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Original research article

Epilepsy identification based on EEG signal using RQA method

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ABSTRACT

Purpose: Epilepsy is one of the most common neurological diseases and its cause is not unequivocal. Thus, additional methods and searches that may help to diagnose the disease are used in the clinical practice. In this study, we tested the possibility of using the Recurrence Quantification Analysis (RQA) method to identify epilepsy and present the analysis of EEG signals of healthy patients and epileptic patients by the RQA method.
Materials/methods: The recordings of signals belong to 13 patients, which were divided into 2 groups: Group A (5 epileptic patients) and Group B (8 healthy patients). In this study Fp1, Fp2, T3 and T4 electrodes were considered in the analysis using the RQA method.
Results: It is difficult to explore the dynamics of signals by linear methods. In this study, another way of analyzing the dynamics of signals by the RQA method is presented. The RQA method revealed differences in the dynamics between the epileptic and normal signals, which seemed important in an organoleptic way. It was found that the dynamics of epileptic signals is more periodic than normal signals. To confirm the correctness of the statements issued for the RQA data the Principal Component Analysis mapping was applied. This method showed more clearly the differences in the dynamics of both signals.
Conclusions: The RQA method can be used to identify nonlinear biomedical signals such as EEG signals.

1. Introduction

Electroencephalogram (EEG) is a recording of bioelectrical brain activity in time. EEG signals are the basis for the detection and monitoring of many neurological diseases, but are mainly used to diagnose epilepsy. Epilepsy is a chronic disease affecting about 1% of the world population. The essence of epilepsy is the recurrent interference with electrical brain activity. The result of the epilepsy is the loss of consciousness with associated seizures, including long-term seizures, which affect the quality of patient's life. The reason for epilepsy may be in different diseases but the cause of epilepsy is difficult to determine. The basis of the clinical classification and the mechanism of seizures is bioelectric brain research [1–3]. Therefore, the EEG allows to know the pivotal pathomechanism member of seizure, i.e. bioelectrical discharge of damaged nerve cells. Nevertheless, the diagnosis of epilepsy is difficult because of the presence of epilepsy patterns in healthy people. Similarly, patients suffering from epilepsy may not have epilepsy patterns. In the search for irregularities, long EEG data are analyzed by highly qualified specialists (neurologists). However, manual analysis is laborious, which results in prolongation of the diagnosis and consequent treatment of epileptic patients. Due to the great need of the society, many computational systems and tools have been developed to support electroencephalogram analysis, but these are often systems that allow linear data analysis by means of digital processing algorithms and spectral analysis [4,5].

Electroencephalographic signals are difficult to study due to their complexity, unsteadiness and partly nondeterministic nature. In the case of the EEG, regularity, sharp peaks and well-defined frequency ranges are not observed, same as in chaotic dynamic systems. Most common signal recording devices representing the electrical activity of the brain include a built-in program for signal analysis using Fast Fourier Transform (FFT). However, this is a traditional linear signal analysis method and may be insufficient. Observing the EEG as a dynamic system requires such method selection, which allows for studying nonlinear and chaotic nature of the signal. Useful methods used to divide the characteristics of the EEG signal are methods borrowed from deterministic chaos theory [6–8].

In many studies [9–12], methods of nonlinear dynamical systems (chaos) have been used to analyze the EEG signals. The authors analyzed indicators of Recurrence Quantification Analysis (RQA) method.

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However, in these studies, only the epileptic signals were analyzed, that were induced at the time of epilepsy examination. The differences between inter-ictal, pre-ictal and ictal stages and the direction of seizures propagation within the part of the brain were sought for. To analyze the dynamical behavior of the EEG data, quantification analysis was proposed [13] which has been successfully used in practice [14–18].

The aim of this study was to analyze the EEG signals using the recurrence plot, the RQA for EEGs of 11 epileptic and 11 healthy patients. Due to the RQA method assumptions, the study was conducted on 13 patients – 5 epileptic and 8 healthy. Patients with epilepsy did not have seizures during the signal acquisition. In this analysis, the focus was set on detecting the differences between the signals of epileptic and healthy persons. These differences can accelerate the classification without inducing any seizures, which have an adverse effect on health. Likewise, to confirm the results obtained from the RQA method, 2d maps were created based on the data from the Principal Component Analysis (PCA) matrix.

