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Nonlinear Features-Based Evaluation of EEG Signal for Epileptic Seizure Detection in Human Temporal Lobe Epilepsy

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Abstract:

Epilepsy is a neurological disorder characterized by recurrent seizures resulting from abnormal brain activity. To understand its underlying dynamics, this study applies nonlinear analysis to EEG data recorded during seizures in patients with temporal lobe epilepsy. Specifically, the study explores the evolution of nonlinear features, such as fractal dimension, correlation dimension, entropy, and Recurrence Quantification Analysis (RQA), to classify seizure patterns. EEG recordings from the Fz-Cz channel of 209 seizures across 24 patients were analyzed. These features were used to perform unsupervised clustering using k-means and hierarchical methods to identify recurring patterns and classify seizure quality. The fractal dimension, which captures signal complexity and self-similarity, proved especially informative by showing clear trends throughout seizure progression. The correlation dimension quantified the spatial structure of the signal's reconstructed phase space, while entropy measured signal unpredictability, typically decreasing during seizures, reflecting a transition from chaotic to more structured brain activity. The clustering analysis grouped seizures into 3 to 5 categories, with most seizures from each patient clustering together, suggesting consistent intra-patient seizure dynamics. Among the features, RQA-based measures were the most effective, clustering 87.7% of seizures into a single group, followed by phase space features (71.54%) and fractal dimension (56%). These findings suggest that seizure dynamics, while complex, exhibit repetitive and deterministic behavior across episodes for the same individual. The study supports the hypothesis that epileptic seizures reduce brain complexity, creating more structured and rhythmic patterns compared to normal function. In conclusion, nonlinear EEG analysis effectively characterizes and classifies seizure events, highlighting the deterministic nature of temporal lobe epilepsy. These insights could improve seizure prediction and aid in developing personalized treatment strategies. Future work should expand to other epilepsy types and explore advanced nonlinear methods to further improve classification and predictive accuracy.

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1. Introduction

Epilepsy is a neurological disorder with recurrent seizures due to abnormal brain activity, which remains a persistent risk for patients. Numerous studies have been conducted in this field, including seizure prediction, onset detection, and diagnostic techniques [1–3]. Many of these studies have attempted to automate these processes using computer-based systems to assist physicians in making accurate clinical decisions. Although difficulties primarily in signal processing methods restrict the clinical faith in these

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techniques, continued engineering improvements and the introduction of optimized methods are progressively strengthening their reliability. The lengthy nature of EEG monitoring in epilepsy, specifically in diagnostic clinics, highlights the growing need for automatic methods.

Epilepsy is a qualitative alteration of brain dynamics. This change can be detected from the neural activity patterns, where the dynamics of the normal brain are often marked by complexity and chaos, while epileptic brains show distinctive patterns that reflect reduced complexity. Especially in the time intervals around seizures, rhythmic and less complex activities are usually observed [4].

