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Research Paper: Classifying the Epilepsy Based on the Phase Space Sorted With the Radial Poincaré Sections in Electroencephalography

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ABSTRACT

Background: Epilepsy is a brain disorder that changes the basin geometry of the oscillation of trajectories in the phase space. Nevertheless, recent studies on epilepsy often used the statistical characteristics of this space to diagnose epileptic seizures.

Objectives: We evaluated changes caused by the seizures on the mentioned basin by focusing on phase space sorted by Poincaré sections.

Materials & Methods: In this non-interventional clinical study (observational), 19 patients with generalized epilepsy were referred to the Epilepsy Department of Razavi Hospital (Mashhad, Iran) between 2018 and 2020, which their disease had been controlled after diagnosis and surgery. In evaluating the effects of this disorder on the oscillation basin of the EEG trajectories, we used the MATLAB@ R2019 software. In this computational method, we sorted the phase space reconstructed from the trajectories by using the radial Poincaré sections and then extracted a set of the geometric features. Finally, we detected the normal, pre-ictal, and ictal modes using a decision tree based on the Support Vector Machine (SVM) developed by features selected by a genetic algorithm.

Results: The proposed method provided an accuracy of 94.96% for the three classes, which confirms the change in the oscillation basin of the trajectories. Analyzing the features by using t test also showed a significant difference between the three modes.

Conclusion: The findings prove that epilepsy increases the oscillations basin of brain activity, but classification based on the segment cannot be applicable in clinical settings.

Keywords: Electroencephalography; Epilepsy; Decision trees

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Highlights

● Epilepsy increases the oscillation basin of the brain electrical activities.

● The size of the statistical population severely affects the classification accuracy.

● Classification based on EEG segments is not suitable for clinical conditions.

Introduction

In today's modern society, humans are under various stresses in their daily lives, and half of them approximately suffer from various neurological disorders [1]. According to the reports of the world health organization, epilepsy is one of these neurological disorders, which has approximately affected 50 million people worldwide [2]. Also, the International Epilepsy Association (ILAE) has reported that 1.5% of adults and 2% of children suffer from epilepsy worldwide [3]. If epilepsy is detected and diagnosed on time, it can be treated in 75% of patients by using medication or surgery [4]. This outcome is an essential factor in family and community health, too [5].

Currently, EEG is a cheap and straightforward method, which is also informative enough for epilepsy diagnosis [6]. However, epilepsy is a transient electrical storm, which may happen once a night and day, so its evaluation in the long-term records of EEG signals is time-consuming and tedious for neurologists. Accordingly, researchers in recent years have tried to overcome this limitation and offered different computer-based recognition algorithms for epilepsy. They mainly include processing techniques based on time [7, 8]; frequency [9]; and time-frequency, such as wavelet transform [10-12], Winger-Will distribution [13], and empirical mode decomposition [11, 14]. Some of these algorithms have also used the feature selection methods, such as sequential [15-17] and random [18, 19] search strategies, which usually improve the computer-based recognition algorithms by removing redundant features. In this regard, some of these algorithms have also employed the feature extraction methods, such as principal component analysis [20], independent component analysis [21, 22], and linear discriminant analysis. They improve the algorithms by transferring features to a new space. Although these techniques have provided relatively good results for diagnosing the epileptic seizures in the EEG records, studies based on the nonlinear dynamic theory currently expresses that the quantities obtained from the time and frequency domain are not enough to evaluate all the behaviors of this system due to the nonlinear dynamic nature of the nervous system [23, 24]. Accordingly, a remarkable part of recent research in evaluating epileptic seizures by using the EEG signals has focused on nonlinear dynamic processing such as Lyapunov exponent [25], correlation dimension [26-28], fractal dimension [29], and entropy of phase space [30]. These research studies have generally shown that techniques based on the nonlinear dynamic methods by evaluating the nonlinear dynamic aspects of brain activities can make a significant contribution to the system identification during epilepsy in addition to improving the diagnosis of epilepsy. Interestingly, some studies have used a combination of linear and nonlinear dynamic processing to diagnose epileptic seizures [6, 31] and have shown that these combinations can improve the diagnosis of epilepsy.

Phase space is one of these nonlinear techniques that can be efficient in detecting variations created in the activity of attractors. This technique is a pattern that can describe the evolution of trajectories obtained from the delayed or spatial phases of Electroencephalography (EEG) signals. It is one of the tools that have already attracted many researchers [32-35]. In this regard, Yaghoobi et al. [36] used the tangent and hyperbolic tangent phases for establishing a new phase space. They claimed that this new space could detect epileptic seizures with significant accuracy by a simple threshold. Sharma and Pachori [37] also provided a new feature extraction method based on the phase space reconstructed from the EEG signal for detecting epileptic seizures, so that they first used Empirical Mode Decomposition (EMD) and decomposed the EEG signals into the intrinsic mode functions. Since the EMD outputs are the components of symmetrical Amplitude and Frequency Modulation (AM-FM) and have an oscillating nature, these researchers evaluated the geometry of phase space reconstructed from the EMD outputs for detecting the epileptic seizures in the EEG signals. They claimed that their method can be employed for diagnosing epilepsy. Zabihi et al. [38] also provided a different method for separating the epileptic seizures by using phase space, so that they first provided a new two-dimensional phase space by using an algorithm of phase extraction based on the Principal Component Analysis (PCA) and then developed classifiers based on statistical features extracted from the collision of phase space trajectories with a linear Poincaré section for various subjects. These researchers finally claimed that the results of their method were superior to that of other diagnostic methods.

Regarding the Poincaré section, Sharif and Jafari [39] argued differently. They first fitted a two-dimensional page on the points of three-dimensional phase space by using the genetic algorithm for estimating the collisions with the two-dimensional Poincaré section. Then, they investigated the sensitivity of a support vector machine developed based on the phase space points located in the neighborhood of the fitted page for diagnosing epileptic seizures. To investigate the effects of the epileptic seizures in the high phase space, Luckett et al. [40] reconstructed the phase space and applied it to the convolutional neural network. They tried to show that variations created in the high dimensions of the phase space can provide valuable information for diagnosing and predicting the epileptic seizures. Although these methods could partly reveal different aspects of phase space (such as the amount of phase scattering), they could not provide enough information about the volume and geometry of the oscillation basin of EEG trajectories in the phase space. Therefore, in this study, we evaluated the geometry of the oscillation basin of phase space trajectories reconstructed from the EEG signals of epileptic patients by focusing on a phase space sorted by a set of radial linear Poincaré sections in normal, pre-ictal, and ictal modes.

Materials and Methods

Study subjects

In this non-intervention clinical study (observational), we used the EEG records of 19 patients with generalized epilepsy aged 25-35 years, 5 of them were female. These records had been selected from EEG archive recorded from patients referred to the Razavi Hospital Epilepsy Department (Mashhad City, Iran) from 2018 to 2020 for the diagnosis and treatment of epilepsy. In this selection, the EEG records relevant to patients had also been selected that their disease had been controlled after diagnosis and surgery.

For monitoring and labeling the seizures in these long-term EEG records, we got assistance from a neurologist (H.NK), which is supported by Imam Reza International University. According to these labels, we had generally received about 4 hours and 15 minutes from 228 (12 × 19) hours of the EEG records, which 92.8 and 31.3 minutes of them were also relevant to the pre-ictal and ictal modes, respectively. The rest of these signals were normal EEG signals, cut from two minutes before the ictal mode. All of these EEG signals according to the international 10–20 system were recorded from the FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, and Pz channels as the unipolar measurement and by using the Natus recording system made in the United States. Its sampling frequency and cutoff frequencies of bandpass filter are 256 Hz and 0.1-70 Hz, respectively.