2. Material and methods

2.1. EEG recordings

The examinations were performed in the Clinic of Children's Neurology and Rehabilitation at the Medical University of Bialystok (Children's Clinical Hospital of L. Zamenhof, Poland). The results of these examinations were EEG signals analyzed in this study. The recordings of signals belong to 22 patients of similar age, males and females. They were divided into two groups: Group A (11 patients with epilepsy) and Group B (11 healthy patients). However, taking into account that the analyzed signals include trends, long-term fluctuations, and noise at the 50 Hz supply network, whose amplitude is close to the amplitude of the signal, the number of patients was reduced from 22 to 13. Electroencephalograms were created using single station electroencephalograph – EEG DigiTrack. This device enables digital registration, ratings and analysis of signals representing electrical brain activity. The EEG DigiTrack registered biopotentials of 12 channels at the same time from 12 different parts of the head. Electrodes were located in frontal, temporal, central, parietal and occipital lobes and these are: Fp1, Fp2, F3, F4, T3, T4, C3, C4, P3, P4, O1, O2. The entire examination, including attaching the electrodes to the patient's head, was performed in accordance with the guidelines of the International Federation of Clinical Neurophysiology (IFCN) [19].

Research presented in this study refers to electrodes Fp1, Fp2, T3 and T4. We chose these four electrodes because seizures in adults are most often registered in the frontal and temporal parts of the brain. Fig. 1 shows one of the EEG signal recordings for Fp1 (Fig. 1a), Fp2 (Fig. 1b), T3 (Fig. 1c) and T4 (Fig. 1d) electrodes for an epileptic patient, while Fig. 2 shows one of the EEG signal recordings for a healthy patient for the same electrodes. Sampling frequency was 250 Hz A reference electrode was located on an ear lobe. Due to the RQA method assumptions, the study was conducted on raw signals without using any filtration and artifacts reduction. The non-parametric Mann-Whitney statistical test was performed in order to present the link between the chosen parameters for epileptic and healthy patients (Table 3).

2.2. Recurrence quantification analysis

Representation of time series dynamics enables reconstruction of the phase space. For visualization, the recurrence plot method was introduced. Recurrence plot (RP) is a graphical method developed by Eckmann et al. [20]. RP is used to visualize recurrence states of an analyzed system or process in m-dimensional phase space. Black dots in the 2D plot represent repeatability states, where both axes are time axes [20,21].

The first step in the process of preparing the RP is the reconstruction of the attractor. In this study, the Takens reconstruction method based on the choice of the time delay τ and the dimension m is used to reconstruct the phase space. To determine the time delay the mutual information method can be used. Whereas to estimate the correct embedding dimension of attractors, the false nearest neighbor algorithm (FNN) can be used [20].

For typical dynamic systems, RP takes characteristic patterns. These

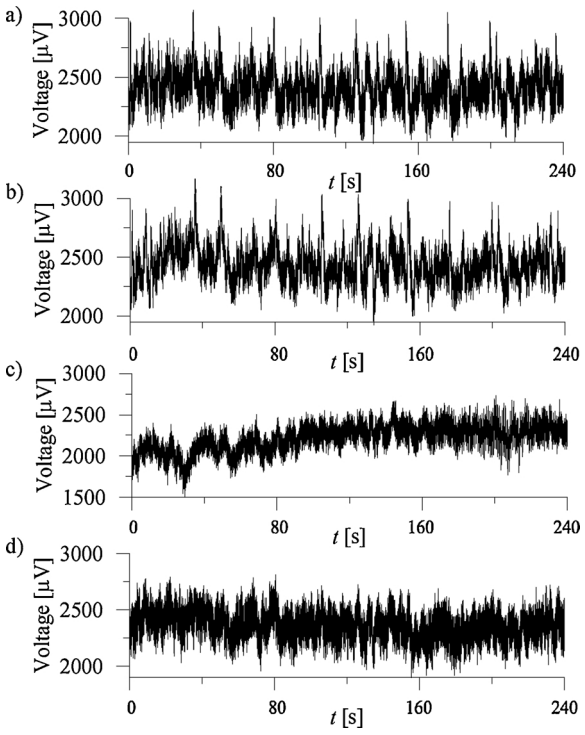

Fig. 1. The recordings of EEG signals obtained from an epileptic patient for electrodes Fp1 (a), Fp2 (b), T3 (c) and T4 (d).

