Journal of Biomedical Analytics
Vol. 3, No. 1 (2020), pp. 1–11
doi:10.30577/jba.2020.v3n1.39

Research Article

Epileptic Seizure Detection Based on Complexity Feature of EEG

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Received: March 4, 2020; revised: March 28, 2020; accepted: April 4, 2020.

Abstract: Brain disorder characterized by seizure is a common disease among people in the world. Characterization of electroencephalogram (EEG) signals in terms of complexity can be used to identify neurological disorders. In this study, a non-linear epileptic seizure detection method based on multiscale entropy (MSE) has been employed to characterize the complexity of EEG signals. For this reason, the MSE method has been applied on Bonn dataset containing seizure and non-seizure EEG data and the corresponding results in terms of complexity have been obtained. Using statistical tests and support vector machine (SVM), the classification ability of the MSE method has been verified on Bonn dataset. Our results show that the MSE method is a viable approach to identifying epileptic seizure demonstrating a classification accuracy of 91.7%.

Keywords: Epileptic seizure, Complexity, Multiscale entropy, EEG signals, Support vector machine

1 Introduction

Epilepsy, according to the world health organization, is considered the second most prevalent brain disorder behind stroke among different neurological disorders. People suffer from epilepsy due to sudden and recurrent incident of epileptic seizures that may increase physical injury and even result in death (Buck *et al.*, 1997). Seizures occur due to transient and unexpected electrical disturbance of the brain that is observed in the electroencephalogram (EEG) signals. Studies show that an estimated 0.6-0.8% of the total world population suffer from epilepsy (Mormann *et al.*, 2007). As a result, the effective detection of epileptic seizure is necessary.

Electroencephalography (EEG) is a valuable tool for the diagnosis and analysis of epilepsy (Rizvi *et al.*, 2013). But detection of epileptic seizures with EEG is time-consuming and error-prone (Wang *et al.*, 2017) because of visual analysis of EEG data by the physician and discriminating opinions on the diagnostic results reported by different experts with differing levels of diagnostic experience (Wang *et al.*, 2016; Yan *et al.*, 2018). Hence, it is urgent to develop an automated, reliable and robust method for detecting epileptic activity in EEG signals.

In the literature, there exists various epileptic seizures detection methods that are categorized into five domains such as time domain (Shanir *et al.*, 2015), frequency domain (Bhople and Tijare, 2012), wavelet domain (time-frequency) (Polat and Ozerdem, 2016), empirical mode decomposition (EMD) (Huang *et al.*, 1998) and rational transform domain (Samiee *et al.*, 2014). Among these five domains, several non-linear methods like Lyapunov exponent (Faust *et al.*, 2015), higher-order spectra (HOS) (Acharya *et al.*, 2012), information theory and entropy (Fu *et al.*, 2015) and intrinsic mode functions (IMF)(Kumar *et al.*, 2010) also exist for detecting epileptic seizures in EEG signals. Since EEG signals are highly non-linear, the existing non-linear methods showed high capability for detecting epileptic seizures rather than linear methods.

In this research, we are considering the MSE (non-linear) approach to detecting epileptic seizure in complexity domain. Before considering MSE approach, we discuss some entropy measures used to characterize EEG signals in complexity domain. Approximate entropy (Pincus, 1991) and sample entropy are considered two such measures. To understand these two entropy measures, we need to realize entropy. Entropy is a non-linear processing tool and is the measure of the irregularity and disorder. For example, entropy refers to the degree of randomness (unpredictability) and irregularity of analysed time series. The entropy of a time series will have a higher value if the time series shows more irregularity in the amount of information and vice versa.

Approximate entropy is used to quantify the complexity of time series. For example, if the time series reveals more irregularity in the amount of information, the complexity of time series will be higher and vice versa. If the complexity of a time series is higher, the approximate entropy will be higher.

Sample entropy is also used to measure the complexity of time series. It is the modification of approximate entropy and obtained by removing bias from the approximate entropy. The sample entropy of a time series will be lower if the time series represents the higher predictability in the amount of information. Moreover, the time series will be less complex because of demonstrating higher regularity. Sample entropy has better performance compared to approximate entropy.

