THE JOURNAL OF COGNITIVE SYSTEMS
Journal Homepage: https://dergipark.org.tr/en/pub/jcs
Vol.8, No.1, 2023

Epileptic Activity Detection using Mean Value, RMS, Sample Entropy, and Permutation Entropy Methods

Ceren Canyurt[1], **Reyhan Zengin**[2]

[1] Inonu University, Department of Biomedical Engineering, Malatya, Turkey. (e-mail: canyurtceren10@gmail.com).
[2] Inonu University, Department of Biomedical Engineering, Malatya, Turkey. (e-mail: reyhan.zengin@inonu.edu.tr).

ARTICLE INFO

Received: April, 21.2023
Revised: May, 23.2023
Accepted: May, 28.2023

Keywords:
Epilepsy
Root Mean Square,
Mean of Signal
Sample Entropy
Permutation Entropy

Corresponding author: Ceren Canyurt
✉ canyurtceren10@gmail.com
☎ +90 5310879299

ISSN: 2548-0650

DOI: https://doi.org/10.52876/jcs.1226579

ABSTRACT

In this study, linear and non-linear signal analysis methods are implemented for epilepsy seizure detection using CHB-MIT EEG data taken from Boston children's hospital. In linear signal analysis, EEG signals are considered linear, although they are not linear. In linear signal analysis methods, root mean square (RMS) and mean of the EEG signals are analyzed. It is detected that the RMS value increased and the mean value moved away from zero in the positive and negative directions during the seizure period. Seizure periods in EEG signals are determined with RMS and mean values with 75 % and 58.4 % accuracy, respectively. Since EEG signals are not linear, the linear analysis is assumed insufficient and so entropy is preferred to linear signal analysis methods. Sample entropy (SmpE) and permutation entropy (PE) are preferred among entropy types. While an increase is observed in the sample entropy values at the beginning of the seizure, a decrease is observed in the permutation entropy values at the same time. When the entropy methods are examined separately, the onset of a seizure is determined with an accuracy of 66.6 % for both methods. However, when the entropy methods are examined together with the increase in the sample entropy value or the decrease in the permutation entropy, the accuracy rate increases to 79.2 % The resultant accuracy rates show that when one entropy method fails to catch the onset of a seizure the other can.

1. INTRODUCTION

Epilepsy has been seen in written sources dating back to 4000 BC. It is defined as the involuntary movement of part or all of the body. The reason for these movements is the electrical discharge in the brain. This electrical discharge can be caused by an infarction, tumor, progressive brain disease (rare), or head injury. However, there are some electrical discharges of unknown cause. Epilepsy is a genetic, non-communicable disease and is not related to age, gender, or race [1,2].

Electroencephalography (EEG) signals have been important in the diagnosis of epilepsy due to the recognition of spikes in EEG signals during epileptic seizures [3]. In epilepsy diagnosis, in addition to EEG, neurological information and neurodiagnostic tests are also used. Electrodes are placed on the scalp in the laboratory environment for EEG recordings. These recordings are classified as ictal, postictal, and interictal. The ictal period is called for during the seizure period, the postictal is called for the post-seizure period and the interictal is for the period between the seizures [4]. Interictal EEG recordings are used in the diagnosis and in the management of the treatment course of epilepsy. In order to diagnose epilepsy, the patient's EEG data, as well as physical examination, seizure history, and neurological tests are taken into account [5]. Of all data, the most important finding is the EEG recordings. Furthermore, having one seizure is not enough to diagnose epilepsy, patients must have at least two or more seizures.

The anti-epileptic drugs are used first in the treatment of epilepsy. The dose of the drug is calculated according to the severity of the seizures of the patient [6]. Drugs can prevent most seizures, however, there are some patients' seizures that cannot be prevented despite using high-dose. Generally, surgical interventions can be a treatment for epilepsy patients. However, there are some cases where surgical intervention is not a solution [7]. Vagus nerve stimulation, in addition to surgical intervention, is a treatment method in which an electrical current is sent to the brain at regular intervals to prevent seizures [8]. Unfortunately, there are some patients who do not respond to any treatment method. In these cases, the moment of seizure should be predicted and it should be ensured that the seizure can be overcome with the least damage. In the diagnosis and treatment stages of epilepsy, it is very time-absorbing to examine long-term EEG recordings by experts and to detect seizures. Therefore, EEG signals are analyzed with linear or nonlinear signal analysis methods in order to detect the epileptic region in EEG. Although EEG signals are not linear, in the linear signal analysis they are considered linear

[9]. In our study, we deal with predicting the moment of the seizure by implementing linear signal analysis methods and nonlinear signal analysis methods of EEG.

In the linear analysis method, EEG signals are analyzed in the time, frequency, and time-frequency domain. In the time domain, energy, power, variance, standard deviation, mean, and root mean square (RMS) of signals are reviewed [9,12,16,17,18,19]. In the frequency domain, spectral power density and subband frequency values are investigated [9,23]. The epileptic region in the signal was identified using the Elman neural network with features extracted in the time and frequency domain [10]. For the diagnosis of seizures in the EEG signal, the signals are separated into subbands by wavelet decomposition and classified by genetic algorithm [11]. A prediction filter has been proposed to show the existence of spikes and sharp waves in seizure regions in EEG signals. In the EEG signals, the seizure region was determined by the increase in the estimation error energy of the filter [12]. The difference between healthy EEG and epileptic EEG signals was shown with the aid of an artificial neural network and genetic algorithm [13]. Furthermore, epilepsy disease was defined by performing EEG signal analysis with a single hidden layer feedforward artificial neural network machine (ELM) in 2012 [14]. The seizure was detected in EEG signals applied to artificial neural networks with multi-stage nonlinear filtering preprocessing [15]. In another study, classifying preictal and interictal EEG signals by using features such as frequency and amplitude in gamma band signal has been shown [16]. Singh et al. classified the EEG signals using the difference in RMS bandwidth and average frequency seen in epileptic zone rhythms [17]. Raghu et al. showed that the epileptic EEG signals have a larger variance, maximum value, wavelet log energy entropy, RMS, and band power properties, while the normal EEG signals have a larger minimum value, wavelet Shannon entropy, and zero-crossing characteristics [18]. Mahapatra et al. classified ictal and interictal EEG signals using the RMS frequency [19]. To distinguish the epileptic region in EEG signals, a feature has been proposed as a time-domain energy-based called exponential energy [20]. In recent studies, the features used for the diagnosis of seizures in the EEG signals were examined. It has been shown that seizures can be determined by using the variance, energy, nonlinear energy, and Shannon entropy calculated in the raw EEG signals or by using the variance, energy, kurtosis, and line length calculated over the wavelet coefficients [21,22]. Ficici et al. analyzed the EEG signals divided into sub-bands with autoregressive coefficients and linear estimation error energy from linear analysis methods, and Shannon entropy and approximate entropy methods from non-linear analysis methods. It has been shown that better accuracy will be obtained with the use of linear and non-linear methods classified as healthy and epileptic EEG signals [23].