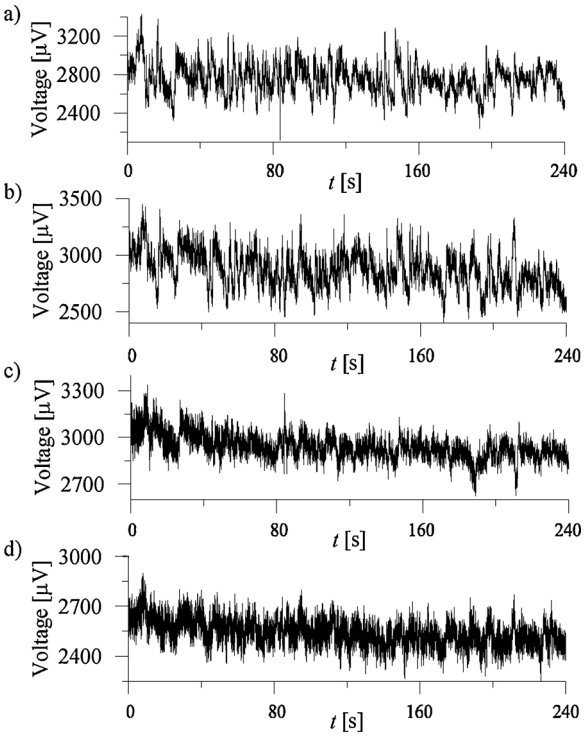

Fig. 2. The recordings of EEG signals obtained from a healthy patient for electrodes Fp1 (a), Fp2 (b), T3 (c), T4 (d).

structures have characteristics related to the dynamics of the analyzed time series. We can distinguish: single random points, regular (cyclic) diagonal lines separated by the same distance, lines (points) centered around the main diagonal line, and irregular shapes (black clusters alternating with white areas). A detailed description of these structures is presented in the study by Marwan et al. [21].

The RQA is the method which allows for quantitative analysis of the characteristic structures of the recurrence plot. The RQA generated parameters can be used to detect the elements of the deterministic dynamic processes, which may apparently look like random) [22–24]. All RQA parameters were described and developed by Marwan et al. [21], these are: recurrence rate (RR), determinism (DET), averaged diagonal line length (L), longest diagonal line (Lmax), divergence (DIV), entropy of diagonal line length (ENTR), laminarity (LAM), trapping time (TT), longest vertical line (Vmax), ratio (RATIO) and recurrence period density entropy (RPDE).

The following characteristic parameters of the recurrence plot were considered [21]:

1) RR is the general indicator characterizing the recurrence plot. It is a measure of the percentage of black dots to all existing recurrence points in the recurrence plot and corresponding to the correlation sum.

2) Indicators describing lines parallel to the main diagonal line of the recurrence plot:

DET is a measure of the percentage of recurrence points forming lines parallel to the main diagonal line.

Lmax - the length of the longest diagonal line

L – the averaged length of the diagonal lines

ENTR - The Shannon entropy of the probability distribution of the diagonal line lengths

3) The characteristics describing vertical lines:

LAM denoting the percentage of recurrence points forming the vertical lines.

Vmax - the length of the longest vertical line

TT describes the average length of a vertical line, according to the line of length, which is bigger than *vmin*.

Recurrence time of 1 st type (T^1) determines the average distance between points belonging to vertical lines.

Recurrence time of 2nd type (T^2) determines the average distance between points belonging to vertical lines. However, in this case, the points lying inside the vertical lines are not taken into account otherwise than in the case of recurrence time of 1 st type.

RPDE is a method that calculates the normalized entropy of the recurrent time for a time series. RPDE is used to detect periodicity or repetition of the signal. It is also able to detect slight changes in the natural biological series [21].

Clustering coefficient and transitivity – quantifiers are based on complex network theory.

2.3. Principal component analysis

Principal component analysis (PCA) [25] is a statistical method that allows for reducing the dimensionality of the data set (in this case there are RQA coefficients) while maintaining a lot of information from the original data set. PCA transforms a set of input data into a new data set, in which the coefficients are called the principal components. It is important that the ingredients in a new data set are sequentially of the largest possible variance. For the RQA analysis the same method was applied in other studies [18,26,27].

2.4. Support vector machine

The support vector machine (SVM) classifier is a classification technique for both linear and non-linear approaches [28]. The SVM method makes the mapping of the data into n-dimensional space (n is the number of features). In order to separate two different classes a decision boundary is used. For this purpose the margin between hyperplanes is maximized. The problem of finding a decision boundary can be solved by using an optimization method - the last squares support vector machine (LS-SVM) [29]. In this work the linear function was used as a kernel of decision boundary.