In this view, epilepsy is a dynamic disorder, one that emerges in an otherwise functional physiological regulatory system and is best characterized by dynamic rather than structural defects. In these systems, normal function exists over a range of internal parameters and inputs, and deviations from this range, occasionally due to unidentified causes, give rise to disease states. Several studies confirm this shift from more complex, quasi-periodic pre-seizure EEG to less complex, more periodic seizure activity [5]. Such transitions suggest a dynamic phase shift, and as such, features must be found that are capable of capturing these shifts. Nonlinear analysis methods have been successful in this endeavor [6–8]. Takens' theorem dictates that the system's dynamics can be reconstructed from any observable time series, e.g., an EEG channel. Time series analysis methods have been developed to allow the discovery of behavior patterns in complex systems [9]. Nonlinear properties, including correlation dimension [10], fractal dimension [11, 12], entropy [13, 14], and Lyapunov exponents [10], are commonly utilized for measuring chaos, complexity, and ordering of systems. Other features have been developed to differentiate between stochastic and deterministic dynamics [6] and to test nonstationarity [15]. Another less explored area in epilepsy research is the analysis of EEG dynamics during seizures, such as the estimation of seizure focus, seizure spread, and changes in seizure intensity. In some studies, the nonstationarity of EEG signals during seizures has been explored [16–18], considering EEG as a traditional example of a nonstationary time series [15]. Continuous changes in EEG patterns occur across a range of mental states [19, 20], especially during seizures [21–22]. These changes have been examined using statistical methods (e.g., power spectrum, wavelet transform [23]) and dynamical methods like recurrence plots [24]. Taylor et al. demonstrated that seizure EEG features cannot be accounted for completely using the power spectrum alone [25]. The discovery of nonlinear dynamics and periodicity in seizures led to hypotheses suggesting deterministic chaos as a possible paradigm [26, 27]. Although these hypotheses were not supported empirically, they initiated significant research into seizure prediction [5, 28, 29], localization [30], and brain network synchronization during seizures [23, 31]. However, studies based on EEG nonstationarity analysis using nonlinear approaches are still relatively uncommon [32, 33]. Research that has utilized recurrence plots has demonstrated that they can maintain the temporal nuances of seizure time series [34], unlike linear statistical analyses that presume linear relationships in data. In a comparison study by Dikanou et al. [34], recurrence analysis was found to reveal more subtle seizure states than wavelet or power spectrum methods, occasionally characterizing 3–4 distinct seizure phases. Many previous studies focus on the recognition of patterns via the utilization of discrete characteristics without examining the temporal evolution of nonlinear indices during seizure events. In addition, seizure quality and variability for seizures that happen in multiple events within the same patient have rarely been investigated. Therefore, this study aims to clarify temporal evolution patterns of nonlinear features while describing both general and patient-specific attributes for seizure quality.

2. Materials and Methods

In this study, long-term EEG monitoring data were used from patients diagnosed with temporal lobe epilepsy who were resistant to treatment. Nonlinear features were extracted and analyzed from the Fz-Cz channel of these EEG recordings. Specifically, correlation dimension, fractal dimension, and Kolmogorov entropy were computed to investigate the temporal changes of these nonlinear features. In addition to these analyses, phase space features and recurrence quantification measures were employed to assess the quality of the seizures. A total of 209 seizures from 24 epileptic patients were processed and analyzed.

2.1. Database

EEG recordings utilized within this study are from the MIT-BIH database concerning patients diagnosed with drug-resistant temporal lobe epilepsy. The recordings correspond to a group of 23 patients consisting of 5 males aged between 3 and 23 years and 17 females aged between 1.5 and 19 years. The recordings were obtained with a sampling frequency of 256 samples per second with a 16-bit resolution. The database includes recordings from 23 channels based on the international 10-20 electrode placement system. Two hundred nine seizure recordings were captured. It should be noted that the dataset is in raw condition and has not been processed for noise reduction and artifact removal [35].

2.2. Phase Space

One of the most fundamental tools in the study of time series dynamics, particularly those biological signals that are predominantly produced by nonlinear systems, is the phase space. Through the application of phase space, some of the behavioral properties , like periodicity, aperiodicity, quasi-periodicity, and chaoticity of the data can be studied. In studies related to biological phenomena where the governing equations of the system are unknown and only a set of observations, such as EEG signal recordings, are available, the system is understood through these observations [9]. As stated by Takens' theorem, a time series belonging to an attractor with a dimensionality of d will have the same topological features as those of the reconstructed attractor in an m-dimensional phase space formed by delay vectors, provided that the condition $m \geq 2d + 1$ holds. For a time series x(n) for n=1,2,…, N samples, the time-delay phase vectors are constructed according to equation (1).

$$X(i) = [x(i).x(i+\tau).x(i+2\tau).\ldots\ldots.x(i+(m-1)\tau)]\ \ i = 1.2.\ldots..N-(m-1)\tau \quad (1)$$

Where τ is the time delay and mmm is the embedding dimension. In the present work, the time delay τ has been calculated using the mutual information method, and the embedding dimension mmm has been determined using the false nearest neighbor method [10].