For determining the minimum sample size (N), the following method was also used (Equation 1) [41]:

$$1.\ N=\frac{Z^2\text{-}aP(1\text{-}P)}{d^2}$$

, where a, Z, and d are error level, confidence level, and acceptable error for research, respectively. They have been usually considered 0.05, 1.96, 0.05, respectively. P is also the prevalence rate of epilepsy in developing countries, which is almost equal to 0.012 according to a previous research (Equation 2) [42].

$$2.\ N=\frac{1.96^2\text{-}0.05\times 0.012\times(1-0.012)}{0.05^2}=17.3<19$$

According to this relationship, 19 patients were enough samples for this investigation.

Our method is a new computational neuroscience method. In the preprocessing phase, we first removed motion artifacts resulting from eye muscles and other body movements by using a user-based computerized approach. In this approach, the user determines the threshold required for cutting and removing the motion artifacts. Then, we filtered the signals of 19 recorded from the 19 EEG channels by a sixth-order low-pass Butterworth filter with the 40 Hz cutoff frequency for removing high frequencies and power line noises. Then, we partitioned these EEG signals into segments of 10 s without any overlap. In this research, all analyzes were performed in MATLAB separation software.

Phase space sorted by linear Poincare sections

Phase space is a space that can represent the status of the system. It is unlike the state space that depicts the status of the system according to the state variables. It can be developed by any delayed or spatial phase taken from system processes [43]. Therefore, this space, like the state space, does not need to know the system state

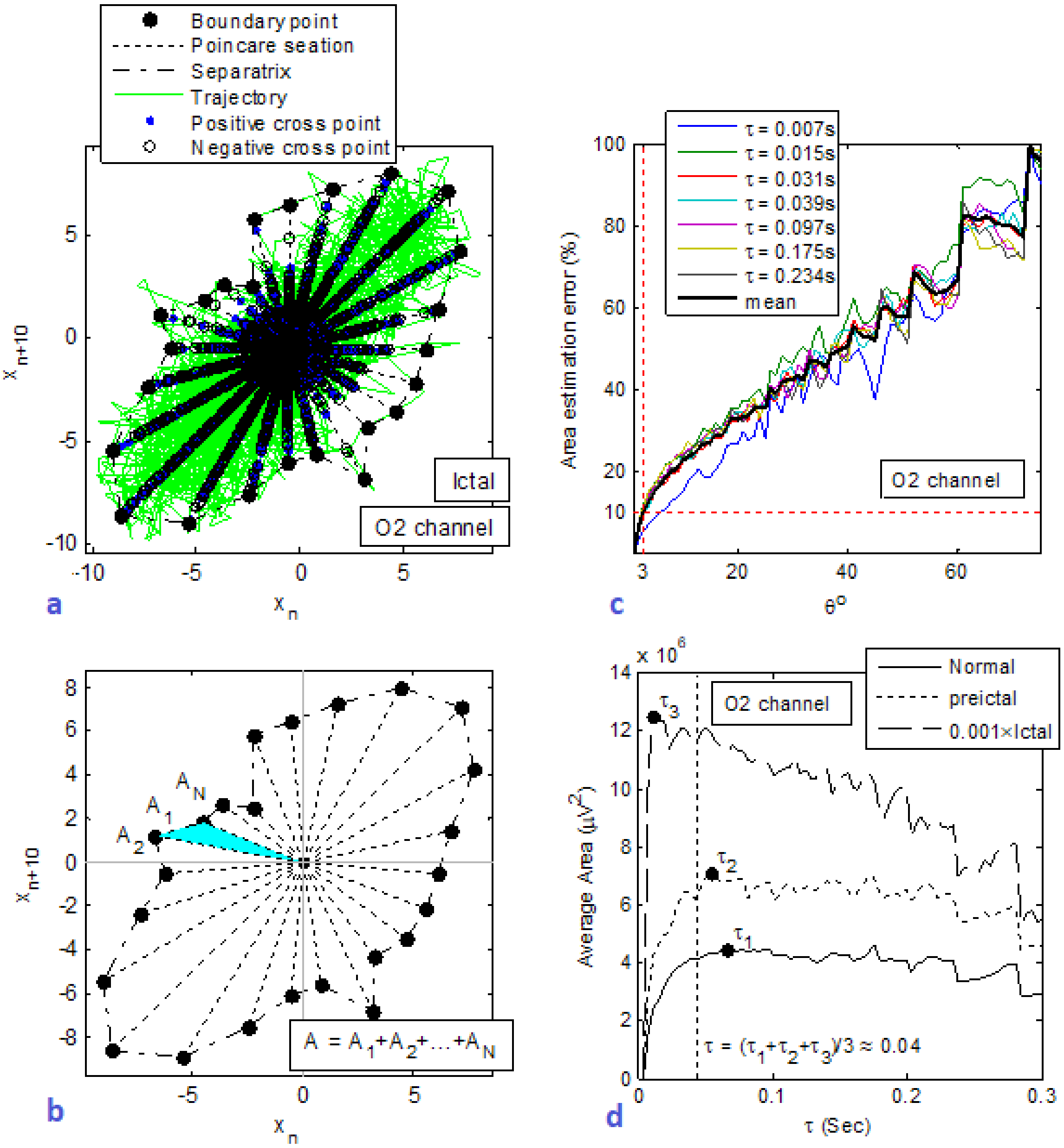

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Figure 1. EEG results

A: The two-dimensional phase space of an EEG segment sorted by the radial, linear Poincaré sections and the boundary points of oscillation basin; B: Computing the approximate area of oscillation basin by the sum of the triangular areas created from the boundary points of the basin and the origin of Cartesian coordinates; C: The curve of θ variations versus the area estimation error of oscillation basin of EEG trajectories; D: The effect of τ parameter on the area of oscillation basin of EEG trajectories in the O2 channels.

variables and can be appropriate (in addition to the deterministic systems) for systems, such as the human brain, which their state variables are not known.

Furthermore, based on the taken theorem, a type of these phases, which can be used for reconstructing the phase space, is the delayed phase [43, 44]. This space can depict the structure of the oscillation basin relevant to the phases of a system by reconstructing a trajectory from the variations of system activities over time.

For evaluating this space structurally and functionally, we need a technique that can quantify the geometric and functional characteristics of the space relevant to the systems with complex behaviors such as chaotic and biotic [44]. One of the techniques, which is now available to

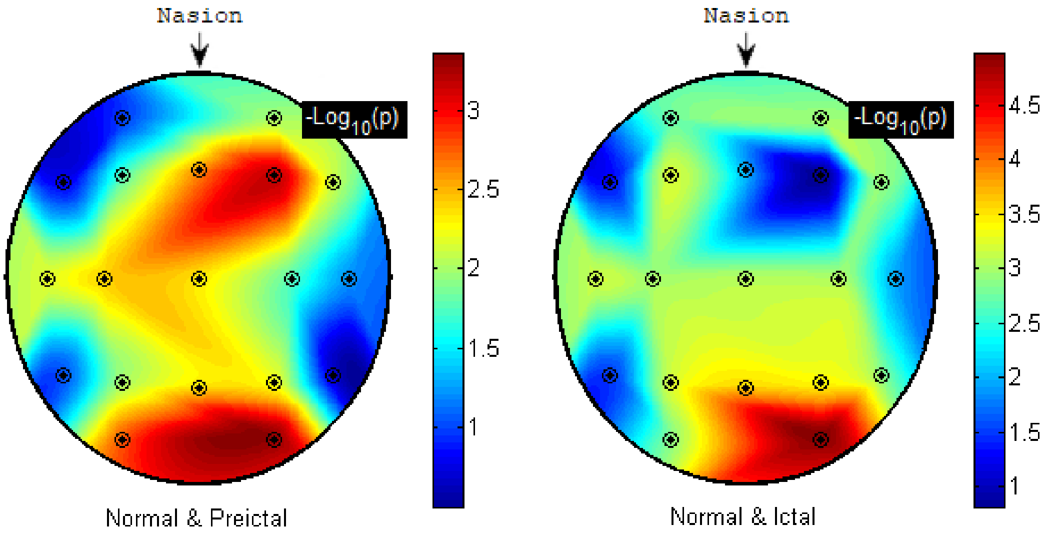

Figure 2. Brain maps are drawn from the negative logarithm value of P values obtained from the t test analysis for distinguishing the normal from pre-ictal mode and normal from ictal mode by using the distribution of the area of oscillation basin of EEG trajectories

evaluate this space, is the phase space sorted by a set of linear Poincaré sections [43]. It can be used to evaluate the functional characteristics besides the geometric characteristics.