Although both approximate entropy and sample entropy quantify the complexity of time series, these two entropy measures do not consider the multiple time scales in time series. As a result, the MSE approach was proposed to quantify the complexity of time series by taking into account the different time scales. Since its beginning, it has been used in various research fields such as biomedical time series (Costa *et al.*, 2005; Humeau *et al.*, 2011; Humeau-Heurtier *et al.*, 2012), electroseismic time series (Guzman-Vargas *et al.*, 2008) and financial time series (Niu and Wang, 2015).

Though the existing non-linear methods analysed EEG signals for detecting epileptic seizures , none of the existing non-linear methods analysed EEG signals in complexity domain. As a result, the MSE approach has been employed to identify epileptic seizure by measuring the complexity of EEG signals.

2 Methods

2.1 Multiscale entropy

The multiscale entropy (MSE) approach (Costa *et al.*, 2002) determines sample entropy (SamEn) (Richman and Moorman, 2000) over different time scales to characterize the underlying complexity of non-linear time series. For calculating the SamEn, the MSE method includes three parameters- τ (time lags), m (embedding dimensions) and r (threshold value). The MSE analysis has the following two steps:

- To define temporal scales of increasing length, apply coarse graining process to the following time series:

  $$\{u_i\}_{i=1}^{N}$$

  where N denotes the number of samples in the time series. For a scale factor ξ, the resulting coarse grained time series is calculated as:

  $$x_j^{\xi} = \frac{1}{\xi} \sum_{i=(j-1)\xi+1}^{j\xi} u_i$$

  where $1 \leq j \leq \frac{N}{\xi}$.
- To plot sample entropy as a function of scale factor ξ, consider the algorithm mentioned in subsection 2.2, and calculate sample entropy for each coarse grained time series x_j^{ξ}.

2.2 Algorithm: Sample entropy

- Form $(N-m)$ vectors $U_m(1), U_m(2), ..., U_m(N-m)$ defined by $U_m(i)$= $[u_m(i), u_m(i+1), ..., u_m(i+m-1)]$, where $i = 1, 2, ..., N-m$.
- Determine the distance between two vectors $U_m(i)$ and $U_m(j)$ as maximum norm $d[U_m(i), U_m(j)] = max_{k=1,...,m}\{|u(i+k-1) - u(j+k-1)|\}$.
- Estimate the frequency of occurrence as $A_i^m(r) = \frac{1}{N-m-1} A_i$ and define a global quantity, $A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r)$, where $d[U_m(i), U_m(j)] \leq r, j \neq i$, r denotes a threshold value.
- Extend the dimension of the vectors to $m+1$ and calculate the frequency of occurrence $A_i^{m+1}(r) = \frac{1}{N-m-1} A_i$ and define a global quantity $A^{m+1}(r) = \frac{1}{(N-m)} \sum_{i=1}^{(N-m)} A_i^{m+1}(r)$, where A_i denotes the number of calculated vectors for a given $U_{m+1}(i)$, such that $d[U_m(i), U_m(j)] \leq r, j \neq i$.
- Finally, calculate the sample entropy by using $S_{En}(m, r, N) = -ln[\frac{A^{m+1}(r)}{A^m(r)}]$ for a tolerance level r, where S_{En} denotes the sample entropy, m is the pattern length and N is the length of the time series.

2.3 EEG dataset

The EEG dataset (Andrzejak *et al.*, 2001)(Bonn dataset) used in this study was collected from the Department of Epileptology, University of Bonn, Germany. The dataset comprises