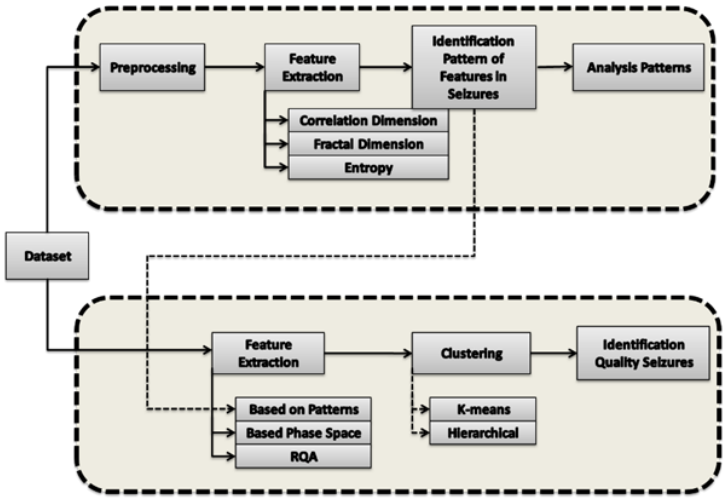


Figure 1. Block diagram of the proposed method.

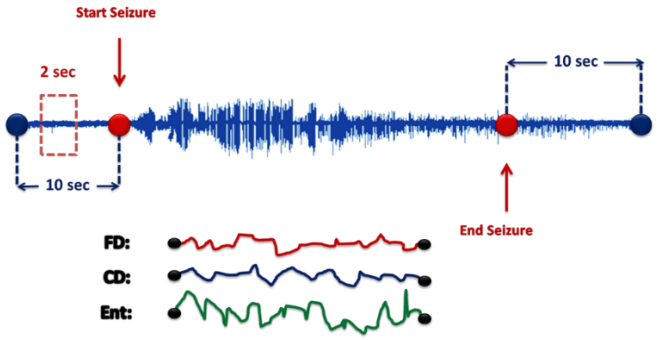


Figure 2. Quantification changes in nonlinear features of epileptic seizures.

2.2.1. Correlation Dimension

The correlation dimension can be computed with the correlation integral [10]:

$$C(\epsilon) = \frac{1}{N^2}\sum_{i,j=1}^{N}\theta(\epsilon - \|x(i) - x(j)\|) \quad (2)$$

where x(i)∈R is the m-dimensional delay vector.

2.2.2. Fractal Dimension

The fractal dimension is a quantitative index of a signal's chaotic quality. In this investigation, the Katz method was used to compute the fractal dimension:

$$D = \frac{log_{10}(L)}{log_{10}(d)} \quad (3)$$

where L is the sum of the distances between consecutive points, and d is the distance between the first point in the process and the furthest point [11].

2.2.3. Entropy

Entropy is defined as the symbolic measure of the rate of information production; generally, a higher entropy will be interpreted as a greater disorder in the signal. In this paper, entropy was computed from the following equation:

$$ApEn = \ln\left(\frac{C_m(r)}{C_{m+1}(r)}\right) \quad (4)$$

where $C_m(r)$ is the mean of the pattern with length m and $C_{m+1}(r)$ is the mean of the pattern with length m+1[13].

2.3. Recurrence Plot

A way of representing information in two dimensions, the premise is simply that in dynamical systems, the recurrence of a system's state to the same areas of the phase space--areas passed over by the trajectory previously is a fundamental property of dynamical systems and can be used to describe system behavior in their phase space [36]. The recurrence of any state at time i at different times j can be represented using a square matrix of zeros and ones, in which the direction of the axes is time for both axes. This plot can be produced by the following equation:

$$R(i,j) = \theta(\varepsilon(i) - \|x(i) - x(j)\|).\, x \in R^m\ i,j = 1 \ldots N \quad (5)$$

where N is the length of the data segment, θ(x) is the step function, ‖·‖ is the norm, and ε(i) is the radius defining the neighborhood for each point x_i. The quantification of hidden patterns in the recurrence plot is called Recurrence Quantification Analysis (RQA) [2].