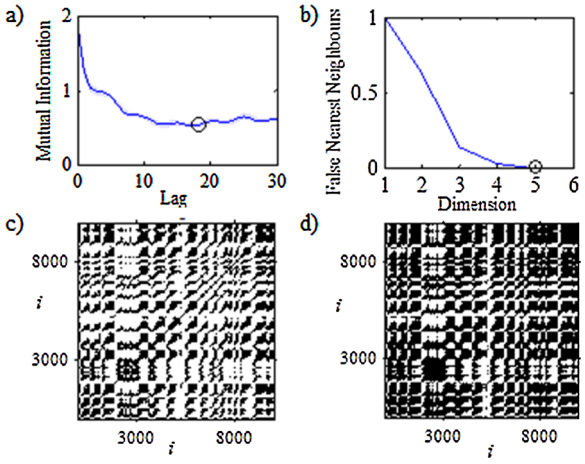

Fig. 3. An example of the reconstruction of the recurrence plot: (a) mutual information with a delay time, (b) fraction of false nearest neighbors, (c) the RP with embedding dimension 3 and time delay 3 and the distance threshold 1, (d) the RP with embedding dimension 3 and time delay 3 and the distance threshold 0.7.

3. Results

For each EEG signal we reconstructed the phase space. The resulting value of the time delay τ and embedding dimension m were used to calculate the recurrence plots. The time delay was selected by the mutual information method and embedding dimension using the FNN method. For each time window of the signal, values of τ and m were changed over time. Sample data for an epileptic patient is shown in Fig. 3.

In Fig. 3 of the RP we present chosen mutual information (Fig. 3a), chosen embedding dimension (Fig. 3b) and recurrence plot (Fig. 3c and d). The circles presented in Fig. 3a and b denote appropriate values of time delay and embedding dimension. In Fig. 3a the circle means the first minimum of mutual information. The circle in Fig. 3b shows embedding dimension on which the fraction of the FNN is reduced to zero. In Fig. 3d we present the recurrence plot obtained for an epileptic patient. Recurrence plot depends on distance threshold (ε). With the increase of ε the number of points on the recurrence plot increases. This relation is shown in Fig. 3c and d. The recurrence plot for which a number of recurrence points is too high is presented in Fig. 3c.

The RQA coefficients for each of the EEG signals were calculated based on the information from the reconstruction of the RP and performed using Matlab package developed by CRP Marwan et al. [22]. The RQA analysis was performed using a sliding window of 10,000 samples size. The window was moving along the recorded signal. For each signal window was selected with the assumption that the signal remains stationary. All RQA coefficients were taken to further analysis and these are: RR, DET, L, Lmax, ENTR, LAM, TT, Vmax, T^1, T^2, RPDE, Clustering coefficient, Transitivity. Tables 1 and 2 show the averaged value of each RQA parameter for the four studied electrodes for each patient from group A and group B.

Comparing the signals shown in Figs. 1 and 2 it can be seen that signal dynamics of epileptic and healthy patients is different. On the signal recorded for an epileptic patient a certain repetition of patterns may be noticed, while the normal signal is chaotic. In this study, differences in the dynamics of both signals are shown by the RQA method. The higher values of RR, DET, L, Lmax, ENTR, LAM, TT, Vmax, Clustering coefficient, Transitivity obtained for group A indicate that the

Table 1
Properties Averaged RQA coefficients values: RR, DET, Lmax, Vmax, RPDE for Fp1 and Fp2 electrodes for each patient.

