Journal of Electrical and Electronics Engineering

http://electroinf.uoradea.ro/index.php/reviste/jeee.html

Vol. 12, Nr. 1, May 2019 - ISSN: 1844-6035

University of Oradea Publisher

JEEE - Journal of Electrical and Electronics Engineering, Vol. 12, Nr. 1, May 2019

Academy of Romanian Scientists

University of Oradea, Faculty of Electrical Engineering and Information Technology

Journal of Electrical and Electronics Engineering

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University of Oradea Publisher

ISSN 1844 - 6035

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SUMMARY

Quantitative EEG based on Renyi Entropy for Epileptic Classification

HADIYOSO Sugondo[1], AULIA Suci[1], RIZAL Achmad[2]

[1]Telkom University, Indonesia,
School of Applied Science,
40257, Bandung, Indonesia, E-Mail: sugondo@telkomuniversity.ac.id; suciaulia@telkomuniversity.ac.id

[2]Telkom University, Indonesia,
School of Electrical Engineering,
40257, Bandung, Indonesia, E-Mail:achmadrizal@telkomuniversiy.ac.id

Abstract* –Analysis on Electroencephalogram (EEG) signal can provide important information related to the clinical pathology of epilepsy. Detecting the onset, prediction and type of seizures based on EEG signals is very important to determine an appropriate treatment for the patients. However, EEGs have the high complexity with non-linear and non-stationary characteristics; hence, an analysis will be very difficult to do through a visual inspection. Signal processing applications are, therefore, needed to make the interpretation easier. In this study, we proposed a method for EEG analysis based on signal complexity for the epileptic EEG classification. The Renyi entropy was used to extract the data of EEG features, which consist of seizure, interictal and normal features. Then, these features became the input to a classification algorithm. SVM (Support vector machine) classifier was applied to determine the type of that epileptic EEG signal and achieved accuracy of 85 %. This study can be a reference for neurology as an efficient method for epileptic EEG classification

***Keywords:* EEG; Renyi Entropy; Epileptic; SVM.**

I. INTRODUCTION

Electroencephalogram (EEG) is a measurement of the electrical potentials produced by the brain. Compared with other biomedical signals, the EEG signal is extremely more difficult for an untrained observer to understand. EEG spectrum consists of four frequency bands: δ (< 4Hz), θ (4Hz - 8Hz), α (8Hz -13 Hz), and β (13Hz - 30Hz). Various techniques have been developed for understanding the EEG signals to analyze epileptic disorders and epileptic seizure detection [1][2][3]. In this work, a method for the classification epileptic EEG signals was presented using Renyi entropy measures as the continuation of previous research [4] with an experiment showing the accuracy of 97.7 % using sample entropy on MSLD (Multi-distance Signal Level Difference) that classified the EEG signals into three classes: (a) epilepsy patient in ictal (seizure), (b) interictal conditions (occurred between seizures) and (c) normal.

Based on the latest research, Renyi entropy was strongly recommended to analyze the EEG signals for epilepsy seizure. The proposed Renyi entropy has successfully distinguished several different EEG signals with good applications prospects in EEG signals analysis [5]. Another research[6] by Amal Feltane et al. suggested that Renyi entropy combined with EMD (Empirical Mode Decomposition) or DWT (Discrete Wavelet Transform) was effective and applicable for discriminating seizures from Normal EEG Epileptic recordings. According the experiment, Renyi entropy combined with EMD achieved the accuracy of 100 % and Renyi entropy combined with DWT achieved the accuracy of 99.95 % using KNN classifier. Sharma [7] compared six entropy measures ; Spectral Entropy (ShEn), Renyi Entropy (RenEn), Approximate Entropy (ApEn), Sample Entropy (SpEn), Phase Entropies S1 (PhEn S2), and Phase Entropies S2 (PhEn S2) from IMFs of the EEG signals to determine the epileptogenic zone of the brain using SVM classifier. The result showed that ShEn and RenEn quantified the degree of regularity present in the spectral components of the signal; while, ApEnAvg and SpEnAvg entropy measures quantified the self-similarity in the time series. The PhEn S1 and S2 are the complexity measures based on the probability density functions of the bi-spectrum of the signals.