In this study, the epileptic seizures change the geometry of the oscillation basin in the phase space, especially its expansion, so we employed this new space to evaluate the geometry of two-dimensional basins developed from the delayed phases of EEG segments. Figure 1A typically shows the new phase space reconstructed from an EEG segment of the O2 channel, including the collision points of the EEG trajectory with the radial linear Poincaré section. As shown in Figure 2, we can geometrically and functionally evaluate the electrical phases obtained from brain activity during the epileptic seizures by using the information obtained from this new space. In the following sections, we evaluated the 19-channel EEG segments taken from the epileptic patients by using the information of this new space.

The θ and τ parameters for establishing the new phase space

As shown in Figure 1, we must determine the angle between the radial Poincaré sections (θ) and delay (τ) for reconstructing the phase space sorted by the radial, linear Poincaré sections. For determining the θ parameter, we employed the average curve of θ effects on the area estimation error of the oscillation basin of trajectories reconstructed from the EEG segments of the O2 channel. Figure 1C represents this curve. We first calculated the crossing points of the EEG trajectories from the radial, linear Poincaré sections in different θ angles (Figure 1A). Then, we calculated the oscillation basin of EEG trajectories in different θ angles according to the farthest crossing point in each Poincaré section as shown in Figure 1B. This computing is also done for the EEG trajectories reconstructed with seven different τ delays (0.007s, 0.015s, 0.031s, 0.039s, 0.097s, 0.127s, and 0.234s), which is shown in Figure 1C. Finally, we drew the curve of θ effect on the area estimation error of the stated oscillation basin in the seven different delays.

For the area estimation error, we considered the area of the oscillation basin relevant to θ=1° as the main area of the basin. We estimated this error by subtracting this area and the area obtained for the different θ angles. Generally, θ=3° was a suitable value for extracting the geometric features of the oscillation basin of the EEG trajectories according to the average curve because this value could create an area estimation error of about 10%, which is almost tolerable in terms of engineering. Accordingly, we used this value for sorting the phase space.

In determining the τ parameter, because the maximum volume of oscillation basin in the phase space in evaluating the states of a system is essential, researchers usually use the linear independence technique of delayed phases for this purpose [45-47]. Nevertheless, these techniques, given that they indirectly intend to create the maximum volume of oscillation basin in the phase space, often have problems.

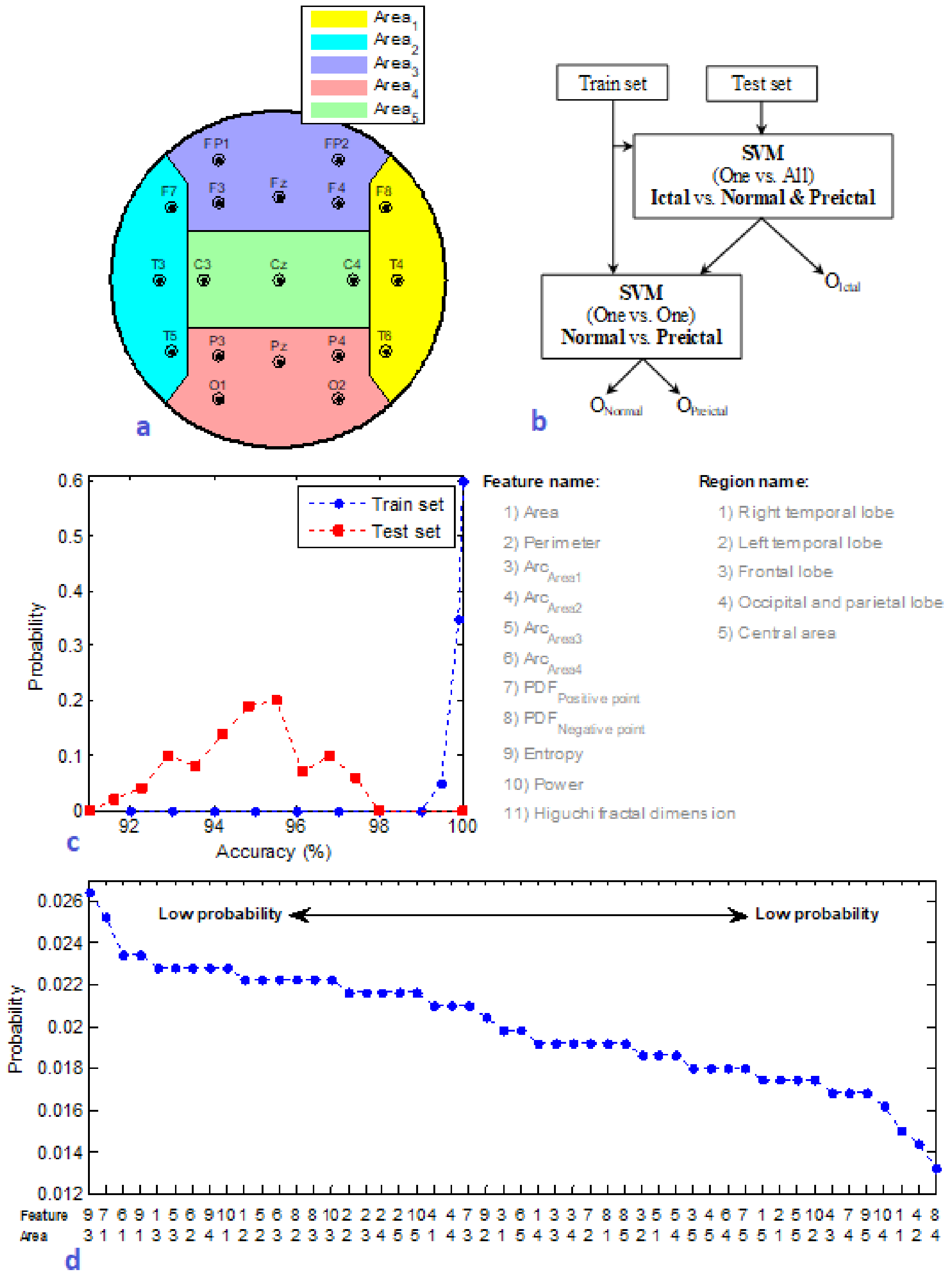

Figure 3. EEG results

A: Regions considered for the feature extraction; B: The structure of the decision tree used in the genetic algorithm; C: The occurrence probability of accuracy based on the 100-fold cross-validation of genetic algorithm for distinguishing the normal, pre-ictal, and ictal modes; D: The occurrence probability of features in 100 optimal combinations obtained from the genetic algorithm.