In linear signal analysis, EEG signals are considered linear, although they are not linear. For this reason, the preference for nonlinear analysis methods (dimension property, Lyapunov exponents, and entropy) may give better information for the diagnosis of epilepsy [25-45]. In a study conducted in 2019, it was stated that structural changes can be detected early using the Lyapunov Exponents values of EEG signals (non-linear dynamic methods) [24]. One other of these methods, entropy is a thermodynamic concept that gives information about system disorder [9]. It is used to measure the irregularity in EEG signals during an epileptic seizure. Kannathal et al. [25] and Song et al. [26] showed the difference between epileptic and healthy EEG signals using the entropy methods such as Shannon entropy, Renyi's entropy, Kolmogorov-Sinai entropy, sample entropy, and approximate entropy. When the entropy values of the epileptic and normal signals were compared, it was observed that the entropy values of the epileptic signal were higher than the normal ones. This indicated a decrease in the flow of information during the seizure [25,26]. In different studies, EEG signals were decomposed into signal subbands by applying discrete wavelet transform at different levels. These decomposed signals were determined for the seizure by using approximate entropy and spectral entropy [26,27]. EEG signals were classified with the calculated wavelet entropy, spectral entropy, and sample entropy values by repetitive Elman-based neural networks and radial-based neural networks [28]. Song et.al. combined the extreme learning machine with the optimized sample entropy (O-SampEn) algorithm. With this combination, it was determined whether there was a seizure in the EEG signals [29].

Nicolaou et al. and Xiang et al. classified the permutation entropy, fuzzy entropy, and sample entropy values of EEG signals calculated by support vector machine [30,31]. It has been shown that fuzzy entropy has a better seizure detection index than sample entropy [31]. In another entropy method, distribution entropy, the epilepsy signal was segmented in three different ways and entropy values were calculated. Distribution entropy has been observed minimally affected in the parameter selection [32]. Raghu et al. used Shannon spectral entropy to differentiate between two groups of patients with idiopathic epilepsy. They showed that Shannon spectral entropy measured in a specific frequency range can serve to follow the development of patients suffering from idiopathic epilepsy [33]. In another study, EEG signals were separated into subbands by discrete wavelet transform. Of the power spectral analysis in the frequency domain and of the amplitude values in the time domain, the sigmoid entropy was calculated. It was concluded that sigmoid entropy, which has less computational complexity, can be used to analyze epileptic seizure behavior, which also includes brain dynamics [34]. In a recent study, it was shown that the patients can be warned before the seizure by determining the time between the preictal and ictal state by inferring the distribution entropy feature has been stated [35]. Multidimensional sample entropy is proposed and compared with sample entropy. They showed that seizure onset was more notable in the multidimensional sample entropy [36].

Li et al. found that the permutation entropy was more sensitive than the sample entropy for recognizing the nonlinear activity in EEG data and predicting absence seizures [37]. Since permutation entropy is a fast complexity measure in time series, it has been used for seizure detection in online devices. It was observed that the permutation entropy makes a reliable distinction, but the sensitivity of the study could not be measured due to limited data [38]. Jouny et al. proposed that seizure detection was attempted with a combination of eighteen different feature extraction methods,

including Shannon entropy, sample entropy, and permutation entropy [39]. In a study in 2012, the permutation entropy was calculated by making different synchronizations of the EEG electrodes. Within the analyzed database, the frontal-temporal scalp areas appeared to be consistently associated with higher permutation entropy levels compared to the remaining electrodes, while lower permutation entropy values were seen in the parieto-occipital areas. It is shown that abnormalities from different parts of the brain were leading to the onset of the seizures [40]. Multiscale permutation entropy (MPE) was proposed to describe the dynamics in EEG recordings and MPE values were classified using linear discriminant analysis. It has been shown that the seizure-free state, pre-seizure, and seizure moments can be differentiated by dynamic features in MPE and EEG. This result supported the opinion that the seizures were predictable from EEG data [41]. Bhanot et al. used four feature vectors for seizure detection: short-term permutation entropy (STPE), STPE gradient (GSTPE), short-term energy (STE), and short-term mean (STM) subtracted from ictal and interictal EEG signals. With these features, RBBoost (Random Balance Boost) algorithm with k-fold cross-validation was used to classify data as ictal and interictal [42]. Peng et al. extracted nine features for each EEG channel, including power spectral density in six subbands, sample entropy, permutation entropy, and spectral entropy. The features of each channel were ordered according to the F-statistic value and the classification results were improved by selecting the most informative features [43]. In a recent study, channel selection has been made in EEG signals to minimize the complexity and computational power of classification. The channels were selected according to their permutation entropy values using the K-nearest neighbor algorithm combined with the genetic algorithm. By channel selection, accuracy, sensitivity, and specificity values in seizure detection were improved. They tried to determine which part of the brain was associated with the onset of seizures for a particular patient and determined that the P7-O1 channel was most effective in the selected patient group. Furthermore, they found that the seizure predictions made by selecting the channel are more accurate and have less computational burden than the seizure predictions made by using all channels [44].

In this study, we prefer to analyze two linear analysis methods, namely the mean of RMS and epileptic EEG signals. We also checked for permutation entropy and sample entropy values for EEG signals, as they have fast complexity measurements in time series. We aimed to predict the seizure moment before a certain time by examining these linear and non-linear methods among themselves.

With this study, the following contributions are made to the ongoing studies on the early detection and diagnosis of seizure activity in EEG signals:

- RMS, mean value, sample entropy, and permutation entropy were used together for the first time for the detection of seizure activity.
- It was determined that the detection rate of seizure activity was higher with non-linear methods.
- It has been determined that using more than one method in detecting seizure activity has higher accuracy than using a single method.
- It has been determined that there are sudden changes before seizure activity.
- It has been shown that sudden changes in EEG signals detected by any method before seizure activity occurs in some methods but not in others. Based on this situation, it has been suggested that using two or more methods for seizure detection will yield better results.

2. MATHEMATICAL MODEL

In the prediction and diagnosis of epileptic seizures, EEG data has an important role. Signal processing of EEG data could be done to detect seizures. It is used to convert features (frequency, energy, power, and complexity of the signal) of EEG signals into numerical data. These features are not clearly visible from the raw EEG data, so they are extracted by linear and non-linear analysis methods [9], which are given in the following sub-sections.

2.1. Linear Analysis Methods

In linear analysis methods, the signal is examined in the time, frequency, and time-frequency domains. In time-domain analysis, statistical properties such as energy, power, mean, standard deviation, variance, and root mean value (RMS) of the signal are generally considered. Of these properties, mean and RMS values are expected to be close to zero if the signal is periodic and sinusoidal. If the signal is not periodic and not sinusoidal, these values are expected to move away from zero, either positively or negatively [45].
The mean (μ) and RMS values of the signal are defined as follows i = 1, 2, .., N for the x signal:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (1)$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (2)$$

where N is the number of samples in the data.

One can comment on the complexity of the signal with its mean value of it. If the mean value of the signal is around zero, the signal is assumed a periodic signal. However, if this value is far away from zero, the signal is assumed a complex signal. This situation is also valid for the RMS value. If the RMS value is around zero, the signal is considered to be regular. If it is far from zero, it may indicate that there is confusion in the signal. In this study, we analyzed the mean and RMS values of EEG signals to deal with their complexity of them.

2.2. Non-Linear Analysis Methods

Linear signal analyzes are preferred because of the ease of implementation and simplicity of the theory. In non-linear

analysis, more detailed information is obtained about the signal. An essential problem in non-linear analysis is the noise of the signal. For better and more accurate analysis, nonlinear analysis methods should be applied after the signal is eliminated from the noise. Nonlinear analysis methods can be considered into three categories. The first is the dimension property, which gives an idea of how complex a system is; the second is the Lyapunov exponents' property which gives an idea of how predictable a system is; and the third is the entropy property, which gives an idea of how random a system is. In this study, we preferred to analyze the entropy property of the signal to pre-predict the seizure a certain time ago using its irregularity of it [9].

Entropy was used for the first time in thermodynamics to give information about the disorder of a system. It is also a measure of randomness and can be calculated based on the different properties of the signals. In general, all entropies give information about the disorder and regularity of the system [9].

In literature, the researchers performed several types of entropy methods such as Shannon, distribution, approximate, permutation, sample, fuzzy, sigmoid, transfer, and spectral entropy [26-37]. In this study, we preferred the sample and the permutation entropy methods.