		RR	DET	L	Lmax	ENTR	LAM	TT	Vmax	T1	T2	RPDE	Clustering	Transitivity
Fp1	Epileptic 1	0.355	0.839	46.681	9936.600	3.937	0.906	52.235	1193.200	2.878	65.382	0.380	0.764	0.749
	Epileptic 2	0.198	0.564	17.062	9828.333	2.957	0.723	22.202	299.667	5.759	48.516	0.435	0.638	0.582
	Epileptic 3	0.485	0.804	44.821	9675.000	3.604	0.833	56.383	1965.000	2.201	32.390	0.256	0.799	0.794
	Epileptic 4	0.207	0.424	27.861	9943.000	3.247	0.207	18.590	335.800	4.909	14.632	0.242	0.626	0.581
	Epileptic 5	0.199	0.402	17.842	9628.400	2.694	0.571	22.675	438.600	6.293	35.399	0.358	0.646	0.600
	Healthy 1	0.134	0.206	16.196	2642.500	2.594	0.114	13.893	140.000	7.508	17.349	0.283	0.578	0.515
	Healthy 2	0.116	0.435	15.887	9893.000	2.704	0.623	19.661	335.000	8.625	59.750	0.436	0.603	0.547
	Healthy 3	0.048	0.218	16.961	9260.800	2.846	0.358	18.745	133.000	24.419	84.408	0.388	0.541	0.466
	Healthy 4	0.118	0.218	14.622	6653.600	2.380	0.407	16.203	194.600	9.192	34.884	0.373	0.586	0.531
	Healthy 5	0.095	0.191	16.044	3937.250	2.590	0.067	12.774	68.250	11.081	21.919	0.302	0.558	0.497
	Healthy 6	0.065	0.126	15.832	1246.000	2.754	0.047	13.326	53.600	17.764	31.932	0.296	0.526	0.465
	Healthy 7	0.089	0.100	14.229	6842.400	2.176	0.167	14.362	128.000	12.495	34.112	0.379	0.541	0.478
	Healthy 8	0.042	0.399	18.424	9317.000	3.015	0.548	20.619	242.500	31.138	161.109	0.405	0.597	0.544
Fp2	Epileptic 1	0.392	0.869	62.155	9936.600	4.189	0.926	70.010	1450.400	2.717	82.917	0.405	0.784	0.779
	Epileptic 2	0.389	0.898	36.125	9714.750	4.159	0.933	51.471	1149.500	2.825	73.703	0.472	0.753	0.722
	Epileptic 3	0.269	0.574	20.596	9284.000	2.928	0.686	24.606	671.500	3.829	27.542	0.294	0.680	0.656
	Epileptic 4	0.261	0.489	25.092	9937.400	3.061	0.578	24.703	617.400	4.032	26.025	0.321	0.683	0.649
	Epileptic 5	0.183	0.457	17.017	9869.800	2.844	0.630	22.305	365.000	5.810	39.614	0.378	0.637	0.588
	Healthy 1	0.167	0.375	19.845	9928.000	2.843	0.434	18.824	358.500	6.005	27.209	0.308	0.628	0.585
	Healthy 2	0.246	0.736	23.948	8355.500	3.339	0.828	31.792	744.500	4.164	54.436	0.406	0.689	0.654
	Healthy 3	0.044	0.292	16.806	9485.000	2.858	0.478	19.379	147.600	24.942	117.375	0.440	0.554	0.472
	Healthy 4	0.052	0.026	13.974	957.000	1.983	0.075	12.131	60.200	20.507	44.471	0.421	0.501	0.431
	Healthy 5	0.147	0.446	17.604	9929.667	2.743	0.620	19.015	311.667	7.484	53.631	0.454	0.607	0.569
	Healthy 6	0.053	0.120	15.717	922.400	2.711	0.034	12.946	46.000	27.646	44.815	0.308	0.531	0.451
	Healthy 7	0.105	0.167	14.124	9868.200	2.243	0.342	15.554	176.400	11.593	47.096	0.421	0.563	0.499
	Healthy 8	0.347	0.874	60.391	9931.200	4.230	0.912	78.873	1094.800	2.904	76.813	0.372	0.777	0.763

dynamics of epileptic signals are more regular than the normal signals. This is confirmed by the obtained average values of the indicators in Tables 1 and 2. To further illustrate this dependency, the PCA method was used. The PCA method was performed on the averaged data presented in Tables 1 and 2. The PCA mapping shows the difference in signal dynamics more clearly. For each electrode, data of group A follows along component 1, while data of group B along component 2. It has been found that three components (with RQA indicators – T^1, T^2 and RPDE) are responsible for the dynamics of healthy patients, while the remaining 10 components are responsible for the dynamics of epileptic patients. The dynamics of a healthy patient changes to a very small extent. This shows the spread of points on the PCA graph (Figs. 4 and 5) for healthy people. By contrast, the dynamics of epileptic people varies widely. The results revealed the evolving dynamics of EEG data between the patient groups.

4. Discussion

The EEG method is important in diagnosing epilepsy and various seizures. It is used in neuropharmacology, psychology and neurophysiology, or in studies of cerebrovascular disorders associated with the nervous system, sleep studies and its disorders. The most common way

Table 2
Properties Averaged RQA coefficients values: RR, DET, Lmax, Vmax, RPDE for T3 and T4 electrodes for each patient.