In this work, we used the effects of different τ values on the area of oscillation basin of trajectories reconstructed from the EEG segments of O2 channels for fixing this problem and reaching the mentioned purpose (Figure 1D) because it can simply estimate the area of the oscillation basin of EEG trajectories according to the sorted phase space (Figure 1B). Therefore, we used the effect of different τ values on the area of the oscillation basin of EEG trajectories relevant to the O2 channel in the normal, pre-ictal, and ictal modes to determine the appropriate τ delay. Based on these average curves, we selected τ≈ 0.04s (Figure 1D) because this value could typically create a maximum area in the oscillation basin of EEG trajectories of the O2 channel for the three studied modes. In the following section, we use this value for reconstructing the phase space and extracting the features.

Feature extraction and selection

Figure 2 shows two brain maps, which we drew according to the negative logarithm value of P obtained from the t test analysis for distinguishing the normal from pre-ictal modes by using the distribution of the area of oscillation basin of EEG trajectories. As seen in these maps, the negative logarithm of P values in most EEG channels (19 channels) was more than 1.3 ($-\log_{10}(p) > -\log_{10}(0.05)$), which indicates a significant difference in the stated distributions in normal, pre-ictal, and ictal modes. Therefore, according to the mentioned conditions in the brain maps, we considered five regions for evaluating the epilepsy effects on all of the EEG channels, which is represented in Figure 3A. Based on these regions, we considered the average value of the feature in the EEG channels located on each region as the feature of that region after extracting the feature from the 19 EEG channels. Features extracted from these regions include:

1. The area of the oscillation basin of EEG trajectory,

2. The perimeter of the oscillation basin of EEG trajectory,

3. The arc length of the oscillation basin of EEG trajectory in four regions of Cartesian coordinates,

4. The statistic of positive and negative crossing (collision) points recorded on all of the linear Poincaré sections (Figure 1A).

Features 1-3 in this set of features quantify the geometry of the oscillation basin of sustainable and reversible EEG trajectory [23, 34]. Feature 4 also quantifies the statistic of in-sets and out-sets relevant to the brain's fixed points. It provides information relevant to the compression, stretching, folding, and complexity of EEG trajectories two-dimensional phase space. Therefore, these features can generally assess any variations in the amplitude and frequency content of the brain's electrical activities. Furthermore, given that three features of Shannon entropy, fractal Higuchi dimension, and EEG power in previous studies [29, 30, 48, 49] have been introduced as optimal features in the diagnosis of epilepsy, we added them to the feature vector to extract another part of information of EEG signals, i.e., the information of amplitude and time complexity of EEG segments. After extracting these features, we normalized them according to their minimum and maximum in the training set (Equation 2).

3. $F_{Normalize} = \dfrac{F_{Row} - F_{Min}}{F_{Max} - F_{Min}}$

, where FMin and FMax are the maximum and minimum values of feature in the training set, respectively. For selecting the optimal features, we used the Genetic Algorithm (GA) for evaluating the features because this algorithm, unlike the sequential search strategies such as sequential forward search, sequential backward search, and sequential floating search strategies, which only search a certain trajectory in the feature space [50-52], can evaluate and search the whole feature space for reducing the computational load and eliminating the redundant features.

Table 1. The parameters used for the genetic algorithm

Parameter	Amount/Type
Initial population	100
Selection	20%
Crossover	40%
Mutation	30%
Reproduction	10%
Genes	55
Fitting function	DTSVM

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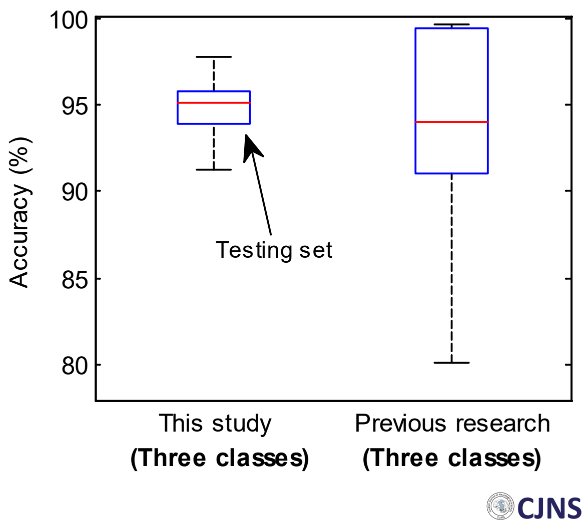

Figure 4. Accuracy distribution in the previous studies for diagnosing the epileptic seizures and accuracy distribution obtained from the proposed technique against changing the input population

Table 1 provides the values of parameters used for the genetic algorithm [43, 53]. We employed a Decision Tree based on the Support Vector Machine (DTSVM) with the Radial Basis Function (RBF) kernel for selecting the combination of features in the genetic algorithm. In other words, the genetic algorithm used the accuracy of the decision tree shown in Figure 3B for finding the optimal combination of features. In addition, as specified in Table 1, the genetic algorithm used four methods of selection, crossover, mutation, and reproduction to generate its generation. The number of genes per chromosome was also equal to the number of extracted features.

Decision tree based on the support vector machine

The Support Vector Machine (SVM) is now a unique classifier in the field of pattern identification because it finds the primary minimum in the error function [54], and does not usually suffer from a later curse in high dimensions [55]. Nevertheless, this classifier only distinguishes two classes from each other and should be used the one-versus-one and one-versus-all methods [56] to distinguish more than two classes. These methods also produce unknown answers, which is a fundamental problem.

Since we separated the three classes (normal, pre-ictal, and ictal), we used the decision tree based on the one-versus-one and one-versus-all methods of the SVM for preventing the unknown answers. Figure 3B is the structure of the proposed decision tree, which we employed as a selection criterion for the GA. As shown, we used both of the one-versus-one and one-versus-all methods in the structure of the decision tree to separate the classes. We first separated the ictal class from the other two classes (normal and pre-ictal) using the one-versus-all method in the tree. Finally, we separated the remaining two classes by using the one-versus-one method.

Therefore, this combination generally solves the problem of the unknown answers. In the next section, we present the results of evaluating the features using this proposed decision tree and the effect of the input population (training and testing sets) on the classification algorithm.

Results

Table 2 provides the 100-fold validation results of the GA for the training and testing sets obtained from the hold-out method with the division rate of 40% for the testing set. Although the GA could improve the classification accuracy of normal, pre-ictal, ictal modes and the computational load by finding an optimal combination in the feature space, the results of Table 2 show that the input population not only significantly affected the parameters of accuracy, specificity, and sensitivity, but it also affected the arrangement of optimal combinations.

Figures 3C and 3D provide the occurrence probability of accuracy and features based on the 100 optimal combinations found by the GA for separating three studied modes and confirm this issue. As shown in both parts of Figure 3C and 3D, the change of input population caused an accuracy distribution of 91.05%-98.12% in 100 optimal combinations of GA for separating the three modes and a different arrangement in the optimal combinations of features. Therefore, this condition indicates that the distribution of the input population has a significant effect on separating epilepsy and cannot be overlooked.

On the other hand, as shown in Figure 3D, different features appear in the different optimal combinations of features obtained from the GA. Of course, some of the features especially features 7 and 9, which are respectively the entropy of EEG signals and the statistic of positive crossing points in the frontal and right parietal lobes, had more probability for the occurrence. It means that they are more efficient for distinguishing epilepsy. Based on the results of Figure 3, the feature extracted from the geometry of the oscillation basin also had a high probability, and they had appeared more in the optimal combinations, although the entropy of EEG signals in the frontal lobe could have the highest probability in these combinations.