Rederico et al. [8] also compared the classification performance among weighted permutation entropy Hw(P), MinEntropy R_∞ (P), permutation entropy H(P) ,Renyi Entropy R_α (P), and Tsallis Entropy S_q (P). The result showed that all entropies were the excellent classifiers that achieved the accuracy greater than 94.5% and sensitivity greater than 97% in every case. Another research of EEG by Chea Yau Kee et al. [9] studied the Renyi entropy to detect the epileptic seizure and monitor the depth of anesthesia as feature extraction method for MI (Motor Imagery) based on BCI (Brain Computer Interface). In that paper, the highest classification accuracy showed that Renyi entropy achieved 91 % from five variances of BCI competition data set. Renyi entropy was also proposed in the paper of Sriraam et al. [10]. The study was suitable for real time epileptic seizures recognition from multichannel EEG recording. Renyi entropy was combined with PSD, energy, and MLPNN classifier and its simulation results showed that renyi entropy sensitivity and specificity achieved 97.8 % and 96.4 %. The latest research by Sopic et al. [11] presented e-Glass for real time detection of epileptic seizures in which their experiment reached the sensitivity of 93.80% and a specificity of 93.37%, using renyi entropy. However, it is still necessary to find the best order that describes the optimum Renyi parameters to simplify in the case of EEG signal classification.

In this study, a system for the classification of epileptic EEG signals using Renyi entropy (REN) was simulated. REN is used to extract features in three data classes consisting of seizure, interictal and normal. REN is simulated in various orders to find the best parameters and accuracy.

II. MATERIAL AND METHOD

The process used in this study is shown in Fig.1 in which Renyi entropy was used as the feature extraction method. The next process was classification using support vector machine (SVM) with several kernels to obtain accuracy. The number of features used then was reduced to test the affection on accuracy. A more detailed explanation of each process is presented in the following sections.

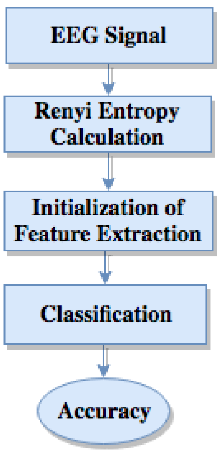


Fig. 1. Proposed Method

A. *Subjects and Data Recording*

In this study, EEG data was used in a freely available database at the University of Bonn [12]. In this study, we used three datasets consisting of seizures, interictal and normal. All subjects were recorded with a 128-channel EEG system. Data were recorded using a sampling frequency of 173.61 Hz, 12 bits resolution and filtered using band pass filter on 0.53–40 Hz (12 dB /oct). Each denoised EEG data had the length of 4098 samples where each data class consisted of 100 data. Example data for each dataset can be seen in Fig.2.

In this research, two pre-processing methods were performed on EEG signals with and without normalization. The normalization process was carried out as shown in Eq.1 and Eq.2.

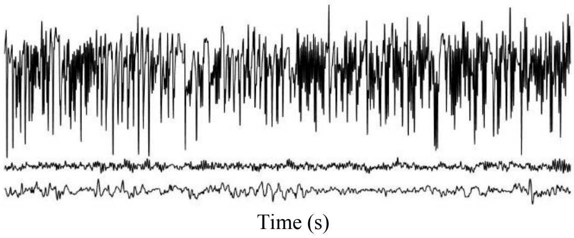


Fig. 2. EEG signal. Top: Seizure EEG, Middle: Normal EEG, below: interictal EEG

$$y(n) = \frac{x(n)}{max|x|} \tag{1}$$

$$y(n) = x(n) - mean(x) \tag{2}$$

By using the two processes above, the EEG signal would have an average of zero and the range of signal -1 to +1.

B. *Analysis using Renyi Entropy*

In this study, we used Renyi entropy to extract the useful features of denoised EEGs. The selection of Renyi entropy as a feature extraction method was based on EEG characteristics, those are non-stationary and tended to be random as a result of complex processes in brain network. Renyi entropy is able to provide information about the diversity or randomness of a system in numerical form. Renyi entropy is the generalizations of Shannon Entropy, which is defined as eq.3 [13] [14][15]:

$$R_{en} = \frac{1}{(1-\alpha)} \ln \sum_{i=1}^{n} p(x_i)^{\alpha} \tag{3}$$

where $p(x_i)$ is a probability distribution on a finite set, α is the order of Renyi entropy to provide a better way to obtain an optimal index [16], which approaches Shanon entropy as 3 , so the Eq.3 is defined as Eq.4 as follows [17] :

$$R_{en} = -\ln \sum_{i=1}^{n} p(x_i) \tag{4}$$

Other equation ways of defining the renyi entropy are the differential renyi entropy as shown by eq.5 [18] and the exponential renyi entropy as shown by eq.7 [19].