		RR	DET	L	Lmax	ENTR	LAM	TT	Vmax	T1	T2	RPDE	Clustering	Transitivity
T3	Epileptic 1	0.147	0.279	19.076	9939.500	2.802	0.407	18.000	259.750	7.436	31.873	0.363	0.609	0.554
	Epileptic 2	0.274	0.594	24.948	9864.000	3.194	0.723	32.323	976.500	4.558	43.301	0.382	0.691	0.656
	Epileptic 3	0.245	0.471	30.182	5885.200	3.277	0.201	18.389	443.400	4.565	11.837	0.207	0.646	0.616
	Epileptic 4	0.132	0.365	26.766	2325.000	3.197	0.014	13.145	92.000	8.036	14.142	0.238	0.585	0.532
	Epileptic 5	0.294	0.394	53.117	9936.600	2.788	0.540	68.670	1525.200	4.517	41.405	0.354	0.690	0.652
	Healthy 1	0.090	0.237	19.065	816.000	2.774	0.011	12.775	42.000	14.903	20.657	0.265	0.563	0.492
	Healthy 2	0.028	0.079	15.096	8342.000	2.219	0.165	13.092	55.000	36.628	105.806	0.496	0.478	0.400
	Healthy 3	0.042	0.014	11.898	35.200	1.842	0.002	11.283	18.600	26.875	39.139	0.372	0.420	0.408
	Healthy 4	0.042	0.008	13.314	218.200	1.753	0.021	11.622	38.200	25.301	44.596	0.436	0.470	0.405
	Healthy 5	0.058	0.212	17.824	660.000	2.503	0.010	11.300	20.000	17.103	19.618	0.221	0.520	0.507
	Healthy 6	0.054	0.149	14.996	757.800	2.635	0.001	11.346	11.800	20.743	26.554	0.278	0.502	0.458
	Healthy 7	0.039	0.095	21.719	350.400	3.452	0.001	11.520	9.200	29.296	36.427	0.363	0.550	0.416
	Healthy 8	0.220	0.523	24.876	9941.800	2.821	0.619	22.686	520.200	4.736	30.433	0.281	0.699	0.667
T4	Epileptic 1	0.178	0.305	20.525	9938.333	2.877	0.379	18.325	351.333	6.635	25.633	0.340	0.618	0.563
	Epileptic 2	0.384	0.655	32.942	9920.600	3.317	0.738	43.090	1567.200	3.312	33.870	0.314	0.742	0.718
	Epileptic 3	0.312	0.588	32.887	5850.500	3.309	0.362	27.383	817.500	5.686	16.068	0.216	0.568	0.647
	Epileptic 4	0.037	0.127	18.883	542.600	2.796	0.002	11.477	24.800	28.159	39.371	0.379	0.490	0.416
	Epileptic 5	0.129	0.159	15.929	7660.600	2.397	0.186	15.306	133.400	8.039	22.021	0.312	0.591	0.528
	Healthy 1	0.144	0.358	21.160	4178.000	2.903	0.079	14.498	305.500	7.586	15.159	0.239	0.597	0.549
	Healthy 2	0.446	0.602	143.308	7928.600	3.649	0.624	209.303	3066.600	4.189	106.916	0.269	0.711	0.731
	Healthy 3	0.038	0.019	14.047	309.400	2.235	0.034	12.007	33.000	43.835	72.420	0.420	0.458	0.407
	Healthy 4	0.035	0.015	14.477	268.800	1.980	0.030	11.686	45.000	30.757	57.787	0.456	0.488	0.404
	Healthy 5	0.037	0.124	22.805	244.500	3.560	0.000	19.000	0.000	27.783	29.695	0.294	0.490	0.456
	Healthy 6	0.043	0.119	14.226	386.800	2.467	0.000	11.258	7.200	28.722	33.399	0.283	0.510	0.451
	Healthy 7	0.038	0.032	14.903	2379.800	2.054	0.030	12.558	58.800	28.627	47.771	0.414	0.530	0.410
	Healthy 8	0.206	0.425	24.207	9941.800	2.784	0.451	18.739	410.600	5.225	22.950	0.261	0.672	0.635

Table 3
The statistical significance (p-values) of RQA coefficients for each electrode using non-parametric statistical Mann-Whitney test.