2.2.1. Sample Entropy

Sample entropy (SmpE) is a method of measuring the regularity of physiological signals regardless of their length. The SmpE(m,r,n) value can be defined as the negative algorithm of the similarity probability of the tolerance value (r) for the points (m) in any time series of length n. The Sample entropy formula is given as [47]:

$$SmpE(m,r,n) = -log\frac{A}{B} \quad (3)$$

where m is the length of the arrays to be compared, r is the tolerance value to accept matches, and n is the length of the original data. A and B are defined as follows:

$$A = \frac{(n-m-1)(n-m)}{2} A^m(r) \quad (4)$$

$$B = \frac{(n-m-1)(n-m)}{2} B^m(r) \quad (5)$$

where Am(r) is the probability that two sequences will match for the m+1 points and Bm(r) is the probability that two sequences will match for the m point. SmpE is consistent for each (m,r) value to be selected [47]. This situation has been effective in the preference of sample entropy in the selection of entropy.

In this study, signals with 256 samples are taken from the data for sample entropy calculation. To calculate sample frequencies, the number of each amplitude repetition is calculated. Then, the possible class probabilities are calculated using the sample frequencies. The resultant probability value is used in the entropy calculation. m is chosen as 1 for this study. Since the sample entropy value increases as the signal become more complex, the sample entropy values will be higher at the beginning of the seizure and during the seizure.

2.2.2. Permutation Entropy (PE)

Another method for evaluating the complexity of the signals in time series is the permutation entropy, which is based on a comparison of neighboring values. In permutation entropy, low noise in the signal does not affect the complexity of the chaotic signal. In this entropy, without requiring pre-processing, robust information can be obtained fast regardless of the size of the data.

The first step in calculating permutation entropy is to convert a one-dimensional time series into a matrix of overlapping column vectors. After, permutation vectors of size M up to M! are generated. Then, the data in each column of the matrix is reconstructed based on the permutation vectors. Reconstructed columns are matched with unique permutations. The relative frequency of each permutation is then determined by dividing the number of times the permutation occurs in the columns by the total number of sequences. Finally, Equation (6) is used to calculate the PE of order M of the signals [48]:

$$PE_M = \sum_{i=1}^{M!} p_i log_2 p_i \quad (6)$$

The embedded parameter, M, should be chosen between 3-7 in order to distinguish the stochastic and deterministic features of the signal. In this study, M is chosen as 3. PE values are in the range of 0-1. In a regular time series, the PE value is close to 0 (zero), whereas in an irregular and random time series, the PE value is close to 1. Since the EEG series becomes regular during the seizure, the PE value is close to zero during the seizure.

3. RESULTS

In this study, CHB-MIT EEG data collected from Boston children's hospital were used. There are 24 subjects; 5 men from 3-22 years old and 18 women from 1.5-19 years old. The EEG data in files 1 and 24 belong to the same person (subject) but they were recorded at different times. EEG signals of 24 patients (subjects) with a 256 Hz sampling rate of 23 channels were recorded as FP1-F7 (1), F7-T7 (2), T7-P7 (3), P7-O1 (4), FP1-F3 (5), F3-C3 (6), C3-P3 (7), P3-O1 (8), FP2-F4 (9), F4-C4 (10), C4-P4 (11), P4-O2 (12), FP2-F8 (13), F8-T8 (14), T8-P8 (15), P8-O2 (16), FZ-CZ (17), CZ-PZ (18), P7-T7 (19), T7-FT9 (20), FT9-FT10 (21), FT10-T8 (22) and T8-P8 (23). The places of electrodes are labeled as FP: frontopolar, F: frontal, T: temporal, O: occipital, C: central, and P: parietal [49]. Fig. 1 shows the electrode diagram of the data and Fig. 2 shows the raw EEG data of a 19-year-old female patient. In this study, the MATLAB program was used for data analysis [50].

In Fig. 3, the RMS value of the P7-O1 channel of a 19-year-old female is calculated. RMS value in the ictal period is higher than it's in the preictal period. Furthermore, the mean value of the same patient moves away from zero in positive and negative directions (Fig. 3). As given in Fig. 4, this situation is also seen in other channels of the same patient.

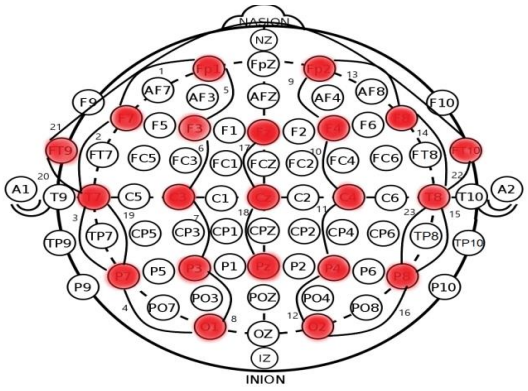


Fig.1. Placement of EEG electrodes for each channel is labeled as red.

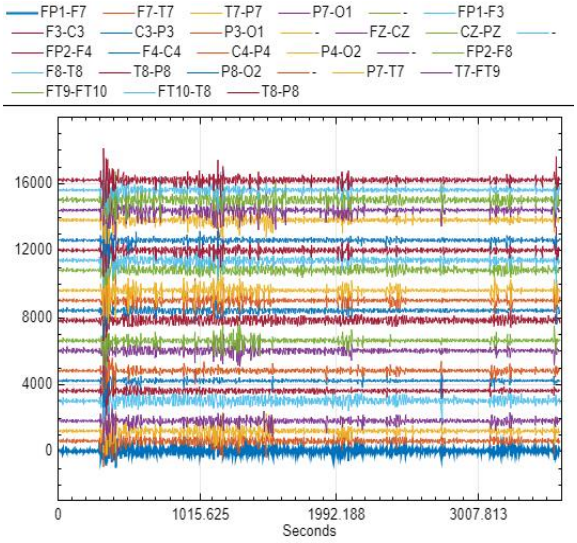


Fig.2. EEG data of a 19-year-old female patient. Each signal is recorded in a specific time period. The signals are separated from each other at 600 μV size.

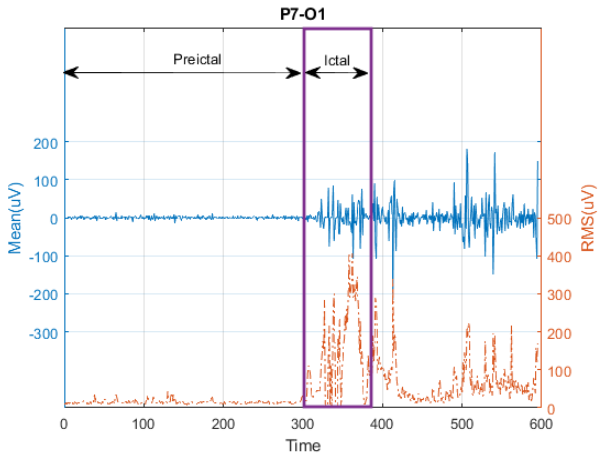
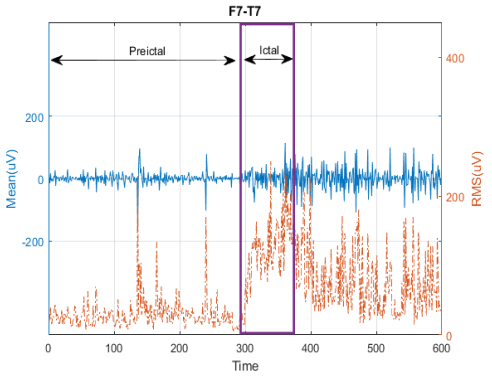
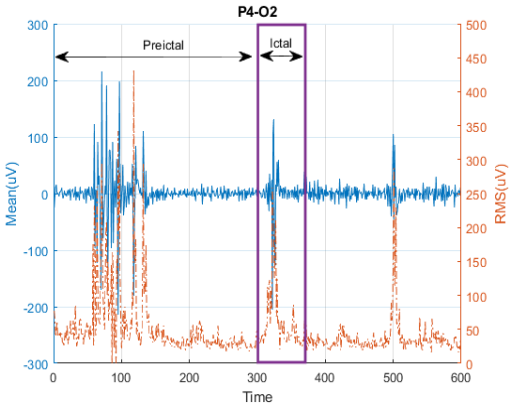