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Table 2. The 100-fold cross-validation results of the genetic algorithm for the training and testing sets

Set	Mean±SD				The Length of Optimal Combination
	Accuracy (%)	Specificity (%)	Sensitivity (%)		
			Pre-Ictal	Ictal	
Train	99.85±0.07	99.76±0.09	99.45±0.23	99.87±0.04	16.43±2.93
Test	94.84±1.44	96.58±1.88	90.62±6.83	98.34±1.25	

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Although comparing the separation of normal, pre-ictal, and ictal modes in this study with the results of previous studies, which had similar database (non-invasive EEG), may be unfair due to the separation of the two classes in the previous studies, their comparison indicates that the proposed technique has sufficient capability to separate three modes. Figure 4 shows the accuracy distribution in the previous studies for diagnosing epileptic seizures and the accuracy distribution obtained from the proposed technique against changing the input population. It is also another confirmation for this topic. It represents that the three-class algorithm proposed for epilepsy detection had an accuracy of about 94.84%, which was higher than the average accuracy of the two classes reported by previous studies. Besides, comparing the results of sensitivity to the diagnosis of epileptic seizures in the proposed method (Table 2) with the results of previous algorithms, especially tracking-based algorithms (Three class diagnosis) in Table 3, also shows that features extracted from the geometry of oscillation basin of EEG trajectories in the phase space contain valuable information. Therefore, it may upgrade classifiers developed for diagnosing epilepsy.

Discussion

As previously stated, epileptic seizures are an uncontrolled storm of electrical activity in the nervous system, which leads to activities outside the normal range in EEG signals, so that these signals, especially the invasive EEG signals, are usually accompanied by spike-shape variations [67]. Therefore, the spike-shape variations are the origin of changes in the frequency content of EEG signals obtained during epileptic seizures. So, researchers often use them to assess the conditions of patients with epilepsy and provide techniques to detect this abnormality [75]. Some researchers also reported that this disorder usually has the greatest impact on the content of low-frequency bands, especially the theta and alpha bands [76]. In other words, researchers have revealed in their reports that the nervous system, due to one of the intrinsic characteristics of its activities, i.e., the 1/f frequency spectrum, can only create considerable variations by using the low-frequency activities [77]. Accordingly, one of the characteristics associated with epileptic seizures is the increase in the volume of the oscillation basin of trajectories reconstructed from brain activities.

Remarkably, our assessment on the area of the oscillation basin of trajectories reconstructed from the EEG segments of normal, pre-ictal, and ictal modes indicated that epilepsy increases the volume of oscillation basin of EEG trajectories at different dimensions of phase space (Figure 1D) so that this increasing also happens in the spaces reconstructed by different time delays. Therefore, this status shows that the volume of the oscillation basin of EEG trajectories contains an essential part of the information generated by the nonlinear dynamics of the nervous system. Thus, it can be used to identify abnormal behaviors in the brain system, such as epilepsy. In this regard, evaluating the area of the aforementioned basin in both of the normal and pre-ictal modes as well as normal and ictal modes by using the t test analysis was coupled by significant differences in most EEG channels, especially occipital, frontal and central regions, which is a confirmation on this issue. Evaluating the geometric features of these basins by using the GA also illustrated that the geometry of oscillation basin of trajectories reconstructed of the EEG segments during the epilepsy corresponds generally with the remarkable changes. Accordingly, its geometric features had a high occurrence probability in the optimal combinations selected by the genetic algorithm (Figure 3D). In other words, the combination of these features with the optimal features of previous research studies could make a significant difference in separating the three modes of epileptic patients.

It was interesting that the evaluation of optimal-feature combinations selected by the genetic algorithm along with the entropy of EEG signals, indicated that the statistics of positive and negative crossing points, which evaluate the in-sets and out-sets of brain's fixed points

Table 3. Non-invasive EEG-based studies for diagnosing the epileptic seizures

Authors	Year	Patients	Methods	Classes	%		
					Accuracy	Sensitivity	Specificity
Das et al. [57]	2018	23	VMD+SF+SSE+PCA	2	72.92	82.55	94.86
Rafiuddin et al. [58]	2011	23	WSF+LDA	2	80.16	NR	NR
Sadeghzadeh et al. [59]	2019	20	MDWT+DM	2	88.76	90.62	88.34
Khan et al. [60]	2012	5	DWT+RVOE +NCOV+ LDA	2	91.8	83.6	100
Chen et al. [61]	2017	18	DWT+WSF+SVM	2	92.3	91.71	92.89
Zabihi et al. [38]	2018	23	SDBDA+SVM	2	92.91	91.55	94.27
Deng et al. [62]	2018	22	WPD+ETTL-TSK-FS	2	94	91.91	93.16
Elmahdy et al. [63]	2015	23	SVCF+SVM	2	94.82	91.64	98.01
Bhattacharyya et al. [64]	2017	23	EWT+JIAAF+ RF	2	99.4	97.9	99.6
Chandel et al. [65]	2018	18	TWD+SF+HOS+KNN(IDA)	2	99.45	98.36	99.62
Jiang et al. [5]	2020	22	SGM+ SVM	2	99.62	97.168	99.718
Osorio et al. [66]	1998	16	TFL+IP+GA	2	NR	91.6	NR
Ahammad et al. [67]	2014	23	DWT+linear classifier	2	NR	NR	98.5
Samiee et al. [4]	2015	23	2DMTF+SVM	2	NR	70.19	97.74
Sharif & Jafari [39]	2017	19	PS+DOFRO-OSF+SVM	Tracking	NR	91.8–96.6	NR
Zheng et al. [68]	2014	10	EMD+PCF+TC	Tracking	NR	25-70	NR
Aarabi & He [32]	2014	21	NLF+TC+RBD	Tracking	NR	90	NR
Eftekhar et al. [69]	2014	21	REPF+TC	Tracking	NR	67–100	NR
Moghim & Corne [70]	2014	21	UF+SVM	Tracking	NR	89–93.5	NR
Li et al. [71]	2013	21	Spike rate+TC	Tracking	NR	72.7	NR
Aarabi & He [72]	2012	11	NLF+TC+RBD	Tracking	NR	90.2	NR
Williamson et al. [73]	2012	19	TD(5)U/MC+SVM	Tracking	NR	86–95	NR
Park et al. [74]	2011	18	USPF+SVM	Tracking	NR	98.3	NR

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VMD: Variational Mode Decomposition; SF: Statistical Features; SSE: Spectral Sample Entropy; PCA: Principal Component Analysis; WSF: Wavelet + Statistical Features; LDA: Linear Discriminant Analysis; MDWT: Making Decision With Thresholding; DM: Decision-Making; DWT: Discrete Wavelet Transform; RVOE: Relative Values of Energy; NCOV: Normalized Coefficient of Variation; SVM: Support Vector Machine; SDBDA: Signal Derived Based Dictionary Approach; WPD: Wavelet Packet Decomposition; ETTL-TSK-FS: Enhanced Transductive Transfer Learning Takagi–Sugeno–Kang Fuzzy System; SVCF: Singular Value + Classical Features; EWT: Empirical Wavelet Transform; JIAAF: Joint Instantaneous Amplitudes and Frequencies; RF, Random Forest; TWD: Triadic Wavelet Decomposition; KNN: K-Nearest Neighbors; SGM: Symplectic Geometry Decomposition; TFL, Time-Frequency Localization; IP: Image Processing; GA: Generic Algorithm; 2DMTF: 2D Mapping and Textural Features; PS: Phase Space; DOFRO-PSF: Distribution of Fuzzy Rules on Optimized Poincaré Samples Features; EMD: Empirical Mode Decomposition; PCF: Phase Coherence Features; TC: Threshold Crossing; NLF: Nonlinear Features; RBD: Rule Based Decision; REPF: Repeating EEG Patterns Features; UF: Univariate Features; USPF: Univariate Spectral Power Features; TDU/MC: Time Delayed Univariate/Multivariate Correlations.

recorded on radial, linear Poincaré sections, had the high occurrence probability in the optimal combinations of the GA. This high occurrence probability in the in-sets and out-sets, with the probability that the EEG signal is a complex process produced by the homoclinic and heteroclinic orbits [44], emphasizes this issue that epilepsy can be a factor for changing the homoclinic and heteroclinic intersections and orbits. Since epilepsy seizures increase energy consumption, these disorders as a mode diverge the activities of the nervous system and can expand the homoclinic and heteroclinic intersections and orbits created by the in-sets and out-set of the brain's fixed points.

