

Epileptic Seizure Detection Using EEGs Based on Kernel Radius of Intrinsic Mode Functions

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Abstract. The study of automated epileptic seizure detection using EEGs has attracted more and more researchers in these decades. How to extract appropriate features in EEGs, which can be applied to differentiate non-seizure EEG from seizure EEG, is considered to be crucial in the successful realization. In this work, we proposed a novel kernel-radius-based feature extraction method from the perspective of nonlinear dynamics analysis. The given EEG signal is first decomposed into different numbers of intrinsic mode functions (IMFs) adaptively by using empirical mode decomposition. Then the three-dimensional phase space representation (3D-PSR) is reconstructed for each IMF according to the time delay method. At last, the kernel radius of the corresponding 3D-PSR is defined, which aims to characterize the concentration degree of all the points in 3D-PSR. With the extracted feature KRF, we employ extreme learning machine and support vector machine as the classifiers to achieve the task of the automate epileptic seizure detection. Performances of the proposed method are finally verified on the Bonn EEG database.

Keywords: Automatic seizure detection · Electroencephalogram (EEG) · Empirical mode decomposition (EMD) · Phase space representation (PSR) · Kernel-radius-based feature · Extreme learning machine (ELM) · Support vector machine (SVM)

1 Introduction

Epilepsy is a serious chronic neurological disorders that has an active incidence of 4–8/1000 and may affect both children and adults [3]. It is characterized by periodic and unpredictable occurrence of seizures, which are resulted from abnormal discharges of excessive amount of brain neurons, and usually appears to be the muscle stiffness, staring and impaired consciousness etc. [6].

As an electrophysiological monitoring approach to record electrical activities of the brain, electroencephalogram (EEG) has been widely applied in clinics due to its potential for exploring the physiological and pathological information in the brain. For epilepsy patients, the seizure detection using EEGs becomes an important and necessary step in the diagnosis and treatment. However, the traditional seizure detection by a trained neurologist always appears costly and

inefficient, as well as sometimes includes subjective factors. Therefore, issues regarding the automatic seizure detection have been raised by more and more researchers in these decades. In order to realize it successfully, extracting proper features from EEG signals, which are then fed into a classifier so that the epileptic EEGs can be distinguished from background EEGs, is acknowledged to be one of the key points.

Since it has been demonstrated that human brain is a nonlinear dynamical system, the application of various nonlinear analysis methods for extracting features from EEGs presents a new avenue to exploit the underlying physiological processes. With the recognition that the system in non-seizure periods is more complex comparing with that in seizure periods, fractal dimension [20], sample entropy [16], permutation entropy [11], correlation sum [17] and recurrence quantification analysis (RQA) [2] have been explored to be the extracted features. Differently, in accordance with the similarity analysis, dynamical similarity index [13], fuzzy similarity index [12] and Bhattacharyya-based dissimilarity index [9], have been proposed to find the transition from a seizure-free state to a seizure state. If a non-seizure EEG segment is defined as the reference template, then the less similar a given present EEG segment is with the template, the more possible it will be the epileptic one. Originated from the fact that the anti-persistence of systems in non-seizure periods is weaker than that in seizure periods, various extraction methods on the basis of detrended fluctuation analysis index and Hurst exponent have been designed in [19]. Meanwhile, from the chaoticity analysis point of view, the Lyapunov exponent of EEG signals has also been taken as the feature for completing the seizure detection in [18]. Furthermore, given an EEG signal, the distribution uniformity and scatter degree of its lagged *Poincaré* plot have been presented in [15], which are defined to measure the difference between seizure EEGs and non-seizure EEGs intuitively.