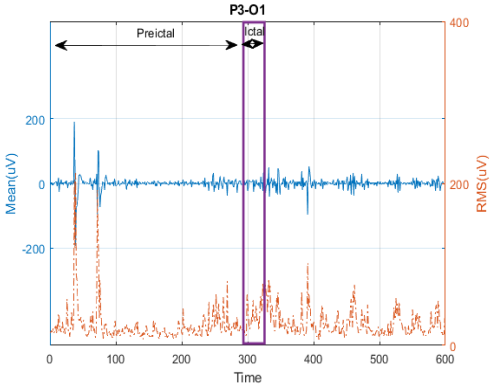
Fig.3. RMS and mean values of the P7-O1 channel of a 19-year-old female patient. The y-axis on the left side of the chart shows the mean values of the EEG signal in µV. The y-axis on the right shows the RMS value of the EEG signal in µV. The X-axis represents the time in s. The ictal state representing the seizure is framed in purple.



(a) F7-T7 channel of a 14-year-old female patient



(b) P4-O2 channel of a 2-year-old female patient



(c) P3-O1 channel of a 7-year-old female patient

Fig. 5. RMS and mean graphs from different channels of different patients.

Fig. 5(a) shows the RMS and mean values of the F7-T7 channel of a 14-year-old female patient. In this graph, it is seen that the RMS value is increased in the ictal state compared to the preictal state, and its mean value is moved away from zero in positive and negative directions when the ictal state is compared to the preictal state. In addition, it is observed that there is a change in the RMS value and the mean value of 50 and 150 seconds before the seizure onset. Fig. 5(b) shows the RMS and mean values of the P4-O2 channel of a 2-year-old female patient. In this patient, an increase in RMS values and a getaway from zero in the mean value are observed in the ictal state compared to the preictal state. More noticeable changes were seen up to 200 seconds before the onset of the seizure. Fig. 5(c) shows the RMS and mean values

 ISSN: 2548-0650 http://dergipark.gov.tr/jcs

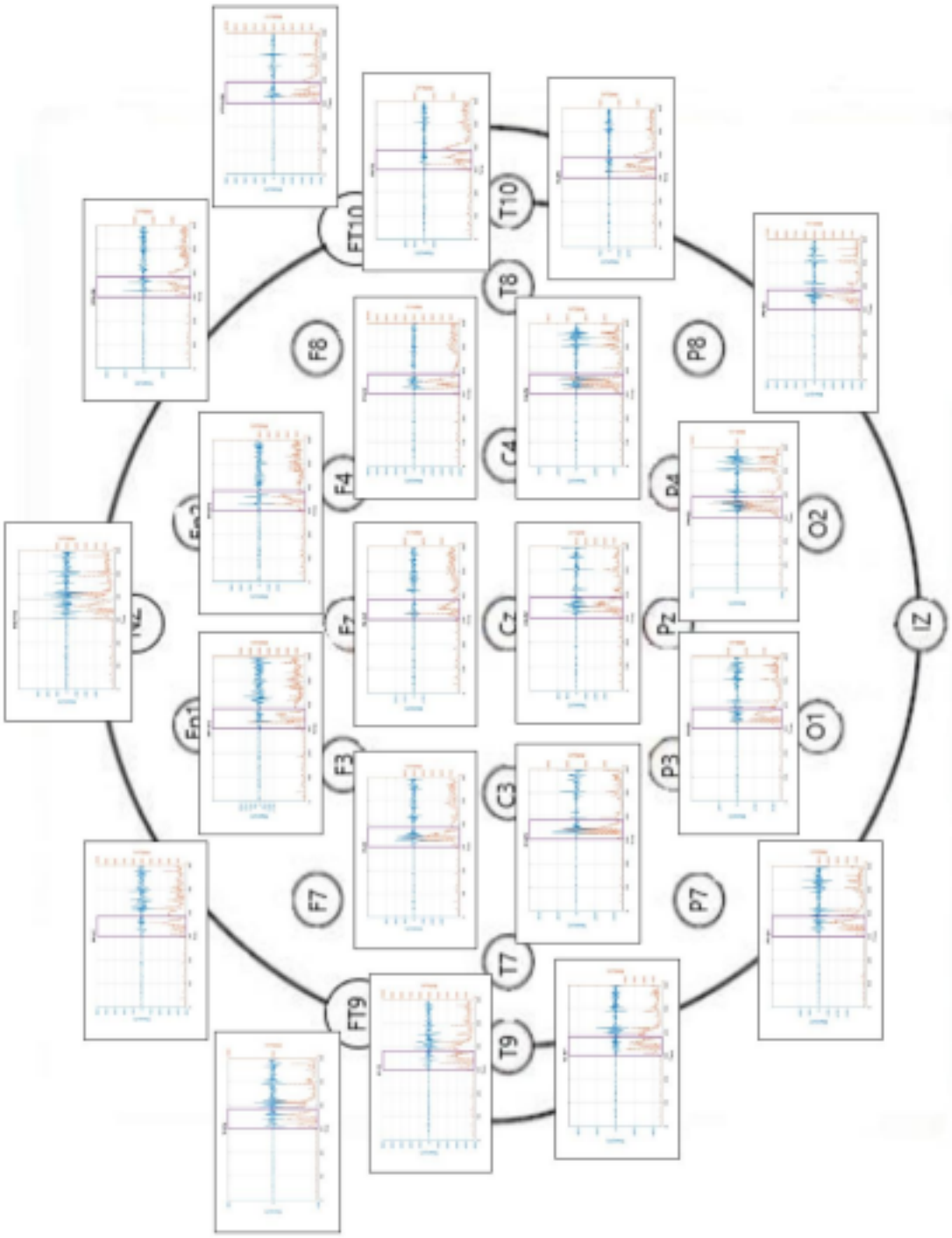
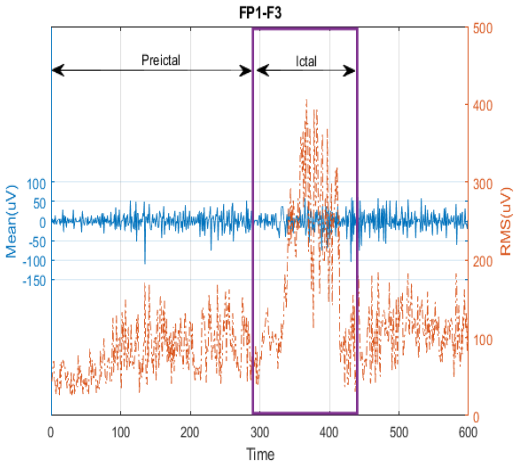
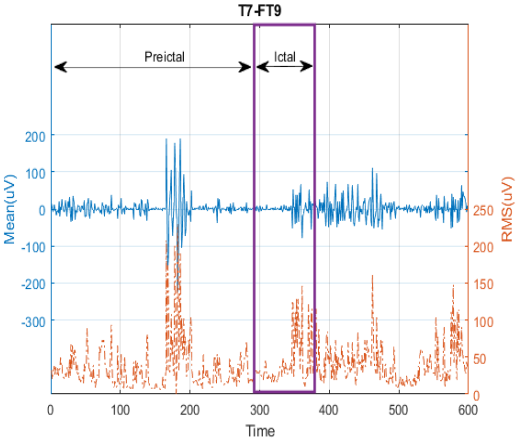


Fig. 4. RMS and mean values of EEG data from all channels of a 19-year-old female patient.

