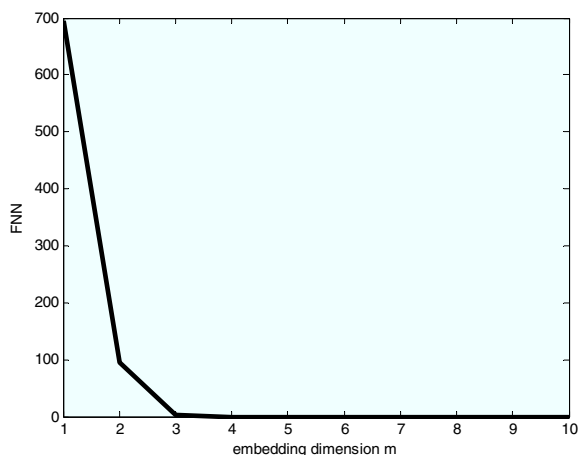

Figure 3. False Nearest Neighbors algorithm for the determination of value of the embedding dimension of the system.

For the selection of noise filter level r an interesting approach is presented in [18]. For the determination of threshold level we propose the Chebyshev inequality presented in Section D.

D. Seizure detection rule

Seizures are detected if specific amount of consecutive ApEn values are below a predefined threshold. This amount depends on the type and length of seizures. In this study, all cases present absence like generalized seizures which last approximately 4-10 sec. According to this, the amount of necessary consecutive ApEn values below the threshold was set equal to the number in samples corresponding to 4sec.

The threshold can be extracted from normal and artifact free EEG periods using the Chebyshev inequality:

$$P\{|Apen(n) - \mu| \geq k\sigma\} \leq \frac{1}{k^2} \qquad (6)$$

where μ, σ are the mean value, standard deviation of the selected ApEn distribution and k the chosen statistical threshold. As ApEn values do not always appear normally distributed, the Chebyshev inequality is a proper measure as it is applicable for any statistical distribution and is not limited only to normal distribution.

III. RESULTS

ApEn was estimated from the EEG signals by sliding overlapping windows of 512 samples in length with a step of 256 samples, with m=2 and r=0.1*standard deviation of each waveform data. The threshold was set so that the confidence level of ApEn values not exceeding it to be 90%. For the final evaluation, a period starting at 17000 samples before and ending at 10000 samples after the seizure was selected. A typical variation of ApEn corresponding to electrode T6 is shown in Fig. 4.
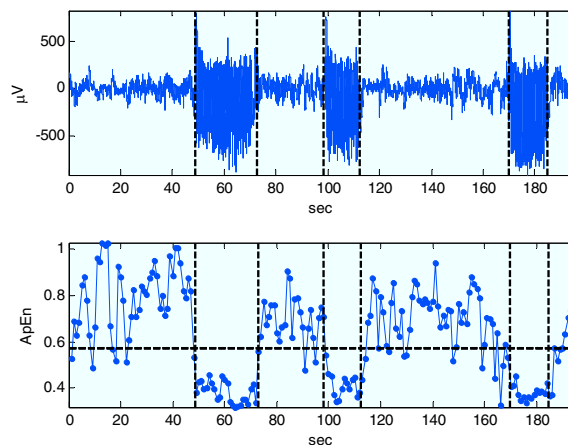

Figure 4. Variation of ApEn for EEG signal containing seizures. Vertical dashed lines denote the start and ending of a seizure. The horizontal dashed line denotes the threshold level.

The seizure detection rule is able to successfully detect the presence/absence of a seizure. It is observed that ApEn decreases during a seizure. A seizure segment presents repetitive patterns resulting in low values, whereas the normal EEG is not predictable regarding its morphology. Besides, 73 EEG normal seizure free segments of 2 min in duration were used in order to check the method's behavior in terms of false positives.

To evaluate the method's performance, sensitivity, specificity and accuracy measures were calculated and are presented in Tables I and II. Sensitivity is the percentage of seizures correctly recognized by the method, specificity represents the percentage of normal EEG segments classified correctly as seizure free, and accuracy represents the percentage of both seizure and non seizure segments correctly classified.

TABLE I
DISTRIBUTION OF CONTINGENCY TABLE

		Seizure		
		Present	Absent	Total
Test	Positive	73	14	87
	Negative	2	73	75
	Total	75	87	162

TABLE II
SYSTEMS' PERFORMANCE MEASURES

	Performance Measures		
	Sensitvity	*Specificity*	*Accuracy*
ApEn classification system	97.33%	83.91%	90.12%

It can be observed that a great value of sensitivity and accuracy is achieved.

ApEn values of epileptic EEG appeared to be significant lower than those of normal EEG (Mann-Whitney Test, $p<0.001$).

IV. DISCUSSION

The detection of epileptic seizure is a laborious task for a trained medical expert. In this study a system for automatic detection of absence like generalized seizures is proposed based on nonlinear analysis methods of ApEn on normal and epileptic EEG signals.

Our study involved 75 seizures from 8 patients suffering from epilepsy. It was found that ApEn is able to efficiently detect the onset and the end of a seizure. The problem with the detection of absence seizures is that their duration is small compared with other seizures. This makes it difficult for signal processing techniques to identify them.

A classification scheme based on thresholding has been implemented in order to classify the cases, using the ApEn values as estimated. The results are promising, indicating that the analysis of the EEG signal may reveal valuable information for the detection of epileptic seizures as the sensitivity achieved is 97.33%, and accuracy is 90.12%.

The results are quite promising for the detection of seizures considering that no sophisticated classification scheme was employed. However, as parameters of window length, noise filter level and embedding dimension affect the method's behavior, a specific methodology of their proper determination should be investigated. A preliminary analysis is performed in this paper mainly for window length and the embedding dimension. Their determination deals with each parameter individually. It is considered that a unified optimization procedure for simultaneously determining parameters would be more appropriate, as it would optimize the combination of parameters in a space of possible solutions. The robustness of the method against artifacts and other epileptic-like brain activity needs also to be tested.

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