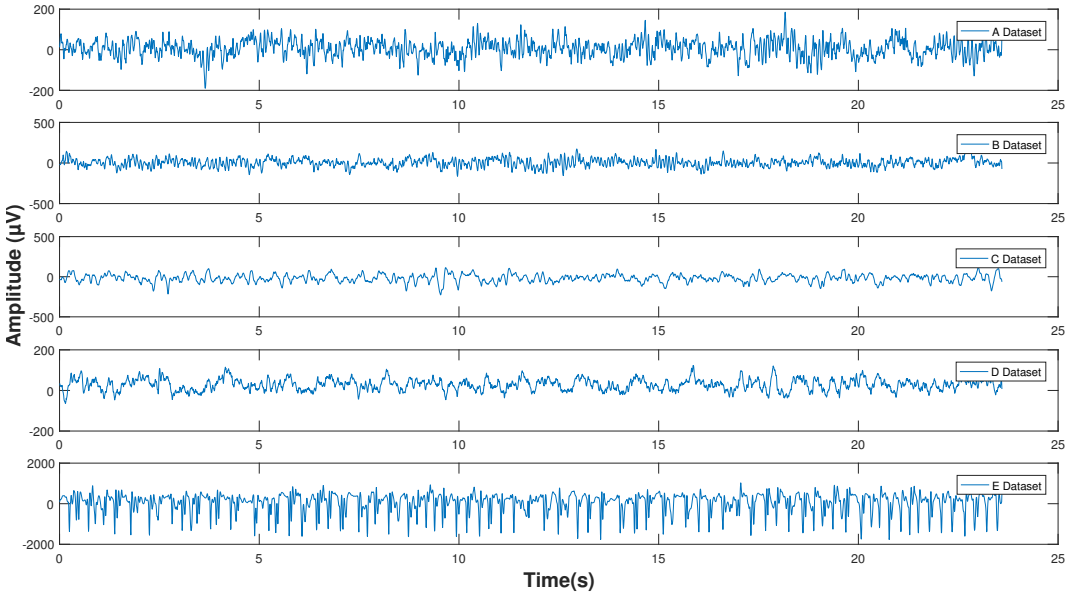

Figure 1: EEG datasets used in this study

of five sets from A to E, each containing 100 single-channel scalp and intracranial EEG segments. Each segment consists of 4097 samples of one EEG time series. The duration of each segment was 23.6 s. Data set A and B represent normal EEG, C and D demonstrate interictal EEG (EEG data collected during seizure-free interval) and E refers to ictal EEG (EEG data collected during seizure activity). The EEG signals were sampled using 12-bit A-D resolution at 173.61 Hz rate. Data was collected with 128-channel amplifier following standard 10-20 electrode placement system. No pre-processing was applied to EEG segments. Table 1 provides the detail information about Bonn dataset. The sample EEG signals of Bonn dataset are shown in Figure 1.

Table 1: Detail of EEG dataset

Dataset	Recorded position	Subject state	Recording Period
A	Cortex	Healthy	Awake and relaxed state with eye open
B	Cortex	Healthy	Awake and relaxed state with eye closed
C	Hippocampal formation	Epilepsy	Seizure-free intervals
D	Epileptogenic zone	Epilepsy	Seizure-free intervals
E	Epileptogenic zone	Epilepsy	Seizure activity

3 Results

3.1 Epileptic seizure estimation based on Bonn dataset

In this subsection, we have analysed the EEG dataset using proposed epileptic seizure detection method (MSE) in terms of complexity. The embedding dimension (m) and time lag (τ) are chosen as 1 and 1 respectively for all results performed in this study. The threshold value r has been selected with trial and error as 20% of the standard deviation of the original signal for better separation among MSE curves. Figure 2 demonstrates that nonseizure activity (A-D) reveals higher complexity in EEG signals than seizure activity (E) due to higher sample entropy values for the majority of the scale factors. During nonseizure activity, the brain contains less functional processes compared to seizure activity, thus makes EEG signals more irregular and increases its complexity. On the other hand, more functional processes are active in the brain during seizure activity. As a result, regular patterns are observed in EEG signals and thus reduces its complexity. Due to non-overlapping behaviour of seizure and nonseizure EEG signals in terms of complexity for the majority of the scale factors, the proposed MSE method can be used to detect epileptic seizure.