Conclusion

Distinguishing the normal, pre-ictal, and ictal modes by using the geometric features extracted from the phase space sorted by Poincaré sections generally indicated that the epileptic seizures increase the oscillation basin of EEG trajectory. Accordingly, developing the decision tree based on the SVM with the geometric features selected by the GA provides significant accuracy for diagnosing the three mentioned modes, and confirms the stated topic. However, the findings of this research indicate that the diagnosis of epilepsy in online clinical applications, which their statistical population, requires a diagnostic technique based on several EEG segments.

Ethical Considerations

Compliance with ethical guidelines

This article was approved by the Ethics Committee of Imam Reza International University (Ethical Code: IR.IRIU.REC.1398.500685-95). All study procedures were done in compliance with the ethical guidelines of the 2013 version of the Declaration of Helsinki.

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Authors' contributions

Methodology and writing: Reyhaneh Zarifiyan Irani Nezhad; Investigation, supervision, and editing: Ghasem Sadeghi Bejestani; Conceptualization, supervision, writing, and editing: Reza Yaghoobi Karimui; Resources: Behnaz Sheikholeslami and Farah Ashrafzadeh.

Conflict of interest

The authors declared no conflict of interest.

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References

[1] Selvakumari RS, Mahalakshmi M, Prashalee P. Patient-specific seizure detection method using hybrid classifier with optimized electrodes. J Med Syst. 2019; 43(5):121. [DOI:10.1007/s10916-019-1234-4] [PMID]

[2] Carney PR, Myers S, Geyer JD. Seizure prediction: Methods. Epilepsy Behav. 2011; 22:S94-S101. [DOI:10.1016/j.yebeh.2011.09.001] [PMID] [PMCID]

[3] Anupallavi S, MohanBabu G. A novel approach based on BSP-CI for quantifying functional connectivity pattern of the brain's region for the classification of epileptic seizure. J Amb Inetl Hum Comp. 2021; 12:4037-47. [DOI:10.1007/s12652-020-01774-w]

[4] Samiee K, Kiranyaz S, Gabbouj M, Saramäki T. Long-term epileptic EEG classification via 2D mapping and textural features. Expert Syst Appl. 2015; 42(20):7175-85. [DOI:10.1016/j.eswa.2015.05.002]

[5] Jiang Y, Chen W, Li M. Symplectic geometry decomposition-based features for automatic epileptic seizure detection. Comput Biol Med. 2020; 116:103549. [DOI:10.1016/j.compbiomed.2019.103549] [PMID]

[6] Sharma M, Pachori RB, Rajendra Acharya U. A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension. Pattern Recognit Lett. 2017; 94:172-9. [DOI:10.1016/j.patrec.2017.03.023]

[7] Gotman J. Automatic recognition of epileptic seizures in the EEG. Electroencephalogr Clin Neurophysiol. 1982; 54(5):530-40. [DOI:10.1016/0013-4694(82)90038-4]

[8] Saab ME, Gotman J. A system to detect the onset of epileptic seizures in scalp EEG. Clin Neurophysiol. 2005; 116(2):427-42. [DOI:10.1016/j.clinph.2004.08.004] [PMID]

[9] Tzallas AT, Tsipouras MG, Fotiadis DI. Epileptic seizure detection in EEGs using time-frequency analysis. IEEE Trans Inf Technol Biomed. 2009; 13(5):703-10. [DOI:10.1109/TITB.2009.2017939] [PMID]

[10] Faust O, Acharya UR, Adeli H, Adeli A. Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. Seizure. 2015; 26:56-64. [DOI:10.1016/j.seizure.2015.01.012] [PMID]

[11] Parvez MZ, Paul M. Epileptic seizure detection by analyzing EEG signals using different transformation techniques. Neurocomputing. 2014; 145:190-200. [DOI:10.1016/j.neucom.2014.05.044]

[12] Rashid MMo, Ahmad M, editors. Epileptic seizure classification using statistical features of EEG signal. Paper presented at: 2017 International Conference on Electrical,

Computer and Communication Engineering (ECCE). 16-18 February 2017; Cox's Bazar, Bangladesh. [DOI:10.1109/ECACE.2017.7912923]

[13] Tzallas AT, Tsipouras MG, Fotiadis DI. Automatic seizure detection based on time-frequency analysis and artificial neural networks. Hindawi Pub Corp. Comput Intel Neurosci. 2007; 2007:ID 080510. [DOI:10.1155/2007/80510] [PMID] [PMCID]

[14] Orosco L, Correa AG, Laciar E, editors. Multiparametric detection of epileptic seizures using Empirical Mode Decomposition of EEG records. 2010 Annu Int Conf IEEE Eng Med Biol. 2010; 2010:951-4. [DOI:10.1109/IEMBS.2010.5627564] [PMID]

[15] Choi K, Zeng Y, Qin J, editors. Using sequential floating forward selection algorithm to detect epileptic seizure in EEG signals. Paper presented at: 2012 IEEE 11th International Conference on Signal Processing. 21-25 Octber 2012; Beijing, China. [DOI:10.1109/ICoSP.2012.6491894]

[16] Ghayab HRA, Li Y, Abdulla S, Diykh M, Wan X. Classification of epileptic EEG signals based on simple random sampling and sequential feature selection. Brain Inform. 2016; 3(2):85-91. [DOI:10.1007/s40708-016-0039-1] [PMID] [PMCID]

[17] Smart O, Tsoulos IG, Gavrilis D, Georgoulas G. Grammatical evolution for features of epileptic oscillations in clinical intracranial electroencephalograms. Expert Syst Appl. 2011; 38(8):9991-9. [DOI:10.1016/j.eswa.2011.02.009] [PMID] [PMCID]

[18] Hsu K-C, Yu S-N. Detection of seizures in EEG using subband nonlinear parameters and genetic algorithm. Comput Biol Med. 2010; 40(10):823-30. [DOI:10.1016/j.compbiomed.2010.08.005] [PMID]

[19] Dhiman R, Saini JS, Priyanka. Genetic algorithms tuned expert model for detection of epileptic seizures from EEG signatures. Appl Soft Comput. 2014; 19:8-17. [DOI:10.1016/j.asoc.2014.01.029]

[20] Shengkun X, Lawniczak AT, Yuedong S, Liò P, editors. Feature extraction via dynamic PCA for epilepsy diagnosis and epileptic seizure detection. Paper presented at: 2010 IEEE International Workshop on Machine Learning for Signal Processing; 29 Aug.-1 Sept 2010; Kittila, Finland. [DOI:10.1109/MLSP.2010.5588995]

[21] De Vos M, Deburchgraeve W, Cherian PJ, Matic V, Swarte RM, Govaert P, et al. Automated artifact removal as preprocessing refines neonatal seizure detection. Clin Neurophysiol. 2011; 122(12):2345-54. [DOI:10.1016/j.clinph.2011.04.026]