In this study, a new kernel-radius-based feature (KRF) extraction method is proposed, where the kernel radius of three-dimensional phase space representation (3D-PSR) of an intrinsic mode function (IMF) is defined to be the feature. The key idea can be summarized as follows. Due to the fact that small change in EEG signals may be amplified when signals are decomposed and analyzed on smaller frequency-bands separately [10], the given EEG signal is first decomposed into different numbers of IMFs adaptively by using the empirical mode decomposition (EMD) method. Then the 3D-PSR is reconstructed for each IMF according to the time delay method. Next, kernel radius of the corresponding 3D-PSR is defined, which aims to characterize the concentration degree of all the points in 3D-PSR. With the extracted KRF, we finally apply support vector machine (SVM) and extreme learning machine (ELM) to achieve the task of epileptic seizure detection automatically.

The remainder of this paper is organized as follows. Section 2 systematically describe the proposed feature extraction method. Section 3 introduces the EEG database and discusses the experimental results, and some remarks are concluded in the last section.

2 Methods

2.1 Empirical Mode Decomposition

Empirical mode decomposition (EMD), which is a fundamental part of the Hilbert Huang Transform (HHT), has been proposed for analyzing non-linear and non-stationary signals by Huang et al. [5]. Applying EMD, a complicated signal can be decomposed into a finite and often small number of components. Such components, which are named as intrinsic mode functions (IMFs), constitute a complete and almost orthogonal basis of the original signal.

An IMF is defined as a function satisfying two conditions: (i) there holds $|a - b| \leq 1$ where a and b denote the numbers of extrema and zero-crossings of the signal; (ii) there holds $\frac{e_+ + e_-}{2} = 0$ at any point where e_+ and e_- represent two envelopes of the signal. The iterative process of extracting IMFs from the given signal can be summarized in the following algorithm [8].

Algorithm I (EMD): Given a signal $\mathbf{s} = \{s(t)\}_{t=1}^N$.

Step 1. Identify the local maxima and local minima from $s(t)$ respectively.

Step 2. Construct the upper envelope $e_+(t)$ and lower envelope $e_-(t)$ of $s(t)$ by using the cubic spline interpolation.

Step 3. Calculate the mean of $e_+(t)$ and $e_-(t)$, which is denoted by

$$m(t) = \frac{e_+(t) + e_-(t)}{2}.$$

Step 4. Extract $h(t)$ from $s(t)$ as

$$h(t) = s(t) - m(t).$$

Step 5. If $h(t)$ satisfies two conditions for IMF, then stop; otherwise, let $s(t) = h(t)$ and repeat steps 1–5 until $h(t)$ satisfies the conditions. According to EMD, the original signal $s(t)$ can be represented by

$$s(t) = \sum_{i=1}^M X_i(t) + r(t), \quad t = 1, 2, \dots, N. \quad (1)$$

Here, $X_i(t)$ denotes the i th IMF, $r(t)$ denotes the residual and M is the number of IMFs of $s(t)$, which is determined by the method adaptively.

Figure 1(a) and (b) illustrate the IMFs of a non-seizure EEG segment and a seizure EEG segment respectively.

2.2 Kernel-Radius-Based Feature Extraction Method

For each IMF, we reconstruct its phase space by time delay method [4]. In our work, we have confined our discussion to the value of embedding dimension as three, because of its visualization simplicity and performance reliability.

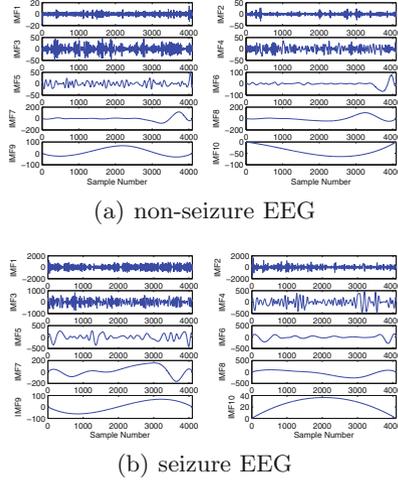


Fig. 1. IMFs of EEG signals decomposed by EMD

We name the corresponding plot as the 3-dimensional phase space representation (3D-PSR) in what follows.

