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Performance Analysis of Entropy Methods in Detecting Epileptic Seizure from Surface Electroencephalograms

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***Abstract*— Physiological signals like Electrocardiography (ECG) and Electroencephalography (EEG) are complex and nonlinear in nature. To retrieve diagnostic information from these, we need the help of nonlinear methods of analysis. Entropy estimation is a very popular approach in the nonlinear category, where entropy estimates are used as features for signal classification and analysis. In this study, we analyze and compare the performances of four entropy methods; namely Distribution entropy ($DistEn$), Shannon entropy ($ShanEn$), Renyi entropy ($RenEn$) and LempelZiv complexity ($LempelZiv$) as classification features to detect epileptic seizure (ES) from surface Electroencephalography (sEEG) signal. Experiments were conducted on sEEG data from 23 subjects, obtained from the CHB-MIT database of PhysioNet. $ShanEn$, $RenEn$ and $LempelZiv$ entropy are found to be potential features for accurate and consistent detection of ES from sEEG, across multiple channels and subjects.**

Keywords— Entropy, Epilepsy, Epileptic Seizure, Seizure detection, sEEG.

I. Introduction

Like brain cancer, Alzheimer's, stroke, and dementia, epilepsy is considered as one of the major brain diseases that affect the Central Nervous System resulting in seizure episodes from uncontrolled brain activity. About 65 million people around the globe suffer from this dangerous disorder. Surface electroencephalography (sEEG) is the most popularly used method for the diagnosis of epileptic seizures (ES).

To extract diagnostic information from the sEEG, several statistical features, both linear and nonlinear have been used [1–4]. Like any other physiological signal, sEEG also exhibits highly complex and nonlinear dynamics [5]. Naturally, popular nonlinear measures like entropy, Poincare plot, Lyapunov exponent, correlation dimension and so on are preferred for such type of signal analysis [6, 7].

In this study, we compare and evaluate the proficiency of different entropy methods in extracting diagnostic information from sEEG, for detecting ES. The entropy of a signal can be defined as a measure of chaos, irregularity or disorder contained in it. In the past, studies have confirmed the usefulness of entropy features for ES detection [1–4, 8–11]. Here, we intend to compare the usefulness of one entropy feature over another, for ES detection from sEEG.

Entropy methods namely Distribution entropy ($DistEn$), Shannon entropy ($ShanEn$), Renyi entropy ($RenEn$) and LempelZiv complexity ($LempelZiv$) are compared in this study. EEG data from the most commonly used Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) database of PhysioNet [12] has been used for the analysis.

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II. Data and Method

A. Data

Publicly available CHB-MIT database contains 24 sets of EEG data, from 23 subjects with focal seizures. Each subject contains anywhere between 9-42 records, where a record represents 1-4 hours of EEG (256Hz sampling frequency) recorded from multiple channels (e.g. bipolar montages of frontal, parietal, occipital and temporal brain lobes). For this study, we have considered all channels from the brain's left hemisphere for analysis as this part is prone to show more activity during ES [13]. This includes 9 channels namely; 'FP1-F7', 'F7-T7', 'T7-P7', 'P7-O1', 'FP1-F3', 'F3-C3', 'C3-P3', 'P3-O1' and 'T7-FT9'. From these 9 channels, every record that contains at least one seizure event is taken. This brings us to a total of 122 records for analysis. Signal segments with a 5-second window were generated from each channel of the record. Each segment was then labeled as 'with seizure' or 'without seizure', depending on the presence or absence of a seizure episode in it. These segments were then used for feature extraction. A total of 1088705 non-seizure and 14344 seizure segments were obtained from this data setup.

B. Method

In the analysis of this study, two main sets of steps were taken. Feature generation and feature importance calculation are the main steps for analysis.

1) Feature generation: Metadata is provided with the dataset that contains information about subjects and EEG recordings. This metadata was accessed to get information about if a record contains seizure(s) and their onset time in the record. Records with at least one seizure event were considered for feature extraction. As the recordings are from multiple channels, the signal from each channel was separated from the record. For each selected channel's signal, segmentation was done considering a 5-second non-overlapping window and all the entropy features were calculated from that segment. This process continued until the feature extraction for all the segments of all the records was completed.

2) Feature importance calculation: To calculate feature importance, the most common and popular statistical analysis was done using the error graph and Area Under the

ROC Curve (AUC). Error graph was used to observe if some features are good enough to separate seizure classes from non-seizure one. Two types of analyses were done based on AUC: channel-wise observation and patient-wise observation. In channel-wise observation, AUC was used to observe the effectiveness of one channel over another in seizure detection. On the other hand, the patient-wise observation investigated if some features were found that can detect epileptic seizures regardless of the signal variation across different patients. All the generated features for the corresponding records were read and categorized as channel-wise and patient-wise data groups. For channel-wise data, the error graph was observed for the identification of the important features based on class separability for all the channels. Later, the observed features were verified with their corresponding AUC values calculated for each channel. Lastly, the selected features based on performance in the previous steps were observed for patient-wise data to check the consistency using AUC. Two main observations were done to choose the best features and the best channel that perform consistently across all the patients.