2.3.1. Recurrence Rate (RR)

Indicates the percentage of recurrence points on the plot and is related to the correlation sum:

$$RR = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{i,j} \quad (6)$$

2.2.4. Determinism (DET)

The percentage of recurrence points forming diagonal lines relative to all recurrence points:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{i,j=1}^{N} R_{i,j}} \quad (7)$$

2.2.5. Longest Diagonal Line (L_max)

Specifies the length of the longest diagonal line:

$$L_{max} = \max(\{l_i; i = 1 \ldots . . N_l\}) \quad (8)$$

2.2.6. Entropy (ENTR)

The entropy of the diagonal line lengths:

$$ENTR = \sum_{l=l_{min}}^{N} P(l)\ln(P(l)) \quad (9)$$

2.2.7. LAM

Determines the percentage of reversal points that form vertical lines.

$$LAM = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)} \quad (10)$$

2.2.8. Trapping time

Determines the average length of the vertical dots.

$$TT = \frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=v_{min}}^{N} P(v)} \quad (11)$$

2.4. Clustering

Clustering is arguably the most critical problem in unsupervised learning. It entails finding structure within a set of unlabelled data. In clustering, the goal is to partition data into clusters, where similarity between data points within each cluster is maximized and between clusters is minimized. In this paper, K-Means and Hierarchical clustering were used to identify not only the overall quality of seizures but also the quality within seizures.

2.4.1. K-Means Clustering

In K-Means, we first randomly select a specified number of cluster centers. The data points are then assigned to clusters based on their proximity to these centers (i.e., similarity to these centers), establishing new clusters. New centers are computed during each iteration as the average of the data points in each cluster, and data points are reassigned to clusters based on the new centers. This process is completed when cluster membership no longer changes.

2.4.2. Hierarchical Clustering

In some cases, data representations use clusters and sub-clusters in a tree representation. There are two types of hierarchical clustering: agglomerative and divisive. The typical way an agglomerative clustering will work is to start with N single clusters and recursively merge clusters down to one cluster. The typical way to do divisive clustering is to start with one cluster, recursively split clusters, and work down to N single samples.

Linkage Plots

When dendrograms are plotted, the relative size of the similarity coefficients reiterates where the data points were combined. Larger distance coefficients and more minor similarities are data points that are not similar being merged, which is undesirable. Variables or data points near each other have smaller distances and higher similarities. The dendogram has a line on the left that connects those variables, which indicates that these variables combined and were similar. In contrast, if the line connecting data points is located on the right side of the dendrogram, those data points or clusters were merged at a larger distance coefficient, meaning those were likely not similar data points or clusters and became one cluster together.

2.4.3. Cluster Validation

The Davies-Bouldin index was used to evaluate the clusters. This metric uses the similarity between two clusters, R_{ij}, and is defined as follows:

$$DB = \frac{1}{n_c}\sum_{i=1}^{n_c} R_i \quad (12)$$

where Ri is defined as:

$$R_i = \max_{j=1\ldots..n_c.\ i=j}(R_{ij}).\ i = 1 \ldots \ldots n_c \quad (13)$$

Here, n_c is the number of clusters. A lower value of this index indicates better clustering results.

3. Results

3.1. Temporal Changes of Indices During Seizures

Initially, the temporal variations of three indices, correlation dimension, fractal dimension, and Kolmogorov entropy, were examined on the Fz-Cz channel for 209 seizures from 24 subjects. Figure 3 shows that the fractal dimension produced regular patterns during seizures, whereas this was not the case for entropy. Similar patterns to the fractal dimension were observed in the correlation dimension. One reason for this can be traced back to the nature of these two indices. Implicitly, the results suggest that indices like fractal dimension and correlation dimension, which are based on evolution and interaction, differentiate themselves from entropy, which lacks such characteristics, in their computations.