[22] González García B, García Vicente AM, Palomar Muñoz A, Poblete García VM, Jiménez Londoño GA, Soriano Castrejón AM. Incidental pathologic extracardiac uptake of 99mTc-tetrofosmin in myocardial perfusion imaging: Importance of patient background evaluation. Rev Esp Med Nucl Imagen Mol. 2015; 34(6):383-6. [DOI:10.1016/j.remn.2015.03.005]

[23] Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P, Elger CE. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. Phys Rev E. 64(6):061907. [DOI:10.1103/PhysRevE.64.061907]

[24] Dehghan-Niri E, Al-Beer H. Phase-space topography characterization of nonlinear ultrasound waveforms. Ultrasonics. 2018; 84:446-58. [DOI:10.1016/j.ultras.2017.12.007]

[25] Güler NF, Übeyli ED, Güler İ. Recurrent neural networks employing Lyapunov exponents for EEG signals classification. Expert Syst Appl. 2005; 29(3):506-14. [DOI:10.1016/j.eswa.2005.04.011]

[26] Lehnertz K, Elger CE. Spatio-temporal dynamics of the primary epileptogenic area in temporal lobe epilepsy characterized by neuronal complexity loss. Electroencephalogr Clin Neurophysiol. 1995; 95(2):108-17. [DOI:10.1016/0013-4694(95)00071-6]

[27] Shayegh F, Sadri S, Amirfattahi R, Ansari-Asl K. A model-based method for computation of correlation dimension, Lyapunov exponents and synchronization from depth-EEG signals. Comput Methods Programs Biomed. 2014; 113(1):323-37. [DOI:10.1016/j.cmpb.2013.08.014]

[28] Sriraam N. Correlation dimension based lossless compression of EEG signals. Biomed Signal Process Control. 2012; 7(4):379-88. [DOI:10.1016/j.bspc.2011.06.007]

[29] Chakraborty M, Das T, Ghosh D, editors. Comparative analysis of different fractal methods in studying post-ictal ECG signals of epilepsy patient. Paper presented at: 2016 IEEE First International Conference on Control, Measurement and Instrumentation (CMI); 8-10 January 2016; Kolkata, India. [DOI:10.1109/CMI.2016.7413743]

[30] Acharya UR, Fujita H, Sudarshan VK, Bhat S, Koh JEW. Application of entropies for automated diagnosis of epilepsy using EEG signals: A review. Knowl Based Syst. 2015; 88:85-96. [DOI:10.1016/j.knosys.2015.08.004]

[31] Adeli H, Ghosh-Dastidar S, Dadmehr N. A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Subbands to Detect Seizure and Epilepsy. IEEE Trans Biomed Eng. 2007; 54(2):205-11. [DOI:10.1109/TBME.2006.886855] [PMID]

[32] Aarabi A, He B. Seizure prediction in hippocampal and neocortical epilepsy using a model-based approach. Clin Neurophysiol. 2014; 125(5):930-40. [DOI:10.1016/j.clinph.2013.10.051] [PMID] [PMCID]

[33] Bajestania GS, Sheikhania A, Golpayeganib MH, Ashrafzadehc F, Hebranid P. Poincar e section-based biomarkers of hemispheric asymmetry applied to autism spectrum disorder. Scientia Iranica D. 2017; 24(6):3257-67. http://scientiairanica.sharif.edu/article_4356_95f2a50049c230377523fab3019b14be.pdf

[34] Sabelli HC. Bios: A study of creation. Singapore: World Scientific Publishing Company; 2005. [DOI:10.1142/9789812701299]

[35] Yaghoobi Karimoi R, Azadi S, Keshavarzi P. The ADHD effect on the actions obtained from the EEG signals. Biocybern Biomed Eng. 2018; 38(2):425-37. [DOI:10.1016/j.bbe.2018.02.007]

[36] Yaghoobi Karimoi R, Yaghoobi Karimoi A. Classification of EEG signals using hyperbolic tangent-tangent plot. Int J Intell Syst. 2014; 6(8):39. [DOI:10.5815/ijisa.2014.08.04]

[37] Sharma R, Pachori RB. Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions. Expert Syst Appl. 2015; 42(3):1106-17. [DOI:10.1016/j.eswa.2014.08.030]

[38] Zabihi M, Kiranyaz S, Rad AB, Katsaggelos AK, Gabbouj M, Ince T. Analysis of high-dimensional phase space via poincaré section for patient-specific seizure detection. IEEE Trans Neural Syst Rehabilitation Eng. 2016; 24(3):386-98. [DOI:10.1109/TNSRE.2015.2505238] [PMID]

[39] Sharif B, Jafari AH. Prediction of epileptic seizures from EEG using analysis of ictal rules on Poincaré plane. Comput Methods Programs Biomed. 2017; 145:11-22. [DOI:10.1016/j.cmpb.2017.04.001] [PMID]

[40] Luckett P, Watts T, McDonald JT, Hively L, Benton R, editors. A deep learning approach to phase-space analysis for seizure detection. Paper presented at: Proceedings of the 10th ACM International Conference on Bioinformatics, Computational Biology and Health Informatics; 04 September 2019; Association for Computing Machinery, New York. [DOI:10.1145/3307339.3342131]

[41] Kwange SO, Budambula NLM. Effectiveness of anti-tuberculosis treatment among patients receiving highly active antiretroviral therapy at Vihiga district hospital in 2007. Indian J Med Microbiol. 2010; 28(1):21-5. [DOI:10.4103/0255-0857.58723]

[42] Akhter N, Kamal Z, Rahman F, Sultana P, Dhurrani Z. Awareness and prevalence of epilepsy: A study in educational hubs at Sheringal, Khyber Pakhtunkhwa, Pakistan. ARC J Neurosci. 2018; 3(1):9-20. [DOI:10.20431/2456-057X.0301003]

[43] Yaghoobi Karimoi R, Azadi S, Keshavarzi P. The ADHD effect on the actions obtained from the EEG signals. Biocybern Biomed Eng. 2018; 38(2):425-37. [DOI:10.1016/j.bbe.2018.02.007]

[44] Strogatz SH. Nonlinear dynamics and chaos: With applications to physics, biology, chemistry, and engineering (2nd ed.). Boca Raton, Florida: CRC Press; 2015. https://doi.org/10.1201/9780429492563

[45] Fraser AM, Swinney HL. Independent coordinates for strange attractors from mutual information. Phys Rev A. 1986; 33(2):1134. [DOI:10.1103/PhysRevA.33.1134]

[46] Olofsen E. The identification of strange attractors using experimental time series [MA thesis]. Holanda: Twente University; 1991. http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=4C68DAFE81AC654D3F9EBDB5DBF20D73?doi=10.1.1.581.4211&rep=rep1&type=pdf

[47] Almasi A, Shamsollahi MB, Senhadji L. Bayesian denoising framework of phonocardiogram based on a new dynamical model. IRBM. 2013; 34(3):214-25. [DOI:10.1016/j.irbm.2013.01.017]

[48] Acharya UR, Molinari F, Sree SV, Chattopadhyay S, Ng K-H, Suri JS. Automated diagnosis of epileptic EEG using entropies. Biomed Signal Process Control. 2012; 7(4):401-8. [DOI:10.1016/j.bspc.2011.07.007]

[49] Acharya UR, Sree SV, Swapna G, Martis RJ, Suri JS. Automated EEG analysis of epilepsy: A review. Knowl-Based Syst. 2013; 45:147-65. [DOI:10.1016/j.knosys.2013.02.014]

[50] Alamedine D, Khalil M, Marque C, editors. Feature selection techniques in uterine electrohysterography signal. In: Roa Romero L. editor. XIII Mediterranean Conference on Medical and Biological Engineering and Computing 2013. IFMBE Proceedings; 2014. [DOI:10.1007/978-3-319-00846-2_193]