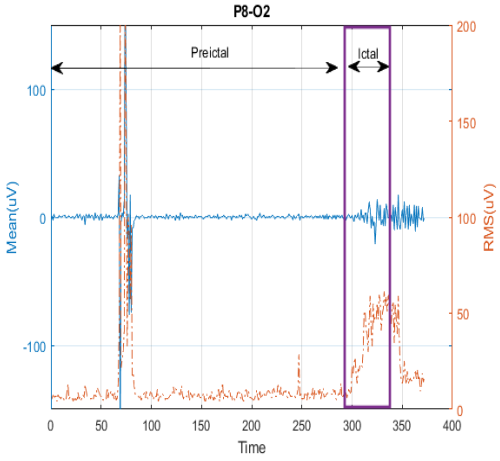
of the P3-O1 channel of a 7-year-old female patient. This patient's RMS and mean values in the ictal state cannot be clearly differentiated from the values in the preictal state. However, an average of 250 seconds before the onset of the seizure, a change is observed in the RMS and mean values.



(a) FP1-F3 channel of another 7-year-old female patient



(b) T7-FT9 channel of a 22-year-old female patient's



(c) P8-O2 channel of a 18-year-old female patient's

Fig. 6. RMS and mean graphs from different channels of different patients.

Fig. 6(a) shows the RMS and means values of the FP1-F3 channel of another 7-year-old female patient. The RMS value increases in the ictal state compared to the preictal state. The difference between the mean value in the ictal state and the preictal state cannot be distinguished. Fig. 6(b) shows the RMS and mean values of the T7-FT9 channel of a 22-year-old female patient. Towards the end of the ictal region, a change is observed in the RMS and mean values. In addition, changes are observed in both RMS and mean values about 100 seconds before the onset of the seizure. Fig. 6(c) shows the RMS and mean values of the P8-O2 channel of an 18-year-old female patient. In the ictal state, an increase in RMS values and a deviation from zero in mean values are observed. RMS and mean values change about 250 seconds before the seizure. The patient data given in Fig. 5 and fig. 6 were randomly selected to show the changes in RMS and mean values. These states are randomly chosen to show the different states observed in entropy values.

In 18 of the 24 patients' data, it was observed that the RMS values increased in the ictal state compared to the pre-ictal state. Furthermore, the mean value gets away from zero in the ictal state compared to the preictal state in 14 of them. That is, regarding the average and RMS values of the EEG signal, the ictal region was determined at the rate of 58.4% and 75%, respectively.

EEG signals are considered linear while using RMS and mean methods. However, EEG signals are not linear. There is an information loss in the linear analysis of non-linear EEG signals. Nonlinear analysis methods should be used to obtain more comprehensive information about epileptic seizures. In this study, we prefer to analyze the permutation entropy and the sample entropy methods of nonlinear analysis methods.

Permutation entropy is a type of embedded entropy that directly uses the time series to estimate entropy. Sample entropy is a method that measures the regularity of physiological signals regardless of their size.

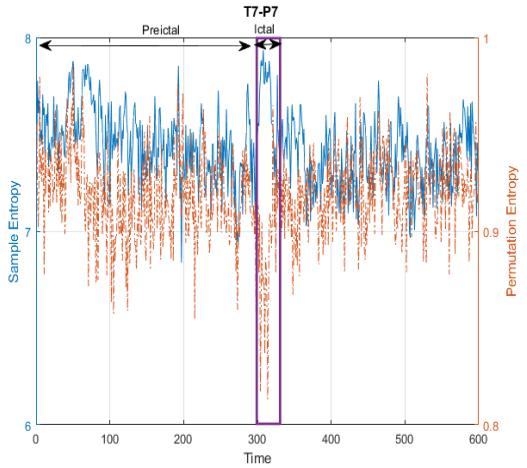


Fig. 7. Sample entropy and permutation entropy values of the T7-P7 channel of an 11-year-old female patient. The y-axis on the left side of the graph shows the sample entropy values. The y-axis on the right shows the permutation entropy values. The x-axis represents the time in s. The ictal state representing the seizure is framed in purple.

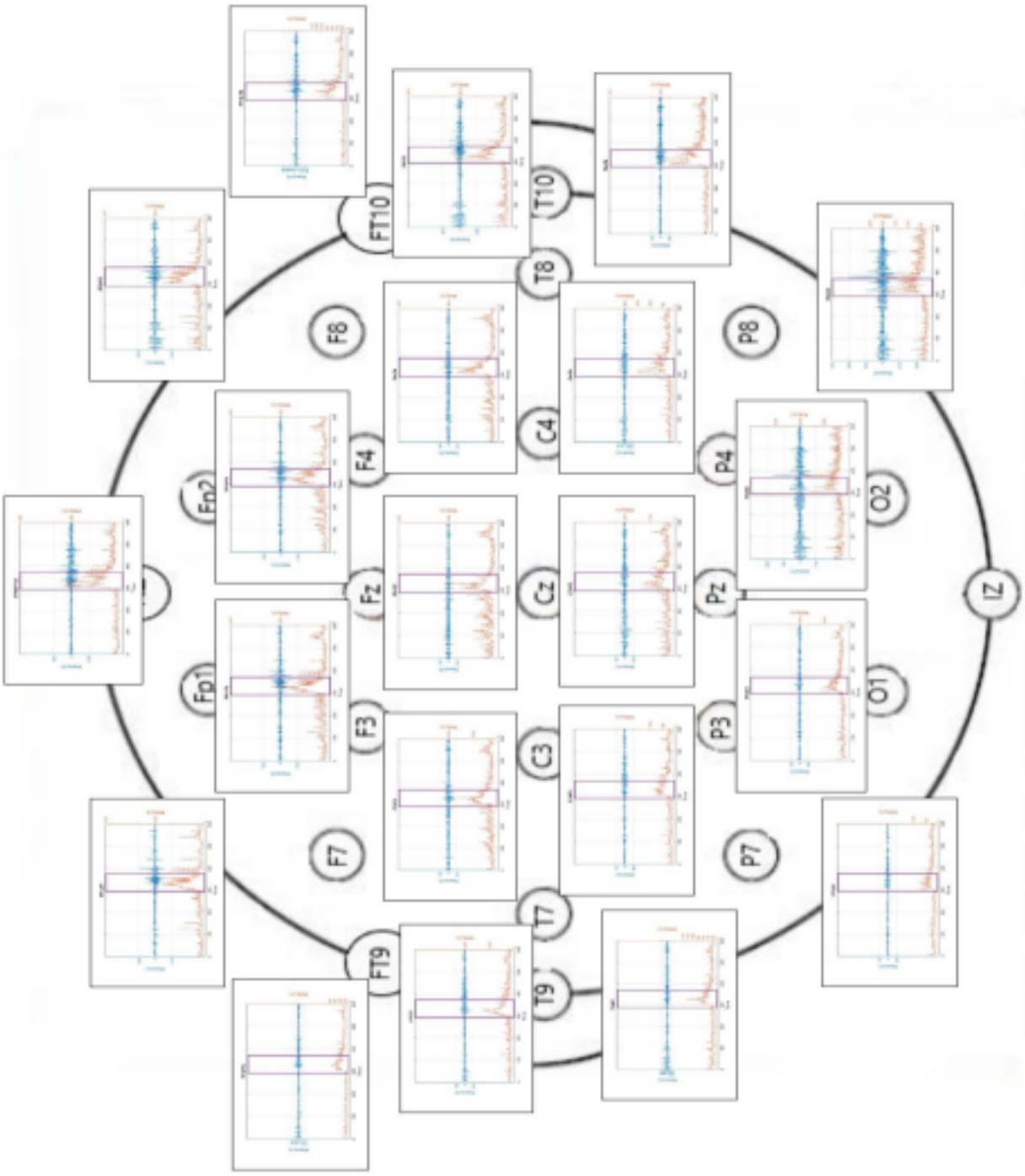
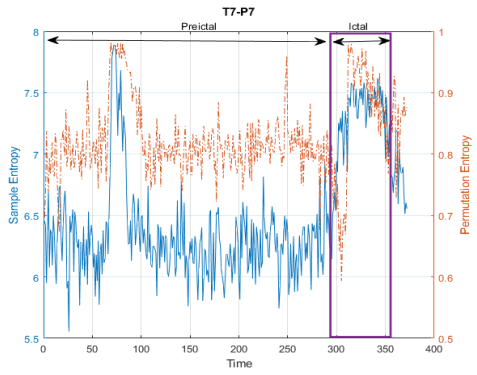
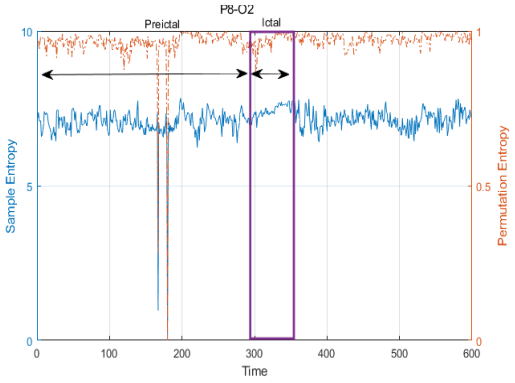