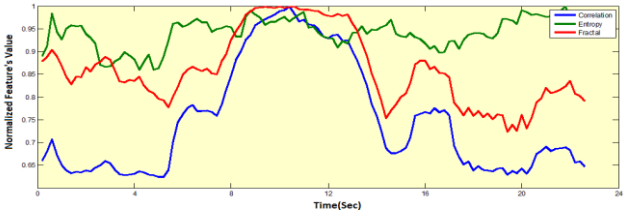


Figure 3. Temporal changes of fractal dimension, correlation dimension, and Kolmogorov entropy during an epileptic seizure.

3.2. Interpretation of Fractal Pattern During Seizures

Although the brain system transitions to a known state, given its nonlinear character, dynamic interactions between brain components would be expected to exhibit different areas of chaotic behavior. Various properties of the interactions between brain components emerge during seizures, generating increasing and decreasing fractal dimension patterns and representing competing fractal dimension states during the seizure time period. Figure 4 illustrates the captured pattern of fractal dimension during seizures in general.

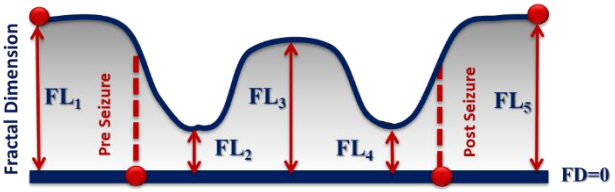


Figure 4. Identified fractal dimension pattern during epileptic seizures.

To apprehend and better quantify the type of pattern outlined, various segments of the pattern, each representing a different quality stage of seizure, were named and calculated. In Figure 4, the points chosen for analysis are labeled, and the explanations are provided in Table 1.
Values FL2 and FL4 indicate that similar interaction states exist at the beginning and end of epileptic seizures, as shown in Figure 5.

Table 1. Calculated parameters in two sections.

Symbol	Description
FL_1	Fractal dimension before the attack
FL_2	Fractal dimension at the first bottom of the pattern during the attack
FL_3	Fractal dimension at the top of the pattern during attack
FL_4	Fractal dimension at the second bottom of the pattern during the attack
FL_5	Fractal dimension after attack
t_1	Time of occurrence of the first bottom of the fractal pattern valley
t_2	Time of occurrence of the top of the fractal pattern valley
t_3	Time of occurrence of the second bottom of the fractal pattern valley

Table 2. Evaluation of fractal dimension during seizures.

Types of occurs	Number of occurs
$FL_2 < 1.2$	209
$FL_4 < 1.2$	103
$FL_3 > 1.8$	96
$FL_4 < 1.2$ and $FL_2 < 1.2$	61
$FL_2 < 1.2$ and $FL_3 > 1.8$	80
$FL_4 < 1.2$ and $FL_3 > 1.8$	13
$FL_4 < 1.2$ and $FL_2 < 1.2$ and $FL_3 > 1.8$	4
$FL_2 < 1.2$	1

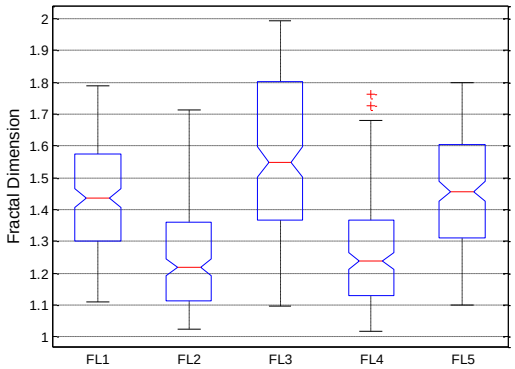


Figure 5. Boxplot of fractal dimension values associated with four different seizure states.