3) Features and Parameters:

The features considered for this study ($DistEn$, $ShanEn$, $RenEn$ and $LempelZiv$) are the entropy-based time domain complex non-linear features.

a) Distribution Entropy: Distribution Entropy was initially proposed to mitigate the parametric dependency of Approximate entropy (*ApEn*) and Sample entropy (*SampEn*). These were not robust enough, especially in the case of small data sets. Later a novel entropy measurement technique based on the distribution of distances between internal vectors in the state space was introduced to deliver great robustness [14].

The simplified form of Distribution entropy (*DistEn*) can mathematically be presented as follows:

$$D(X) = \frac{1}{log_b(M)} \sum_{i=1}^{M} P(x_i) \log_b(P(x_i)) \tag{1}$$

Here X is any discrete random variable (signal segment in this case) with possible values $x_1, x_2, ..., x_n$ and it is same for eq.(1)-(3). The length of X is denoted by n. $P(x_i) = Pr(X = x_i)$ is the conventional probability mass function or the probability that X has the value x_i, where $0 \leq P(x_i) \leq 1$. For the analysis of this study, the parameter 'base' b is set to 2 and bin size $M = 500$ as found promising in [15] and this same setup was used in our experiment.

b) Shannon Entropy: Entropy is the measure of uncertainty or randomness of a variable. In information theory, the Shannon entropy (*ShanEn*) is the level of "information", or "uncertainty" on average that is essential in the corresponding random variable's possible results [16]. For any signal X of length n, with possible results $x_1, x_2, ..., x_n$ which occur with probability $P(x_1), P(x_2), ..., P(x_n)$ the *ShanEn* of X is formally defined as:

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log_b(P(x_i)) \tag{2}$$

For the analysis of this study, the parameter 'base' b is set to 2 to make it comparable with $DistEn$. Several studies were conducted for epileptic seizure detection that used this feature [15, 17].

c) Renyi Entropy: $ShanEn$ is the most common method of measuring information, but there are other similar approaches. Renyi entropy ($RenEn$) is a generalized version of $ShanEn$ that preserves the uncertainty and diversity properties of a random variable to a certain extent [18]. The $RenEn$ is the basis of the idea of generalized dimensions in fractal dimension estimation. The Rényi entropy of order α, where $\alpha \geq 0$ and $\alpha \neq 1$, is defined as

$$H_\alpha(X) = \frac{1}{1-\alpha} \log \left(\sum_{i=1}^{n} (P_i)^\alpha \right) \tag{3}$$

Here, the corresponding probabilities $P_i \doteq \Pr(X = x_i)$ for a signal $X = x_1, x_2, ..., x_n$ of length n. Following [4], the convention for the value of the order $\alpha = 2$ is used for feature extraction.

d) LampelZiv Complexity: The LampelZiv Complexity ($LempelZiv$) is used to determine the repetition complexity of signals. The higher the $LempelZiv$ value, the more repetitive the signal [19]. To calculate $LempelZiv$, numeric values from the segment (X) are encoded to symbolic sequence (Y) and then the distinct sub-sequences from that sequence are searched for their repetition. For any symbolic sequence of length n, $c(n)$ denotes the complexity counter or the length of the encoded sub-sequence. $c(n)$ is increased by one unit every time a new sub-sequence of consecutive characters is encountered. At this time the number of different sub-sequences in Y is $c(n)$ [20]. Then the normalized $LempelZiv$ can be defined as-

$$C_{lz} = \frac{c(n) \log_2(n)}{n} \tag{4}$$

Repetition patterns are helpful in investigating signal features sometimes. For experimentation, all other common parameters were kept the same across all the features.

4) Statistical Analysis: For result analysis, popular graphical and statistical measures like error graph and AUC were used for all the features. AUC (Area Under the Receiver Operating Characteristics) represents the measure of separability between different data classes. AUC implies the measurement of importance of corresponding features in classification. The higher value represents that the feature is better in classification. AUC value from > 0.5 to closer to 1.0 is considered as important but $= 0.5$ means that the data is inseparable by that feature.

III. Experimental Result and Discussion

A. Analysis based on channels

The variation of mean and standard deviation (SD) is shown in Fig. 1 for each of the features used; $DistEn$, $ShanEn$, $RenEn$ and $LempelZiv$, in classifying signal segments with seizure from the non-seizure ones. Each subplot of Fig. 1 shows the above mentioned variation for each individual channel used in seizure detection.