$$R_{en}|f| = \frac{1}{(1-\alpha)} \ln\left(\int_{-\infty}^{\infty} \left(\frac{dF}{d\mu}\right)^{\alpha-1} dF\right) \tag{5}$$

where $\Omega, \mathcal{A}$, and μ are the probability spaces and F is the probability measure defined as :

$$F(E) = \int f(x) d\mu(x), \forall E \in \mathcal{A} \tag{6}$$

$$R_{en}^{exp}(X) = \exp\left(R_{en}(X)\right) = \left(\int (f_X(x))^{\alpha} dx\right)^{\frac{1}{(1-\alpha)}} \tag{7}$$

where $\alpha \in [0,1]$. In this work Shannon entropy and Renyi entropy were used with q = 2-100 as a feature. Totally, there were 100 features produced and would be reduced every 10 features until reaching 10 features and then reduced by each one feature. This was done to see the effect of the number of features on accuracy.

C. Support Vector Machine (SVM) and N-fold Cross Validation

In this study, SVM was proposed to predict the qualitative properties of EEG data, they are seizure, interictal and normal EEG data. In this case, high accuracy was the main goal in this research that was very dependent upon the quality of features as the SVM input. Therefore, the feature selection scenario was very important for determining the accuracy. SVM was chosen as it has a good ability in medical applications, one of which is to classify epilepsy as reported in research [1] and [23]. SVM, in essence, is a linear classifier with a hyperline in a flat plane as a separator between classes. However, many cases must be solved non-linearly, so the SVM concept was developed to solve non-linear cases using kernel tricks. SVM is able to map the features set to the new spaces so that the separation between classes becomes clearer (see Fig. 3).

From the explanation above, it is clear that SVM is able to find the best hyperplane to separate two data classes [20]. The best hyperplane is obtained by maximizing a margin between the different feature sets of the class. Margin is the distance between the hyperplane and the closest pattern in each data class (see Fig.4). The closest position between the patterns of each class is called as support vector. In this study, Quadratic SVM and Cubic SVM were used as the linear comparison of SVM.

Because SVM is a method that requires a supervised learning, N-fold cross validation (NFCV) in this study was used to separate the training data and test data. In NFCV, each data class was divided into N data sets. N-1 data set was used as training data and one data set was used as test data. The process was repeated up to N times so that each data set has become test data and training data [21]. Accuracy was taken from the average of all trials conducted [22]. The advantage of this method compared to the distribution of training data and test data randomly was the deviation of the lower accuracy value. The performance parameters of the proposed method were accuracy that was the amount of data, which was correctly classified by the system.

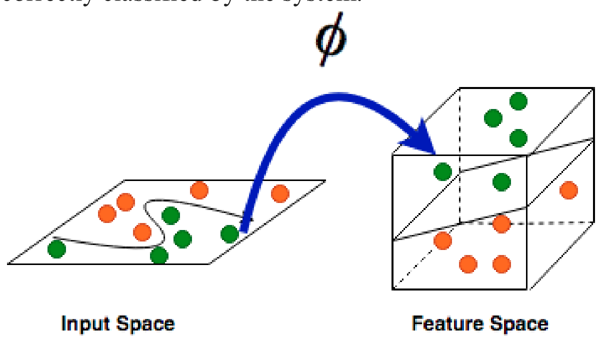


Fig. 3. Transform feature sets to other dimensions.

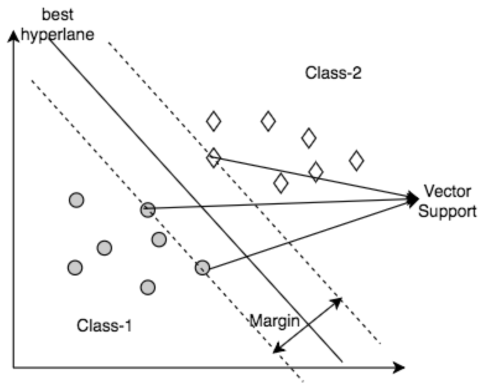
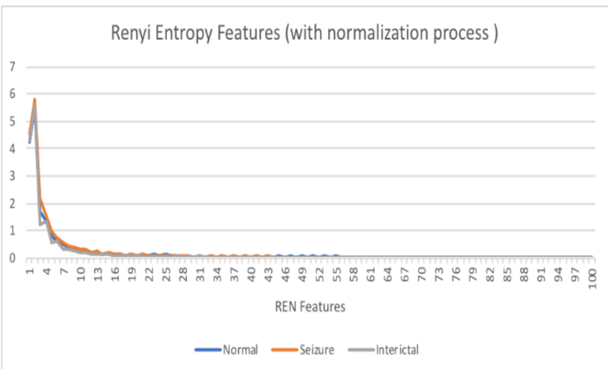