From Figure 3, it is observed that normal EEG signals show higher complexity rather than interictal and ictal EEG signals. As normal and interictal EEG signals do not represent seizure activity, the higher complexity exists in these two signals than ictal EEG signals. Since ictal EEG signals were recorded during seizure activity, its structure is more regular and thus shows lower complexity. As a result, the epileptic seizure can be detected by the proposed MSE algorithm in the complexity domain.

3.2 Model evaluation

To validate the results obtained using the MSE method, 40 mean sample entropy values [20 from each class (A vs. E, B vs. E, C vs. E and D vs. E)] and 60 mean sample entropy values [20 from each class (normal, interictal and ictal)] are applied to the input of a classifier (SVM) to measure the sensitivity, specificity and classification accuracy. Since SVM provided a promising classification accuracy compared to other classifiers, it has been used as a classifier. Student t-test and One-way ANOVA test have also been used to verify the MSE method. In this work, 5 fold cross validation is performed to avoid biased classification performance and the statistical parameters (sensitivity, specificity and accuracy) are used to quantify the classification performance of the MSE method in the complexity domain. The statistical parameters are defined as follows:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \quad (1)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \quad (2)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (3)$$

where TP and TN refer to the total number of correctly identified true nonseizure events and true seizure events respectively and FP and FN represent the total number of incorrectly identified true nonseizure events and true seizure events respectively.