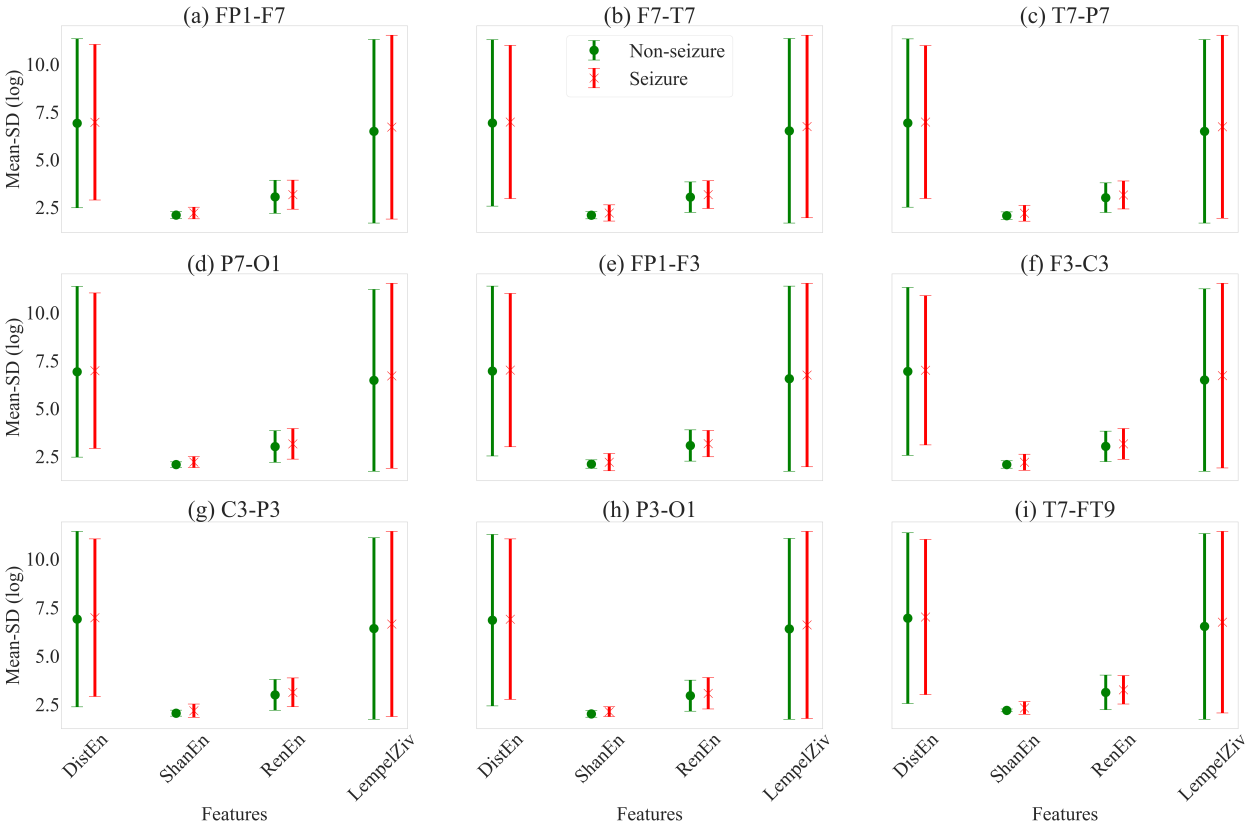

Fig. 1: Mean and SD (standard deviation) variation of feature values for seizure and non-seizure groups of signal segments. Each subplot shows the variation in an individual EEG channel; (a) FP1-F7, (b) F7-T7, (c) T7-P7, (d) P7-O1, (e) FP1-F3, (f) F3-C3, (g) C3-P3, (h) P3-O1 and (i) T7-FT9.

From visual inspection of Fig. 1, we can see that $DistEn$ shows similar mean, in fact almost close to being equal mean values for seizure and non-seizure segments. And they also have completely overlapping SD levels. This pattern can be seen repeatedly in all the nine channels (all subplots of Fig. 1). This would imply that the features, $DistEn$ might not be able to classify the two groups properly, across all nine channels. But on the other hand $ShanEn$, $RenEn$ and $LempelZiv$ show relatively higher variations in seizure and non-seizure segments having significantly higher mean value for seizure segments. They also have noticeable non-overlapping SD levels which indicates the separability of those features. In order to further validate our observation, the AUC value of all features were calculated for each channel and this is shown in Fig. 2.