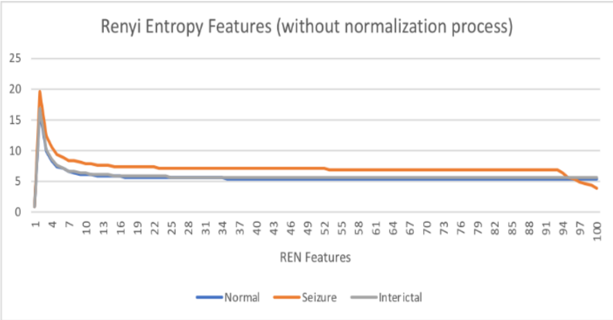
Fig. 4. Optimal hyperplane by SVM.

III. RESULTS AND DISCUSSION

In this study, the application of algorithms including computation of REN and SVM was carried out using MATLAB 2016. Two scenarios (signals with normalization and without normalization) were applied to tests for analysis, whose procedures had the best performance. Figure 5 shows the average REN value (q = 1-100) for each data class. As seen in the graph, the range value of REN (*q* = 20-100) tends to be uniform for both scenarios. Visually, the value of REN without signal normalization showed a significant difference between classes compared to the normalized signal. If we observe the value of signal complexity based on entropy, it appears $REN_{normal}<REN_{interictal}<REN_{seizure}$, indicates that epileptic EEG signals are more complex than normal EEGs as reported in the study [24]. This is reaffirmed in Figure 6 showing the standard deviation of REN for signals without normalization greater than the normalized signal. When considering all values of REN, it was possible to make a feature reduction due to the significant difference in the value of REN only found in some of *q* ranges. The next process was the classification and reduction of features to observe the accuracy produced in each testing scenario.



(a)



(b)

Fig. 5. The average Renyi Entropy value for each class a) with normalization, and b) without normalization.

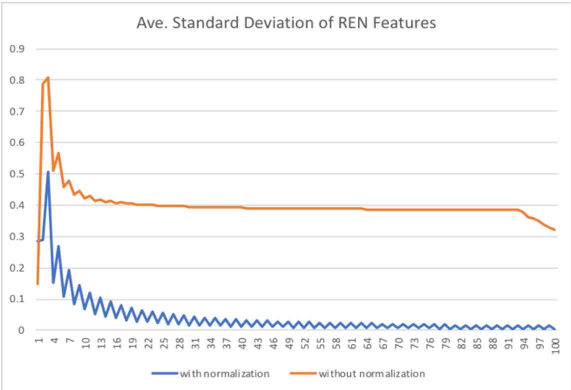


Fig. 6. The standard deviation of EEG signals with normalization process and without normalization process

The process of signal normalization as in Equations (1) and (2) results the fluctuations signal in seizure conditions being invisible because the signal becomes uniform in its range. As seen in Fig.2, the EEG signal in the sizure condition has a very high fulture signals compared to the interictal and normal conditions.
This normalization process affects the accuracy of signal classification as shown in Fig.7- Fig.10. In the EEG signal with normalization as seen in Figure 7 and Figure 8, the highest accuracy of 76.3% was achieved using the 1-6 order entropy characteristic using quadratic SVM. Meanwhile for EEG signals without normalization, the highest accuracy was achieved of 85% using 1-5 order entropy and cubic SVM as shown in Figure 9 and Figure 10. The use of entropy in the EEG signal without the normalization process was superior compared to the EEG signal with normalization in two ways: higher accuracy and fewer number of features.

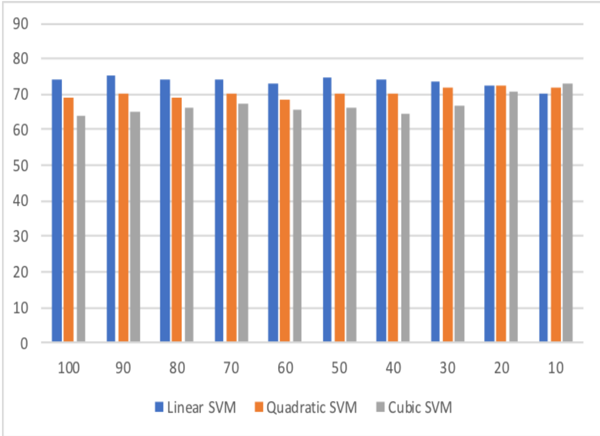


Fig. 7. Accuracy (%) on EEG signals with normalization with 10 - 100 order of Renyi entropy