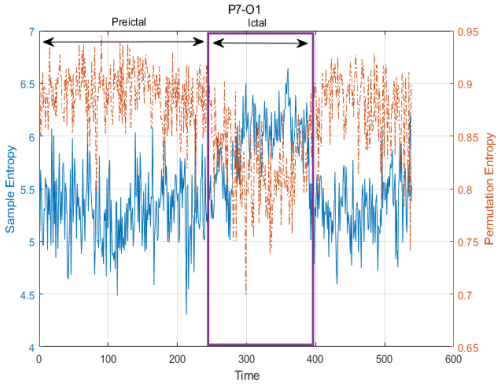
Fig. 8. Sample entropy and permutation entropy values of all channels of an 11-year-old female patient.



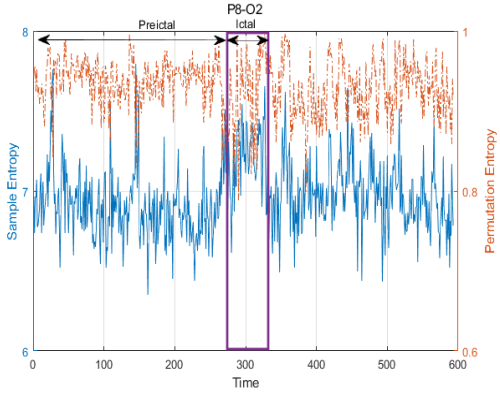
(a) T7-P7 channel of an 18-year-old female patient



(b) P8-O2 channel of a 22-year-old male patient



(c) P7-O1 channel of a 16-year-old male patient



(d) P8-O2 channel of a 12-year-old female patient

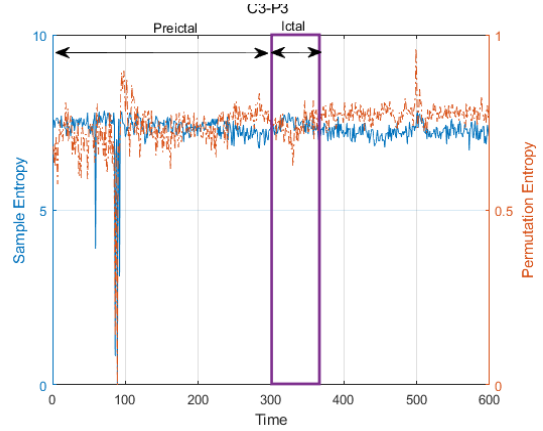
Fig. 9. Sample entropy and permutation entropy values of different channels of different patients.

In epileptic seizures, the whole brain is usually affected. In the passage from the preictal state to the ictal state, complexity occurs in the signals. Due to this complexity, it is expected that while the sample entropy value will increase at the onset of the seizure [37], permutation entropy is expected to decrease at the onset of the seizure [40]. In this study, it is observed that the permutation entropy value is decreased in the majority of the patients at the onset of the seizure. In Fig. 7, the sample and permutation entropy values of the T7-P7 channel of an 11-year-old female patient are given. In this figure, it is seen that the sample entropy value increases at the beginning of the seizure, while the permutation entropy decreases. In other words, the ictal region can be determined by regarding the sudden decreases and increases in entropy values. Fig. 8 shows the sample entropy and permutation entropy values of all channels of the same patient.

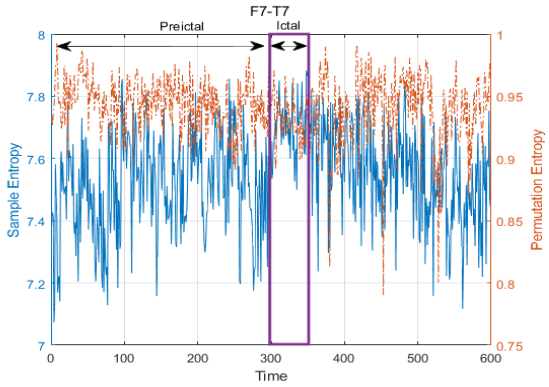
Fig. 9(a) shows the entropy values of the T7-P7 channel of an 18-year-old female patient. There was an increase in both entropy values in the ictal state compared to the preictal state. In addition, changes in entropy values are observed about 250 seconds before the onset of the seizure. Fig. 9(b) P8-O2 channel values of a 22-year-old male patient are shown. The distinction between the ictal state and the preictal state cannot be seen completely with both entropy methods. However, a sudden change in entropy values is observed up to 120 seconds before the onset of the seizure. Fig. 9(c) shows the entropy values of the P7-O1 channel of a 16-year-old male patient. While the sample entropy value increases in the ictal state compared to the preictal state, it decreased in the permutation entropy value. Fig. 9(d) shows the values of the P8-O2 channel of a 12-year-old female patient. In this patient, while the sample entropy value increases in the ictal state, it is not possible to distinguish between the ictal state and the preictal state in permutation entropy.

Fig. 10(a) shows the values of the C3-P3 channel of a 2-year-old female patient. In the sample entropy of the ictal state, there is a slight increase compared to the preictal state, while there is a slight decrease in the permutation entropy. In addition, there was a sudden change in both entropy values about 210 seconds before the onset of the seizure. Fig. 10(b) shows the entropy values of the F7-T7 channel of a 3-year-old female patient. The difference between the ictal state and the preictal state cannot be distinguished in both entropy methods. Fig. 10(c) shows the values of the P3-O1 channel of a 19-year-old female patient. While there is an increase in both entropy values at the beginning of the seizure, sudden decreases are observed in both entropy values during the seizure. Fig. 10(d) shows the sample entropy and permutation entropy values of the T7-P7 channel of a 7-year-old female patient. The seizure duration was very short. With both entropy methods, the difference between ictal and preictal states could not be determined. In addition, a sudden change is observed in both entropy methods about 250 seconds before the onset of the seizure. These states are randomly chosen to show the different states observed in entropy values.