	RR	DET	L	Lmax	ENTR	LAM	TT	Vmax	T1	T2	RPDE	Clustering	Transitivity
Fp1	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	n.s.	n.s.	< 0.001	< 0.001
Fp2	< 0.001	< 0.001	< 0.001	< 0.01	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	n.s.	n.s.	< 0.001	< 0.001
T3	< 0.001	< 0.001	< 0.001	< 0.001	< 0.05	< 0.001	< 0.001	< 0.001	< 0.001	< 0.05	n.s.	n.s.	< 0.001
T4	n.s.	< 0.05	n.s.	< 0.05	n.s.	n.s.	n.s.	< 0.05	< 0.05	< 0.05	n.s.	n.s.	n.s.

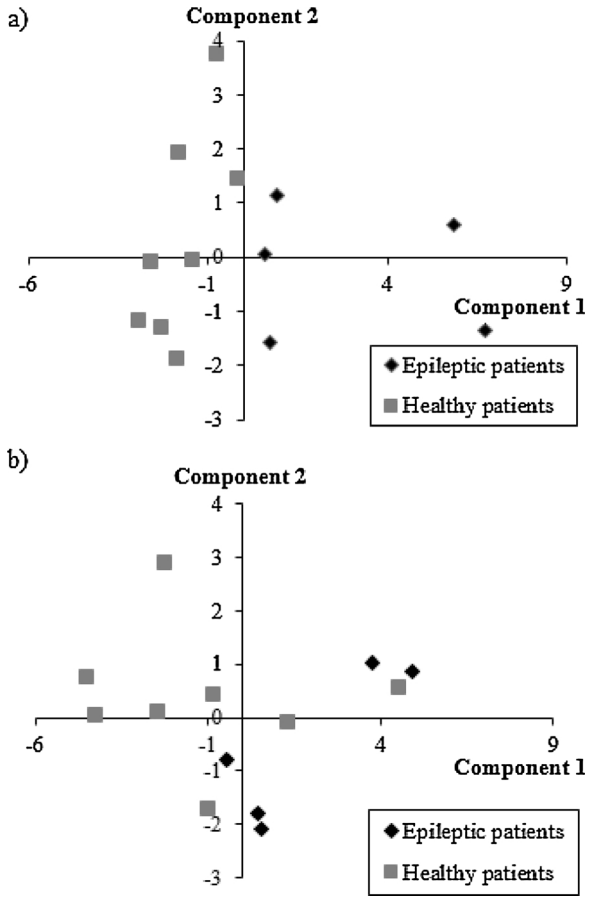

Fig. 4. Deploy of PCA parameters on 2D map obtained using the PCA method for (a) electrode Fp1 and (b) electrode Fp2.

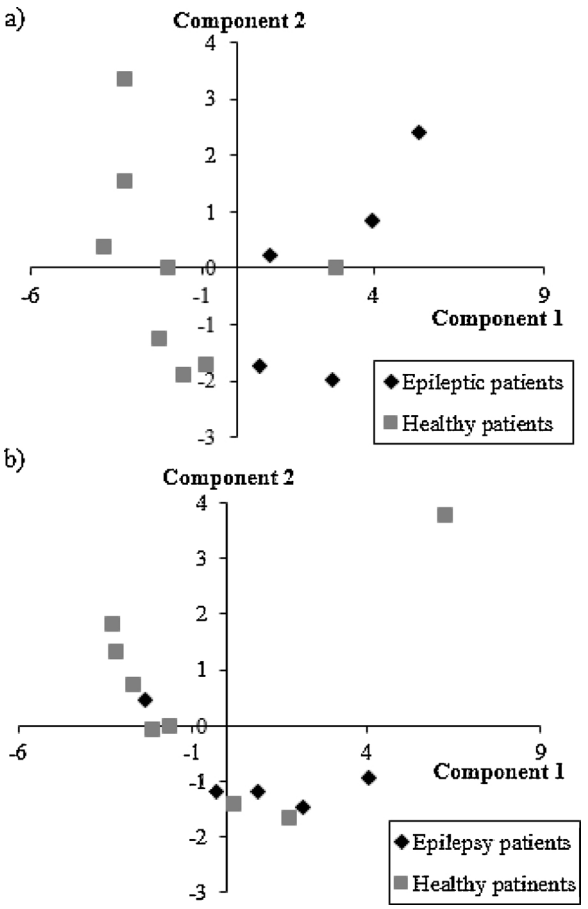

Fig. 5. Deploy of PCA parameters on 2D map obtained using the PCA method for (a) electrode T3 and (b) electrode T4.

to obtain information about the neurophysiological systems is to analyze signal characteristics using the basic techniques of time series processing. The use of mathematical methods in the analysis of EEG signals is based on linear methods. Unfortunately, these methods do not provide complete information about neurophysiological systems. Therefore, it seems necessary to use techniques based on nonlinear methods.