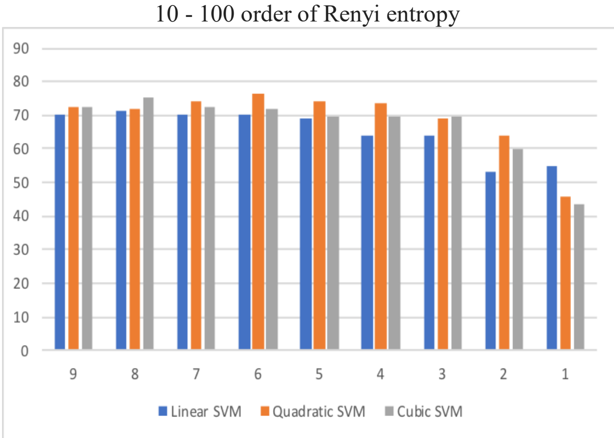


Fig. 8. Accuracy (%) on EEG signals with normalization with 1-9 order of Renyi entropy

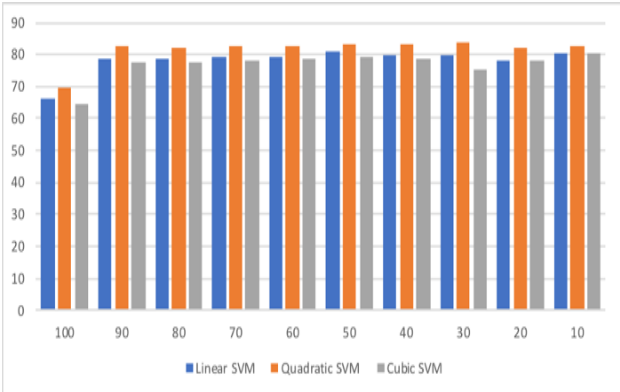


Fig. 9. Accuracy (%) on EEG signals without normalization with 10 - 100 order of Renyi entropy

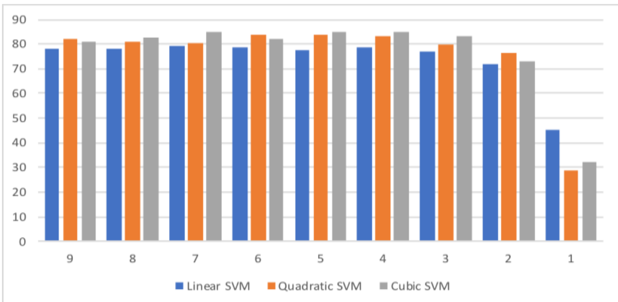


Fig. 10. Accuracy (%) on EEG signals without normalization with 1-9 order of Renyi entropy

In this research, was proposed the use of Renyi entropy using various orders as a feature method of the epileptic EEG classification. The advantage of this method is that no other characteristics are needed for classification. The characteristics between data classes still looks slightly different so the resulting accuracy was not as high as other methods. Some researchers use the same method (Renyi Entropy) for analyzing other biomedical signals, such as used to classify ECG signals in cases of premature ventricle contraction (PVC) [23] and achieved of 95.8% accuracy using the order of entropy 1-6 with fine Gaussian SVM as the classifier. Meanwhile in another study, Renyi entropy was used to classify ECG signals in normal cases, congestive heart failure, and atrial fibrillation [25] was reached of 100% the highest accuracy using three order entropy.

The use of entropy for analysis of epileptic EEG signals usually combined with other methods for manipulating signals. Sample entropy combined with multidistance signal level difference provides up to 97.7% of accuracy for three classes of EEG signals [4]. Meanwhile empirical mode decomposition (EMD) combined with Renyi entropy produced the highest accuracy of 97.3% using the same dataset of EEG signals [26]. Even though the proposed method produced lower accuracy, the use of entropy Renyi for EEG signal analysis still has development potential. The selection of the entropy Renyi order as a feature of the EEG signal using the feature subset selection method can be done in the next study.

IV. CONCLUSION

In this study, extracting characteristics of the epileptic EEG classification was described using Renyi entropy. Renyi netropy was calculated in various orders so that the range of EEG signal complexity values can be seen in normal, interictal, and seizure cases. The highest accuracy of 85% was achieved using 1-5 order and cubic SVM as the classifier. The EEG signal without normalization was execute to maintain the differences of fluctuations signal among three data classes. The advantages of the proposed method were a simple computation and no other characteristics needed for the classification of EEG signals. Combining Renyi entropy with a multiscale method can improve classification accuracy. Exploration further entropy for analysis of biological signals is interesting to do in the next study.

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