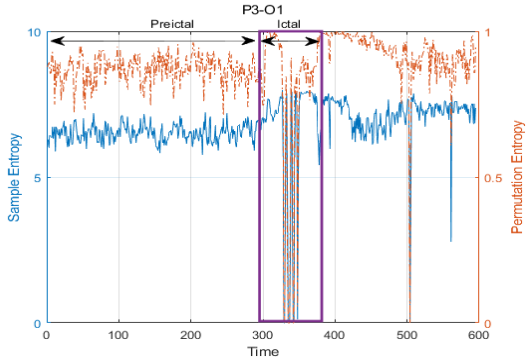
 ISSN: 2548-0650 http://dergipark.gov.tr/jcs



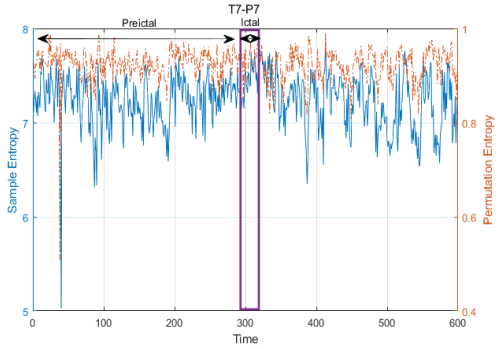
(a) C3-P3 channel of an 2-year-old female patient



(b) F7-T7 channel of a 3-year-old female patient



(c) P3-O1 channel of a 19-year-old female patient



(d) T7-P7 channel of a 7-year-old female patient

Fig. 10. Sample entropy and permutation entropy values of different channels of different patients.

When the sample entropy and permutation entropy values are analyzed one by one, it is observed that the sample entropy value increase in 16 (66.6 %) of the 24 patient data in the ictal state compared to the preictal state. A decrease in permutation entropy is observed at the onset of seizure in 16 (66.6 %) of 24 patients. When both entropy methods are examined together, two different situations emerged. In the first situation, it is observed that during the seizure, the sample entropy value increases, and the permutation entropy value decreases in 13 (54,2 %) patients. In the second situation, during the seizure, the increase in the sample entropy value or the decrease in the permutation entropy is observed in 19 (79,2 %) patients.

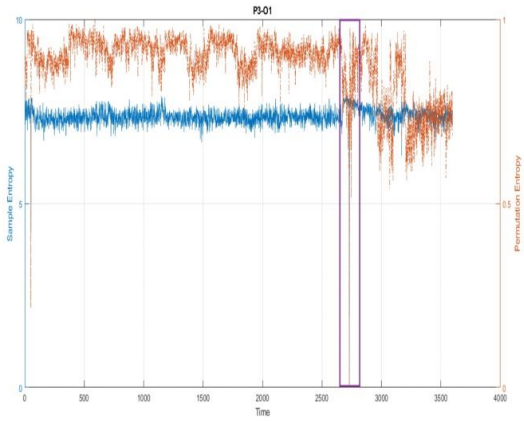


Fig. 11. Sample entropy and permutation entropy values of an hour EEG signals of the P3-O1 channel of a 3.5-year-old male patient.

Sample entropy and permutation entropy values of an hour's EEG recordings of channel P3-O1 of a 3.5-year-old male patient are shown in fig. 11. As seen in this figure, changes in entropy values can be detected in one-hour EEG recordings. The seizure period is seen more clearly in the parts taken 5 minutes before and 5 minutes after the seizure onset.

4. CONCLUISONS

In this study, epileptic EEG signals were examined and the prediction of epileptic seizure onset (ictal region) was investigated. First, EEG signals were accepted as linear. In linear analysis, RMS and the mean value of the signals were calculated. The epileptic seizure onset was determined by RMS and mean value methods with a success rate of 75 % and 58.4 %, respectively. However, since the EEG signals are not linear, these examinations were not considered sufficient, and then entropy methods were used for epileptic region detection. Among the entropy methods, sample entropy is preferred due to its consistency feature, and permutation entropy is preferred because the noise in the signal affects the analysis least. When both entropy methods were preferred separately, the onset of seizure was found with a success rate of 66.6 %. When the entropy methods are considered together, the success rates have changed. When seizure was considered using both sample entropy and permutation entropy, it was determined with a success rate of 54.2 %, while considering sample entropy or permutation entropy, it was determined with a success rate of 79.2 %.

Consequently, when one entropy method could not catch the onset of the seizure, the other might have the possibility to catch it.

In future studies, epileptic EEG signals can be analyzed with more entropy methods. Furthermore, different studies can be carried out to determine the changes that occur before the seizure with different feature extraction methods.

REFERENCES

[1] E. Foundation, What is epilepsy?, 2022. URL: https://www.epilepsy.com/what-is-epilepsy.

[2] WHO, Atlas Epilepsy Care İn The World, 2005.

[3] F. A. Gibbs, H. Davis, W. B. Lennox, The electroencephalogram in epilepsy and in eonditions of impaired consciousness, American Journal of EEG Technology 8 (2015) 59–73.

[4] R. S. Fisher, H. E. Scharfman, M. deCurtis, How can we identify ictal and interictal abnormal activity?, Adv Exp Med Biol 813 (2014) 3–23.

[5] J. Pillai, M. R. Sperling, Interictal eeg and the diagnosis of epilepsy, Epilepsia 41 (2006) 14–22.

[6] D. Schmidt, S. C. Schachter, Drug treatment of epilepsy in adults, Phys. Rev E. (2014) 254.

[7] C. Anyanwu, G. K. Motamedi, Diagnosis and surgical treatment of drugresistant epilepsy, Brain Sciences 8 (2018) 49.

[8] J. Yang, J. H. Phi, The present and future of vagus nerve stimulation, J Korean Neurosurg Soc 62 (2019) 344–352.

[9] A. Varsavvsky, I. Mareels, M. Cook, Epileptic Seizures and the EEG Measurement, Models, Detection and Prediction, 2011.

[10] V. Srinivasan, C. Eswaran, N. Sriraam, Artificial neural network based epileptic detection using time-domain and frequency-domain features, J Med Syst 29 (2005) 647–660.

[11] H. Ocak, Optimal classification of epileptic seizures in eeg using wavelet analysis and genetic algorithm, Signal Processing 88 (2008) 1858–1867.

[12] S. Altunay, Z. Telatar, O. Erogul, Epileptic eeg detection using the linear prediction error energy, Expert Systems with Applications 37 (2010) 5661–5665.

[13] S. Koçer, M. R. Canal, Classifying epilepsy diseases using artificial neural networks and genetic algorithm, J Med Syst 35 (2011) 489–498.

[14] Y. Kaya, R. Tekin, Epileptik nöbetlerin tespiti için aşırı Öğrenme makinesi tabanlı uzman bir sistem, Bilişim Teknolojileri Dergisi 5 (2012) 33–40.

[15] V. P. Nigam, D. Graupe, A neural-network-based detection of epilepsy, A Journal of Progress in Neurosurgery, Neurology and Neurosciences 26 (2013) 55–60.

[16] M. Z. Parvez, M. Paul, Eeg signal classification using frequency band analysis towards epileptic seizure prediction, 16th Int'l Conf. Computer and Information Technology (2014) 126–130.

[17] P. Singh, S. D. Joshi, R. K. Patney, K. Saha, Fourier-based feature extraction for classification of eeg signals using eeg rhythms, Circuits Syst Signal Process 35 (2016) 3700–3715.

[18] S. Raghu, N. Sriraam, A. S. Hegde, Features ranking for the classification of epileptic seizure from temporal eeg, 2016 International Conference on Circuits. Controls, Communications and Computing (I4C) (2016) 1–4.