Denote by $\mathbf{X}_i = \{X_i(1), X_i(2), \dots, X_i(N)\}$ the i th IMF, we then construct its 3D-PSR as

$$\mathbf{Y}_i = \{Y_i^{(k)} : k = 1, 2, \dots, N - 2\tau\}$$

where

$$Y_i^{(k)} = [X_i(k), X_i(k + \tau), X_i(k + 2\tau)]^T, \\ k = 1, 2, \dots, N - 2\tau.$$

For visualization, we write $P_i^{(k)}$ to denote the corresponding point of $Y_i^{(k)}$ in the 3D phase space, and $\mathbf{PSR}_i = \{P_i^{(k)} : k = 1, 2, \dots, N - 2\tau\}$ the collection of all points in terms of \mathbf{X}_i . Figure 2 illustrates the 3D-PSR plots of non-seizure EEG and seizure EEG respectively.

It can be easily seen from Fig. 2 that the points in 3D-PSR of seizure EEG distribute more sparse than those of non-seizure EEG. Therefore, we focus on characterizing the concentration degree of the points in \mathbf{PSR}_i to be the extracted feature, which can be then applied to discriminate the seizure EEGs from non-seizure EEGs.

Firstly, we define the center $O_i = (a_i, b_i, c_i)$ of \mathbf{PSR}_i according to the following way:

$$a_i = \frac{1}{N - 2\tau} \sum_{k=1}^{N-2\tau} X_i(k),$$

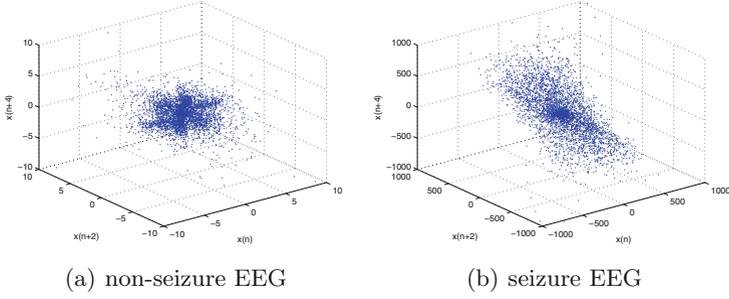


Fig. 2. The 3D-PSRs of IMF₁ corresponding to the non-seizure EEG and seizure EEG

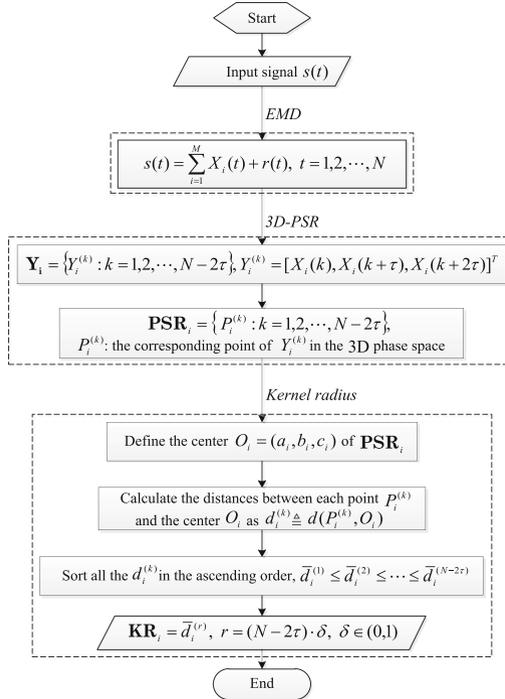


Fig. 3. The flowchart of KFR feature extraction method

$$b_i = \frac{1}{N - 2\tau} \sum_{k=1}^{N-2\tau} X_i(k + \tau),$$

$$c_i = \frac{1}{N - 2\tau} \sum_{k=1}^{N-2\tau} X_i(k + 2\tau).$$

Secondly, we calculate the distance between point $P_i^{(k)}$ and center O_i as

$$d_i^{(k)} \triangleq d(P_i^{(k)}, O_i), k = 1, 2, \dots, N - 2\tau$$

where $d(\cdot, \cdot)$ is the Euclidean distance. Denote by $D_i = \{d_i^{(k)} : k = 1, 2, \dots, N - 2\tau\}$ be the set of all distances.