In contradiction, statistics indicate that fractal dimension and correlation dimension indices decreased in the epilepsy state. It was observed that during some seizures, the values of the fractal dimension increased compared to the normal state (FL3 in Figure 5). Therefore, the fractal dimension range alone is insufficient for judgment and deserves consideration regarding which value the index is tending to. Table 2 summarizes the number of occurrences indicating synchronized states of the brain system. As the fractal dimension in the normal brain state was between 1.4 and 1.6, two thresholds of 1.2 and 1.8 were selected to evaluate the synchronization during seizures.
Reviewing the chart and figures, one can determine that the values of the peak and trough phases come reasonably close to integer values, not in every case, but in many. Thus, two forms of synchronization occur during seizures; the trough phases have a much greater contribution than the peak phases.

3.3. Phase Space Analysis

Figure 6 depicts the EEG signals' phase space in normal and epileptic seizure state. Since the brain system experiences a loss of chaoticity during epileptic seizures, the degrees of freedom of the system are also condensed. Thus, the phase space trajectories can only move along considerably limited paths, increasing the signal's contraction with respect to its expansion.

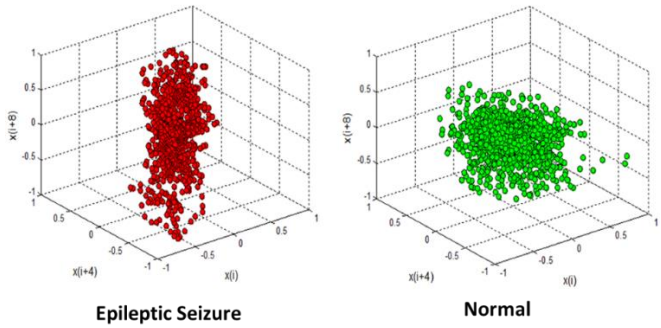


Figure 6. Phase space of EEG signals in normal and epileptic seizure states.

Since phase space angles characterize the changes in the spatial arrangement of points, they seem applicable in assessing seizure quality. Figure 7 depicts the frequency distribution of both seizure phase and phase space angles for a seizure event.

Table 3. Extracted features from the phase space angles of seizures.

Symbols	Description
PRP_{Mean}	The angle around which the phase space angles of the attacks are grouped, or clustered
PRP_{Std}	The dispersion of the phase space angles about the mean value
PRP_{Range}	The variation range of phase space angles for each attack
PRP_{IQR}	The range which includes 50% of the middle phase space angles
PRP_{Prc25}	The angle below which 25% or fewer of the phase space angles fall
PRP_{Prc50}	The angle below which 50% or fewer of the phase space angles fall
PRP_{Prc75}	The angle below which 75% or fewer of the phase space angles fall
PRP_{Kurt}	The degree of elongation of the phase space angle histogram

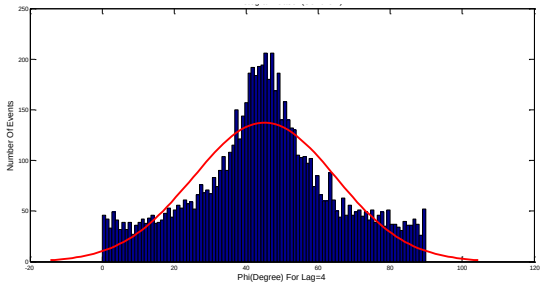


Figure 7. Histogram of phase space angles relative to a seizure in a Lag=4.

The angle frequency histogram revealed that the phase space angles cluster around 45 degrees, and the average mean angle across all the seizures is 44.98 degrees. This is an indication of the assumptions made about epilepsy that the system will naturally move toward and exhibit synchrony. In the construct of the phase space, the point density that surrounds the bisector indicates that the system is moving toward quasi-periodicity, but the contraction of the brain system to move precisely away from expansion is much greater. Therefore, by defining features based on phase space angles, we can begin to show the similarities and differences between the seizures. A set of statistical features based on angle distributions, termed a PRP, was extracted and given in Table 3.

3.4. Recurrence Plot Analysis

As shown in Figure 8, there are deterministic and quasi-periodic behaviors (illustrated by square shapes in the plot) in the dynamics of the EEG signal during epileptic seizures. In the normal state, the number of recurrence points is much lower, suggesting the least amount of signal determinism and possibly indicating chaotic behavior instead. It is abundantly clear that the different levels of EEG signal chaoticity and the presence of a quasi-periodic behavior can be present in different seizures. Hence, recurrence quantification measures can identify various types of similarities and differences among seizures.