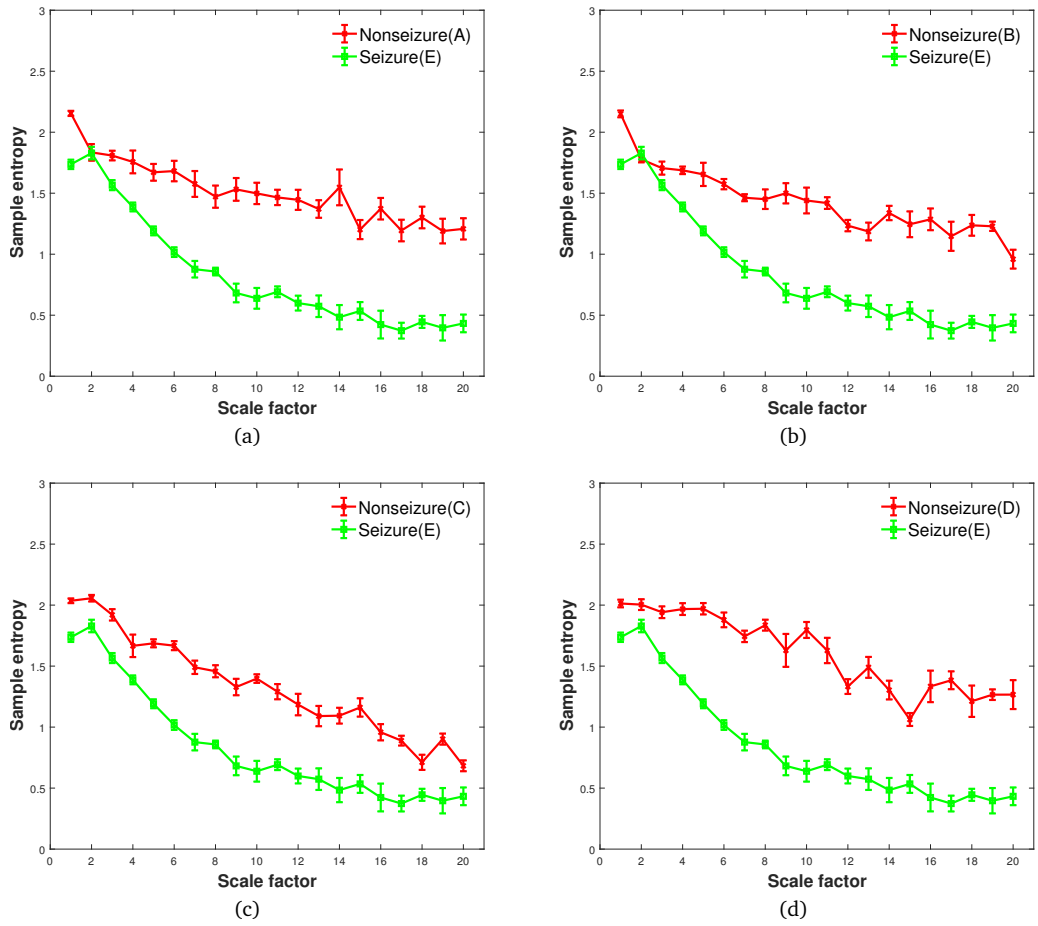

Figure 2: MSE analysis of EEG time series (a) During eyes open (nonseizure) and seizure activity (b) During eyes closed (nonseizure) and seizure activity (c) During seizure-free interval (nonseizure) and seizure activity (d)During seizure-free interval (nonseizure) and seizure activity. The points on the curves represent mean value and error bars represent the standard deviation.

The classification results obtained by SVM have been shown in Table 2, Table 3 and Table 4. Table 2 demonstrates that the SVM has classified nonseizure and seizure EEG signals (A vs. E, B vs. E, C vs. E and D vs. E) with an accuracy of 92.5%, 90%, 90% and 92.5% respectively. Moreover, student t-test has justified that seizure (A,B,C,D) and nonseizure (E) EEG signals are statistically significantly different due to p <0.01 (null hypothesis rejection). According to the confusion matrix of table 3, 5 mean sample entropy values from the ictal EEG class are classified incorrectly, as mean sample entropy values from interictal EEG. However, 20 mean sample entropy values of interictal EEG and 20 mean sample entropy values of Normal EEG are classified accurately by the classification algorithm.

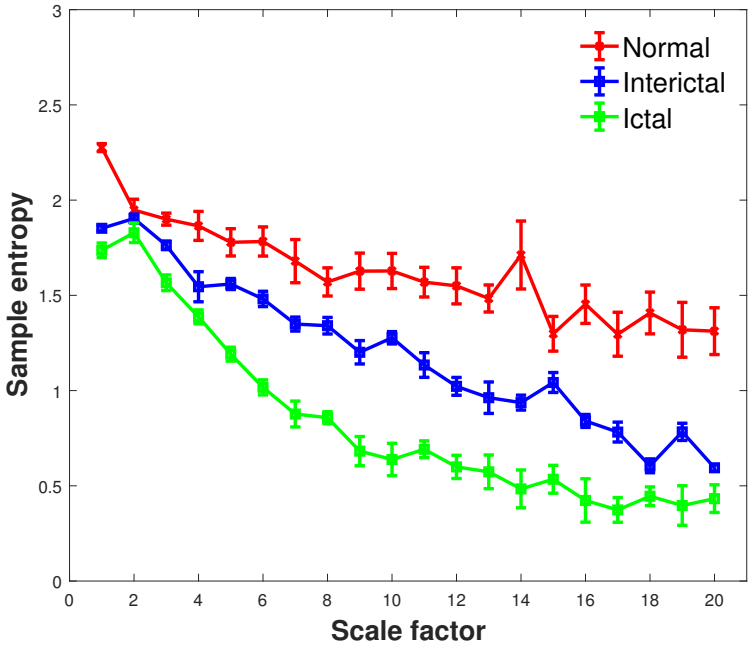

Figure 3: MSE analysis of normal, interictal and ictal EEG signals. The points on the curves represent mean value and error bars represent the standard deviation.

Table 2: Classification Accuracies of two classes (A vs E, B vs E, C vs E and D vs E)

EEG Dataset	Sensitivity (%)	Specificity (%)	Accuracy (%)
A vs. E	100	85	92.5
B vs. E	100	80	90
C vs. E	90	80	90
D vs. E	100	85	92.5

Table 3: Confusion matrix of SVM classifier output

True/Predicted	Ictal EEG	Interictal EEG	Normal EEG
Ictal EEG	15	5	0
Interictal EEG	0	20	0
Normal EEG	0	0	20

Table 4: Classification accuracy of three classes (normal, interictal and ictal EEG)

EEG recordings	Sensitivity (%)	Specificity (%)	Total Accuracy (%)
Ictal EEG	75	100	91.7
Interictal EEG	100	87.5	
Normal EEG	100	100	

Table 4 shows that the classification algorithm has classified normal, interictal and ictal EEG signals with an overall accuracy of 91.7%. Besides, statistically significant difference has been found among normal, interictal and ictal EEG signals as One-way ANOVA test demonstrated $p < 0.01$.