As can be seen from Fig. 2, $ShanEn$, $RenEn$ and $LempelZiv$ clearly outperforms $DistEn$ in classifying seizure from non-seizure segments. These features show a consistently high AUC value (> 0.75), across all channels, the highest being 0.82 corresponding to channel T7-P7. Interestingly, $ShanEn$ and $LempelZiv$ are having same average AUC level (overlapped dotted lines in the graph) and all three features shows a similar pattern for all the corresponding channels. $DistEn$ is an exception found here in the graph showing a moderate level of consistent AUC across all the channels with the average AUC value of 0.68.

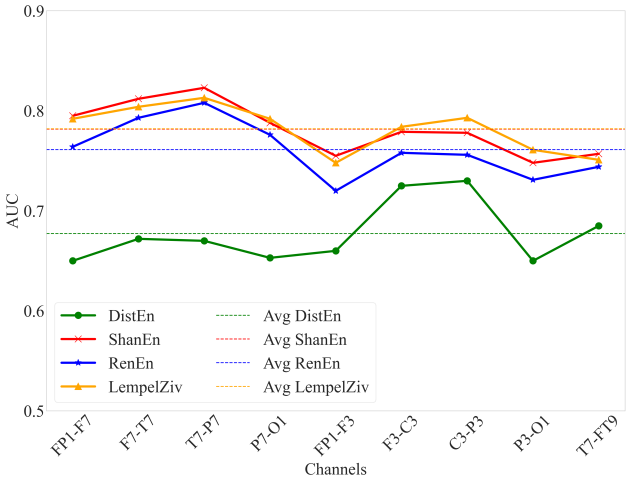

Fig. 2: Variation of AUC with EEG channels. AUC values correspond to each entropy feature: $DistEn$, $ShanEn$, $RenEn$ and $LempelZiv$.

B. Analysis based on patients

Although $ShanEn$, $RenEn$ and $LempelZiv$ showed comparable performance for epilepsy detection, $ShanEn$

and $LempelZiv$ are found to be the best features across all nine channels. To further investigate the capacity of these features, we perform a subject-wise analysis on channel T7-P7, which showed the maximum AUC values for $ShanEn$, $RenEn$ and $LempelZiv$ features. Fig. 3 shows the AUC values of the three best performing features, $ShanEn$, $RenEn$ and $LempelZiv$ for the channel T7-P7 for individual subject.

The observation that can be made from Fig. 3 is that there is a strong inter-subject variability in the performance of studied entropy features. This indicates the need for multi-channel sEEG signal in developing generalised model for seizure detection. All three features have shown similar pattern of variation across all subjects and their mean and standard deviation of AUC further supports this observation (see TABLE I). This means, there is no single feature that is standing out from others.

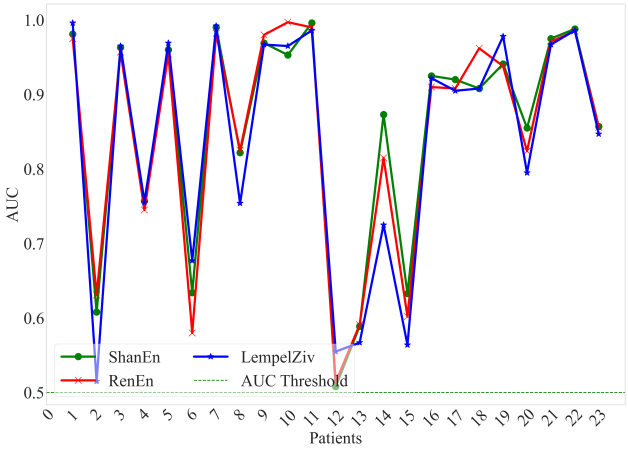

Fig. 3: Variation of channel T7-P7's AUC with subjects. AUC values correspond to each feature: $ShanEn$, $RenEn$ and $LempelZiv$.

TABLE I: Mean and SD AUC of $ShanEn$, $RenEn$ and $LempelZiv$ for channel T7-P7 in differentiating seizure from non-seizure events for all subjects.

Feature	Mean AUC	SD AUC
$ShanEn$	0.85	0.15
$RenEn$	0.84	0.14
$LempelZiv$	0.85	0.15

IV. Conclusion

Entropy is a nonlinear measure of irregularity or chaos present in a signal. Entropy methods are largely used for diagnostic information retrieval from physiological signals like ECG and EEG. In this study, we analyze and compare the performances of a set of entropy methods; namely $DistEn$, $ShanEn$, $RenEn$ and $LempelZiv$ to extract information for epileptic seizure detection from sEEG signals. $RenEn$, $ShanEn$ and $LempelZiv$ methods show high potential to be used for accurate ES detection from EEG, across multiple sEEG channels.

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