Figure 9 displays boxplots for the three features: DET, ENTR, and LAM. The results for the DET feature show that determinism increases during epileptic seizures over the normal state.

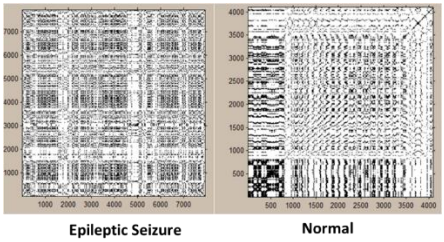


Figure 8. Recurrence plots in normal and epileptic seizure states.

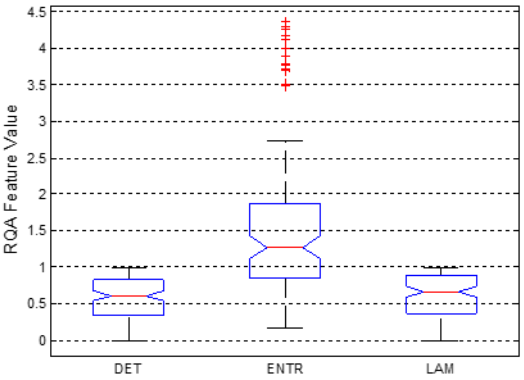


Figure 9. Boxplots of DET, ENTR, and LAM features during epileptic seizures.

3.5. Identifying Seizure Quality

In previous sections, we extracted and then qualitatively evaluated seizure quality based on features predominantly from three different approaches (fractal pattern, phase space, and recurrence plot), calculated three sets of features based on our analyses, and applied the feature set to the recognition system to identify seizure quality. Seizure Quality by Individuals K-Means clustering was then done subsequently on 209 recorded seizures from 24 patients with temporal lobe epilepsy. The data is presented in Tables 4-6, with variations in the number of clusters.

3.6. Identifying the Best Clustering

Since we made no prior assumption about how many clusters we would like to have to categorize the quality of seizures, we applied the Davies–Bouldin validation index to identify the best clusters. The Davies–Bouldin index was calculated for the three clustering results using k=2 to k=10. The Davies-Bouldin index curve versus several clusters is shown in Figure 10. The minimum location gives you the optimal number of clusters to implement.

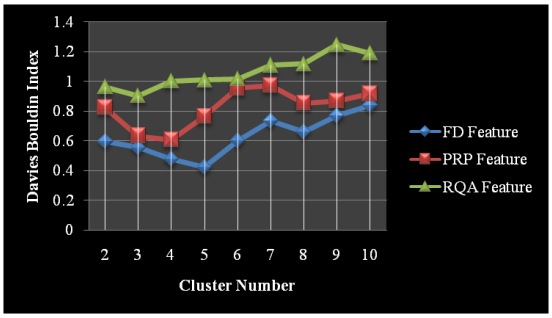


Figure 10. K-Means clustering validation using the Davies–Bouldin index for the three feature sets.

As evident, using three different approaches, the clustering with respect to seizure qualities produced a set of 3-5 quality levels for all 209 seizures. Based on the calculated values from the Davies-Bouldin index method, the best clustering results were obtained through the fractal pattern features, followed by results from the phase space and results based on recurrence quantification features.

3.7. Analysis of Subject-specific Seizure

For quality or subject-specific analyses of variation in seizure quality, first, we examined the K-Means clustering results, and then provided the hierarchical clustering results for a subject with 40 seizures (Figure 11). Use the information with caution and limit the information from a subject to either K-Means or hierarchical clustering, as data from a subject with multiple seizures can double account for variations in quality.