In the present study, we analyzed the EEG signals by using nonlinear dynamical systems identification method, borrowed from the theory of deterministic chaos. The use of the nonlinear mathematical methods for electroencephalography began in 1985. One of the most promising approaches to defining and determining complexity, nonlinearity and nonstationarity of EEG signals is the recurrence plot method. This method allows for distinguishing the analyzed time series from stochastic noise, detecting disturbed deterministic changes etc.

The EEG signal analysis based on nonlinear dynamic systems methods are focused on the possibility of identifying seizures. In their study Rabbi et al. [1] presented an analysis of changes in dynamic EEG characteristics using RQA for 4 adult rats to determine the pre-ictal and ictal characteristic changes. It was found that decreasing brain dynamics was observed for RR and DET for ictal stages, while ENTR for pre-ictal stages. Also, the analysis of EEG signals using recurrent plots was used on signals recorded for humans. Acharya et al. [11] described the automatic identification of epileptic EEG signals. Authors noted that RQA measures, such as Vmax, Lmax, ENTR, TT and L, progressively increase from normal, inter-ictal and ictal classes. It was found that the SVM classifier was able to identify the EEG class with an average field of 95.6%.

In the present study, we focused on detecting differences between the signals of people with epilepsy and healthy people. The RQA method was able to detect significant differences in signal dynamics and to distinguish the epileptic signal from normal. Higher values of the RQA coefficient were obtained for epileptic patients. This dependence indicates that the normal signal is more chaotic, while epileptic signal is more stationary. Also, PCA mappings were used to indicate signal differences. The combined use of RQA and PCA methods produced effective results obtained in the study by Zhang et al. [18]. Applying PCA methods for EEG patterns allow for reducing the dimensionality of feature vectors in order to observe the variation of EEG patterns in time of intermittent hypoxic training. The authors noticed that the variation of EEG patterns after intermittent hypoxic training on the 3D PCA map

were more convergent than before intermittent hypoxic training. The map obtained in that work can distinguish the received patterns. In our study, the PCA method illustrated the difference in dynamics of signals on 2D maps. The best separation of groups A and B on the PCA map was obtained for the Fp1 electrode, because the epileptic spikes were the most evident over the Fp1 electrode [30]. In addition to the PCA mapping, patient classification for the Fp1 electrode was performed applying the SVM classification. This method is used to confirm the classification of bioelectric parameters [31]. As a result of the SVM classification, the RQA data were classified as 86.8%.

The use of mathematical methods to analyze the EEG signals may increase the chance of detecting differences in a normal and epileptic signal. Using the RQA method applied to the EEG signals and observing the change in RQA variables gives hope for detecting significant changes in the dynamics that may inform about the moment of epileptic seizure in a convenient period. The management of the patient at risk of an upcoming seizure should combine clinical examination as well as evaluation of biophysical methods. The existing differences in bioelectrical brain activity in patients with symptoms of epilepsy suggest that RQA + PCA method can be helpful in predicting the pre-epileptic EEG pattern.

This study presents potential future clinical application in patients with suspected seizures. Introducing programs supporting automatic diagnostics can help to expand access to healthcare what can be referred to the UK National Health Service (NHS), which currently has a chronic lack of trained clinical neurophysiologists to interpret the EEG [32]. Automatic seizure detection can therefore be a viable solution in the automatic identification of seizures. The use of RQA + PCA analysis methods results in combination with learning algorithms (artificial intelligence) will automate the process of predicting the pre-epileptic EEG patterns.

5. Conclusions

In this work, the analysis of EEG data was focused on detecting differences between epilepsy and normal EEG signal. These differences can accelerate the classification without causing seizures, during data recording in an epileptic patient, that have a negative impact on health.

The RQA method shows that pattern of signals changes occur more often in epileptic signals, while normal signals is chaotic. The proposed method of analyzing EEG signals enables visualization of the differences observed in the dynamics of both signals using 2D maps. The compliance level of identification by means of the SVM classification is 86.8%. It seems that the using special filtering methods maybe will increase the obtained results.

The obtained results indicate that the RQA method has perspectives in the analysis of EEG signals.

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Conflict of interest

The authors declare no conflict of interests.

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