4 Discussion

In this work, characterization of EEG signals collected from Bonn dataset has been represented in complexity domain to detect epileptic seizure. Although there are various epileptic seizure detection methods (Guo *et al.*, 2011; Yuan Q, 2011; Nicolaou and Georgiou, 2012; Kumar *et al.*, 2014; Song *et al.*, 2016; Zhang *et al.*, 2019) in the state of literature, the proposed method based on complexity is novel. The complexity curves showing non-overlapping behaviour for the majority of the scale factors have proved that epileptic seizure can be detected in complexity domain. These complexity results have been verified using support vector machine (SVM) and statistical tests (student t-test and One-way ANOVA test). SVM has been used as it provided promising classification accuracy compared to other classifiers.

As the SVM has provided the sensitivity, specificity and classification accuracy for non-seizure vs. seizure data sets (A vs. E, B vs. E, C vs. E and D vs. E) as 90%-100%, 80%-85% and 90%-92.5% respectively, it can be inferred that the complexity features of seizure and nonseizure EEG signals are distinguishable in complexity domain. Also, this complexity profiles have been justified using t-test (p <0.01).

The complexity profiles of normal, interictal and ictal EEG signals have demonstrated clear distinction among them. The 75% sensitivity and 100% specificity of ictal EEG, 100% sensitivity and 87.5% specificity of interictal EEG, 100% sensitivity and 100% specificity of normal EEG and total accuracy of 91.7% reveal that these three EEG signals are differentiable in complexity domain. Moreover, One-way ANOVA test has also provided p <0.01 to distinguish these three signals.

Although the MSE method has shown feasible results with classification accuracy of 91.7%, this accuracy result is not so promising compared to some other studies (Guo *et al.*, 2011; Kumar *et al.*, 2014; Song *et al.*, 2016; Zhang *et al.*, 2019)(Table 5). This is the limitation of our study.

Table 5: Comparison among methods applied on the Bonn dataset

Authors	Year	Methods	Accuracy (%)
Guo et al. (Guo *et al.*, 2011)	2011	Genetic programming+ K-nearest neighbor classier	93
Yuan et al. (Yuan Q, 2011)	2012	Approximate entropy + ELM	88.00 $\pm$ 0.75
Nicolaou et al. (Nicolaou and Georgiou, 2012)	2012	Permutation entropy + SVM	83.13
Kumar et al. (Kumar *et al.*, 2014)	2014	Fuzzy approximate entropy + SVM	95.85
Song et al. (Song *et al.*, 2016)	2016	a novel fusion feature + SVM	93.67
Zhang et al. (Zhang *et al.*, 2019)	2019	W-FPE-F + SVM	99.56
This paper		MSE+SVM	91.7

5 Conclusion

This research employs a complexity analysis method to characterize the complexity of EEG signals with a view to detecting the epileptic seizure. The complexity curves reveal that the proposed method is feasible to distinguish normal, interictal and ictal EEG signals in the complexity domain. Using support vector machine (SVM) and statistical tests, the effectiveness of distinguishing ability of the proposed method has been verified with the promising classification accuracy of 91.7% and p <0.01.

Acknowledgments

The authors are thankful to R. G. Andrzejak et al. for their EEG data which is publicly available on: http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3. The authors would like to acknowledge the financial support of the Research and Expansion Center of Jatiya Kabi Kazi Nazrul Islam University. The authors would also like to thank the reviewers for their insightful comments that helped them to improving the manuscript significantly.

Declarations

Funding: This research was funded by the Research and Expansion Center of Jatiya Kabi Kazi Nazrul Islam University, Trishal, Mymensingh, Bangladesh.
Conflict of interest: The authors declare no conflict of interest.
Ethical approval: Not applicable.

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