As observed, for the fractal dimension features, clustering points occurred at a higher distance coefficient, indicating that even though similarity was low and the clusters were eventually combined into a single cluster, this outcome demonstrates that features based on fractal pattern delineated greater differentiation of intra-individual seizure quality than the other two sets of features, which suggests that the individual experienced a larger range of seizure qualities over multiple episodes. In comparison, the dendrograms based on the other two approaches show more similar intra-individual seizure qualities.

Table 4. K-Means clustering results based on fractal pattern features.

	Seizures in Cluster					
Clusters	K=2	K=3	K=4	K=5	K=6	K=7
1	87	96	25	23	24	21
2	122	63	69	74	22	20
3	-	50	39	47	56	45
4	-	-	76	38	32	16
5	-	-	-	27	64	5
6	-	-	-	-	11	32
7	-	-	-	-	-	70

Table 5. K-Means clustering results based on phase space features.

	Seizures in Cluster					
Clusters	K=2	K=3	K=4	K=5	K=6	K=7
1	120	66	70	62	52	52
2	89	74	64	41	1	33
3	-	69	20	70	35	3
4	-	-	55	1	17	17
5	-	-	-	35	42	42
6	-	-	-	-	62	61
7	-	-	-	-	-	1

Table 6. K-Means clustering results based on recurrence quantification measures.

	Seizures in Cluster					
Clusters	K=2	K=3	K=4	K=5	K=6	K=7
1	173	32	12	20	143	23
2	36	164	5	156	6	2
3	-	13	29	18	22	6
4	-	-	163	4	9	17
5	-	-	-	11	2	139
6	-	-	-	-	27	9
7	-	-	-	-	-	13

4. Discussion and Conclusion

In this study, and considering the nature and dynamics of the EEG signal we were looking at, we tried to investigate domains relevant to this nature - for example, phase space - for signal processing. We then compared the results. The identification of changes in temporal patterns during seizures, the development of pattern-dependent features, features from phase space, and the method we used to identify seizure quality and variability across individual-specific seizures have not been previously reported in the literature. Many different features were compared and distinguished from seizures based on a particular context. In wearable health systems, such as seizure prediction or detection, that should work without relying on individual differences, features could rely on quantifiers based on shared characteristics of seizures. Whereas, when trying to find characteristics of seizures that are individual-specific,

the features used to extract these individual-specific characteristics have to be more discriminative.

As shown in Figure 10, the most successful clustering created by features from the fractal pattern showed that features based on phase space and features based on recurrence quantification resulted in lower performance. Furthermore, a few seizure qualities were represented across multiple seizures for each subject, as shown in Figures 12 and 13. On average, for optimal clusters, there was 56% agreement of seizures within the same cluster (quality) using fractal pattern features, 71.54% agreement using phase space features, and 87.7% agreement using recurrence quantifiers for each person.

In addition, for the fractal feature group, 74.12% of the seizures from the 17 subjects who had more than two seizure qualities were represented by two clusters. Additionally, 78.38% of the seizures from five subjects who had more than three seizure qualities were represented by three clusters. Those 17 subjects with fractal feature data did not record individuals with five different seizure qualities. Similarly, for the phase space features, 77.7% of the seizures in four subjects who showed more than two seizure qualities were represented by two clusters, while 87.5% of the seizures in the subject who showed more than three seizure qualities were represented by three clusters. With respect to the recurrence quantifiers, 83.9% of the seizures in four subjects had more than three seizure qualities, and they were also represented by three clusters.

These findings suggest, on the whole, that seizure quality does not significantly differ for each subject despite differences between subjects. In fact, it may be inferred that the changes in features in recurrent seizures occur in a continuous and structured manner. The one derived conclusion of the study is that generally, a limited and consistent set of qualities is experienced in an overall consistent way in multiple episodes by subjects with temporal lobe epilepsy. Also, as the study subjects were drug therapy-resistant patients, the presence of homogeneity across different seizure events was quite possible. Also, as each subject presented with a particular subset of qualities in their seizures, the disorder meets the requirements for repetitive behavioral patterns in the condition, confirming the disturbing assumption that epilepsy has deterministic dynamics.

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