[51] Peng HY, Jiang CF, Fang X, Liu JS. Variable selection for Fisher linear discriminant analysis using the modified sequential backward selection algorithm for the microarray data. Appl Math Comput. 2014; 238:132-40. [DOI:10.1016/j.amc.2014.03.141]

[52] Ke L, Feng Z, Ren Z. An efficient ant colony optimization approach to attribute reduction in rough set theory. Pattern Recognit Lett. 2008; 29(9):1351-7. [DOI:10.1016/j.patrec.2008.02.006]

[53] Huang CL, Wang CJ. A GA-based feature selection and parameters optimizationfor support vector machines. Expert Syst Appl. 2006; 31(2):231-40. [DOI:10.1016/j.eswa.2005.09.024]

[54] Obdrzalek D, Gottscheber A. Research and Education in Robotics-EUROBOT 2011. Paper presented at: International Conference, Prague, Czech Republic. 15-17 Juneuary 2011. Springer Science & Business Media, Prague. [DOI:10.1007/978-3-642-21975-7]

[55] Salimi A, Ziaii M, Amiri A, Zadeh MH, Karimpouli S, Moradkhani M. Using a feature subset selection method and support vector machine to address curse of dimensionality and redundancy in Hyperion hyperspectral data classification. Egypt J Remote Sens Space Sci. 2018; 21(1):27-36. [DOI:10.1016/j.ejrs.2017.02.003]

[56] Kolekar MH, Dash DP. A nonlinear feature based epileptic seizure detection using least square support vector machine classifier", TENCON 2015. Paper presented at: 2015 IEEE Region 10 Conference. 1-4 November 2015; Macao, China. [DOI:10.1109/TENCON.2015.7373164]

[57] Das P, Manikandan MS, Ramkumar B. Detection of epileptic seizure event in EEG signals using variational mode decomposition and mode spectral entropy. Paper presented at: 2018 IEEE 13th International Conference on Industrial and Information Systems (ICIIS). 1-2 December 2018; Rupnagar, India. [DOI:10.1109/ICIINFS.2018.8721426] [PMCID]

[58] Rafiuddin N, Khan YU, Farooq O, editors. Feature extraction and classification of EEG for automatic seizure detection. 2011 International Conference on Multimedia, Signal Processing and Communication Technologies. 17-19 December 2011; Aligarh, India. [DOI:10.1109/MSPCT.2011.6150470]

[59] Sadeghzadeh H, Hosseini-Nejad H, Salehi S. Real-time epileptic seizure prediction based on online monitoring of pre-ictal features. Med Biol Eng Comput. 2019; 57(11):2461-9. [DOI:10.1007/s11517-019-02039-1] [PMID]

[60] Khan YU, Rafiuddin N, Farooq O. Automated seizure detection in scalp EEG using multiple wavelet scales. Paper presented at: 2012 IEEE international conference on signal processing, computing and control. 15-17 March 2012; Solan, India. [DOI:10.1109/ISPCC.2012.6224361]

[61] Chen D, Wan S, Xiang J, Bao FS. A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG. PloS one. 2017; 12(3):e0173138. [DOI:10.1371/journal.pone.0173138] [PMID] [PMCID]

[62] Deng Z, Xu P, Xie L, Choi KS, Wang S. Transductive joint-knowledge-transfer TSK FS for recognition of epileptic EEG signals. IEEE Trans Neural Syst Rehabilitation Eng. 2018; 26(8):1481-94. [DOI:10.1109/TNSRE.2018.2850308] [PMID]

[63] Elmahdy AE, Yahya N, Kamel NS, Shahid A. Epileptic seizure detection using singular values and classical features of EEG signals. Paper presented at: 2015 International Conference on BioSignal Analysis, Processing and Systems (ICBAPS). 26-28 May 2015; Kuala Lumpur, Malaysia. IEEE. [DOI:10.1109/ICBAPS.2015.7292238]

[64] Bhattacharyya A, Pachori RB. A multivariate approach for patient-specific EEG seizure detection using empirical wavelet transform. IEEE Trans Biomed Eng. 2017; 64(9):2003-15. [DOI:10.1109/TBME.2017.2650259] [PMID]

[65] Chandel G, Upadhyaya P, Farooq O, Khan Y. Detection of seizure event and its onset/offset using orthonormal

triadic wavelet based features. IRBM. 2019; 40(2):103-12. [DOI:10.1016/j.irbm.2018.12.002]

[66] Osorio I, Frei MG, Wilkinson SB. Real-time automated detection and quantitative analysis of seizures and short-term prediction of clinical onset. Epilepsia. 1998; 39(6):615-27. [DOI:10.1111/j.1528-1157.1998.tb01430.x] [PMID]

[67] Ahammad N, Fathima T, Joseph P. Detection of epileptic seizure event and onset using EEG. Biomed Res Int. 2014; 2014:450573. [DOI:10.1155/2014/450573] [PMID] [PMCID]

[68] Zheng Y, Wang G, Li K, Bao G, Wang J. Epileptic seizure prediction using phase synchronization based on bivariate empirical mode decomposition. Clin Neurophysiol. 2014; 125(6):1104-11. [DOI:10.1016/j.clinph.2013.09.047] [PMID]

[69] Eftekhar A, Juffali W, El-Imad J, Constandinou TG, Toumazou C. Ngram-derived pattern recognition for the detection and prediction of epileptic seizures. PloS One. 2014; 9(6):e96235. [DOI:10.1371/journal.pone.0096235] [PMID] [PMCID]

[70] Moghim N, Corne DW. Predicting epileptic seizures in advance. PloS One. 2014; 9(6):e99334. [DOI:10.1371/journal.pone.0099334] [PMID] [PMCID]

[71] Li S, Zhou W, Yuan Q, Liu Y. Seizure prediction using spike rate of intracranial EEG. IEEE Trans Neural Syst Rehabilitation Eng. 2013; 21(6):880-6. [DOI:10.1109/TNSRE.2013.2282153] [PMID]

[72] Aarabi A, He B. A rule-based seizure prediction method for focal neocortical epilepsy. Clin Neurophysiol. 2012; 123(6):1111-22. [DOI:10.1016/j.clinph.2012.01.014] [PMID] [PMCID]

[73] Williamson JR, Bliss DW, Browne DW, Narayanan JT. Seizure prediction using EEG spatiotemporal correlation structure. Epilepsy Behav. 2012; 25(2):230-8. [DOI:10.1016/j.yebeh.2012.07.007] [PMID]

[74] Park Y, Luo L, Parhi KK, Netoff T. Seizure prediction with spectral power of EEG using cost-sensitive support vector machines. Epilepsia. 2011; 52(10):1761-70. [DOI:10.1111/j.1528-1167.2011.03138.x] [PMID]

[75] Assi EB, Nguyen DK, Rihana S, Sawan M. Towards accurate prediction of epileptic seizures: A review. Biomed Signal Process Control. 2017; 34:144-57. [DOI:10.1016/j.bspc.2017.02.001]

[76] Singh RK, Singh AK. Frequency analysis of healthy & epileptic seizure in EEG using fast fourier transform. Int J Eng Res Gen Sci. 2014; 2(4):683-91. http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=E896EEDBC299FEB785D30AFEF8EB9538?doi=10.1.1.476.5040&rep=rep1&type=pdf

[77] Kannathal N, Choo ML, Acharya UR, Sadasivan P. Entropies for detection of epilepsy in EEG. Comput Methods Programs Biomed. 2005; 80(3):187-94. [DOI:10.1016/j.cmpb.2005.06.012] [PMID]