[19] A. G. Mahapatra, K. Horio, Classification of ictal and interictal eeg using rms frequency, dominant frequency, root mean instantaneous frequency square and their parameters ratio, Biomedical Signal Processing and Control. 44 (2018) 168–180.

[20] O. K. Fasil, R. Rajesh, Time-domain exponential energy for epileptic eeg signal classification., Neuroscience Letters 694 (2019) 1–8.

[21] P. Boonyakitanont, A. Lek-uthai, K. Chomtho, J. Songsiri, A review of feature extraction and performance evaluation in epileptic seizure detection using eeg, Biomedical Signal Processing and Control. 57 (2020).

[22] V. Harpale, V. Bairagi, An adaptive method for feature selection and extraction for classification of epileptic eeg signal in significant states, Journal of King Saud University - Computer and Information Sciences. 33 (2021) 668–676.

[23] C. Ficici, O. Eroglu, Z. Telatar, Epileptic activity detection in eeg signals using linear and non-linear feature extraction methods, 2019 11th International Conference on Electrical and Electronics Engineering (ELECO). 392 (2019) 449–455.

[24] T. V. Yakovleva, I. E. Kutepov, A. Yu Karas, N. M. Yakovlev, V. V. Dobriyan, I. V. Papkova, Z. M. V., O. A. Saltykova, A. V. Krysko, T. Yu Yaroshenko, N. P. Erofeev, K. V. A., Eeg analysis in structural focal epilepsy using the methods of nonlinear dynamics (lyapunov exponents, lempel–ziv complexity, and multiscale entropy), The Scientific World Journal. (2020).

[25] N. Kannathal, M. Lim Choo, U. R. Acharya, P. Sadasivan, Entropies for detection of epilepsy in eeg, Computer Methods and Programs in Biomedicine. 80 (2005) 187–194.

[26] Y. Song, J. Crowcroft, J. Zhang, Eepileptic eeg signal analysis and identification based on nonlinear features, 2012 IEEE International Conference on Bioinformatics and Biomedicine. (2012) 1–6.

[27] H. Ocak, Automatic detection of epileptic seizures in eeg using discrete wavelet transform and approximate entropy, Expert Systems with Applications. 36 (2009) 2027–2036.

[28] A. Mirzaei, A. Ayatollahi, P. Gifani, L. Salehi, Eeg analysis based on wavelet-spectral entropy for epileptic seizures detection, 2010 3rd International Conference on Biomedical Engineering and Informatics, 878-882 (2010) 878–882.

[29] S. P. Kumar, N. Sriraam, P. Benakop, B. Jinaga, Entropies based detection of epileptic seizures with artificial neural network classifiers, Expert Systems with Applications. 37 (2010) 3284–3291.

[30] Y. Song, J. Crowcroft, J. Zhang, Automatic epileptic seizure detection in eegs based on optimized sample entropy and extreme learning machine, Journal of Neuroscience Methods. 210 (2012) 132–146.

[31] N. Nicolaou, J. Georgiou, Detection of epileptic electroencephalogram based on permutation entropy and support vector machines, Expert Systems with Applications. 39 (2012) 202–209.

[32] J. Xiang, C. Li, H. Li, R. Cao, B. Wang, X. Han, J. Chen, The detection of epileptic seizure signals based on fuzzy entropy, Journal of Neuroscience Methods. 243 (2015) 18–25.

[33] P. Li, C. Yan, C. Karmakar, C. Liu, Distribution entropy analysis of epileptic eeg signals, 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). (2015) 4170–4173.

[34] J. A. Urigüen, B. García-Zapirain, J. Artieda, J. Iriarte, M. Valencia, Comparison of background eeg activity of different groups of patients with idiopathic epilepsy using shannon spectral entropy and cluster-based permutation statistical testing, PLOSE ONE. (2017).

[35] S. Raghu, N. Sriraam, Y. Temel, S. V. Rao, A. S. Hegde, P. L. Kubben, Performance evaluation of dwt based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using svm classifier, Computers in Biology and Medicine. 110 (2019) 127–143.

[36] S. T. Aung, Y. Wongsawat, Prediction of epileptic seizures based on multivariate multiscale modified-distribution entropy, PeerJ Computer Science. (2021).

[37] Q. Zhang, J. Ding, W. Kong, Y. Liu, Q. Wang, T. Jiang, Epilepsy prediction through optimized multidimensional sample entropy and bi-lstm, Biomedical Signal Processing and Control. 64 (2021) 102293.

[38] X. Li, G. Ouyang, D. A. Richards, Predictability analysis of absence seizures with permutation entropy, Epilepsy Research. 77 (2007) 70–74.

[39] A. A. Bruzzo, S. M. Gesierich, B. and, C. A. Tassinari, N. Birbaumer, G. Rubboli, Permutation entropy to detect vigilance changes and preictal states from scalp eeg in epileptic patients. a preliminary study, Neurological Sciences. 29 (2008) 3–9.

[40] C. C. Jouny, G. K. Bergey, Characterization of early partial seizure onset: frequency, complexity and entropy, Clinical Neurophysiology. 123 (2012) 658–669.

[41] N. Mammone, D. Labate, A. L. Ekuakille, L. C. Morabito, Analysis of absence seizure generation using eeg spatial-temporal regularity measures, International Journal of Neural System. 22 (2012) 1250024.

 ISSN: 2548-0650 http://dergipark.gov.tr/jcs

[42] G. Ouyang, J. Li, X. Liu, X. Li, Dynamic characteristics of absence eeg recordings with multiscale permutation entropy analysis, Epilepsy
Research. 104 (2013) 246–252.
[43] N. Bhanot, N. Mariyappa, H. Anitha, G. K. Bhargava, J. Velmurugan, S. Sinha, Seizure detection and epileptogenic zone localisation on heavily skewed meg data using rusboost machine learning technique, International Journal of Neuroscience. 132 (2022).
[44] G. Peng, M. Nourani, J. Harvey, H. Dave, Feature selection using f-statistic values for eeg signal analysis, 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society. (2020) 5963–5966.
[45] J. S. Ra, T. Li, Y. Li, A novel permutation entropy-based eeg channel selection for improving epileptic seizure prediction, Sensors. (2021) 7972.
[46] F. Kalın, A. T. Ç., D. Turkpence, S. Seker, U. Korkmaz, Detection of epileptic seizure using stft and statistical analysis, Advances in Neural
Signal Processing. (2020).
[47] J. S. Richman, J. R. Moorman, Physiological time-series analysis using
approximate entropy and sample entropy., Am. J. Physiol. – Heart Circ.
Physiol (2000) 2039–2049.
[48] sC. Bandt, B. Pompe, Permutation entropy: A natural complexity measure for time series, Physical Review Letters. (2002).
[49] A. H. Shoeb, Application of machine learning to epileptic seizure onset
detection and treatment., Massachusetts Institute of Technology. Cam-
bridge. MA. USA. (2009).
[50] MathWorks, Matlab [online], https://www.mathworks.com/products/matlab.html, 2021.

BIOGRAPHIES

Ceren Canyurt obtained her BSc. degree in Biomedical Engineering from Inonu University (IU) in 2020. She received an MSc. degree from Inonu University (IU) Institute of Natural and Applied Sciences, Department of Biomedical Engineering in 2022.

Reyhan Zengin received her BSc. degree in Electrical and Electronics Engineering from İnönü University (IU) in 2001. She received his integrated doctorate education in Electrical-Electronics Engineering at the Middle East Technical University (METU) Institute of Science in 2012. In 2018, she joined the Department of Biomedical Engineering at Inonu University as an Assistant Professor.