Thirdly, we sort all elements in D_i in the ascending order, denoted by

$$D_i = \{\bar{d}_i^{(1)}, \bar{d}_i^{(2)}, \dots, \bar{d}_i^{(N-2\tau)}\},$$

where $\bar{d}_i^{(1)} \leq \bar{d}_i^{(2)} \leq \dots \leq \bar{d}_i^{(N-2\tau)}$.

Finally, we define the kernel radius of \mathbf{PSR}_i in terms of a given threshold $\delta \in (0, 1)$ to be

$$\mathbf{KR}_i = \bar{d}_i^{(r)}$$

where

$$r = (N - 2\tau) \cdot \delta.$$

With the proceeding preliminaries, the kernel-radius-based feature (KRF) extraction method can be summarized as the flowchart shown in Fig. 3.

3 Experiments

3.1 Database

This work applies Bonn EEG database, which is taken from the Department of Epileptology, Germany [1]. The details of Bonn database is shown in Table 1. Because it is the most difficult for seizures to be detected between ictal EEGs and inter-ictal EEGs, we only verify the performance of the proposed method on sets D and E in this paper. Figure 4 illustrates one inter-ictal EEG segment in D and one ictal EEG segment in E .

Table 1. Detail EEG information of Bonn database

Data set	Recording electrodes	Recorded position	Subject state
A	Scalp electrode	Cortex	Awake and relaxed state with eye open of five healthy people
B	Scalp electrode	Cortex	Awake and relaxed state with eye closed of five healthy people
C	Intracranial electrode	Hippocampal formation	Period of inter-ictal of epilepsy patients
D	Intracranial electrode	Epileptogenic zone	Period of inter-ictal of epilepsy patients
E	Intracranial electrode	Epileptogenic zone	Period of ictal of epilepsy patients

¹Each data-set comprises 100 epochs of single-channel EEG signal, which are 23.6s single-channel EEG signals with 173.61 HZ sampling rate.

²There is no artifact in all EEGs.

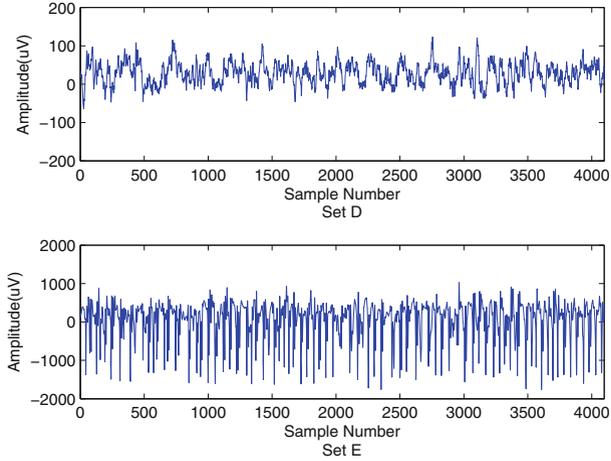


Fig. 4. Sample EEG recordings in set D (inter-ictal) and set E (ictal)

Table 2. Specified parameter in the experiments

Methods	Parameter	Symbol	Specified values
ELM	Number of hidden nodes	L	10
SVM	Regularization parameter	C	2^{-5}
SVM	Kernel width	g	2^{-6}
Kernel radius	Threshold parameter	δ	0.5

3.2 The Experimental Results and Discussions

This subsection will verify the performance of the proposed automated seizure detection method, which combines the kernel-radius-based feature (KRF) with extreme learning machine (ELM) and support vector machine (SVM) respectively.

In ELM, the additive hidden nodes $G(\mathbf{a}, b, \mathbf{x}) = g(\mathbf{a} \cdot \mathbf{x} + b)$ are applied and the optimal number of hidden nodes is determined by ten-fold cross validation. Here, (\mathbf{a}, b) are weight and bias of the hidden-node, and β is the output weight. In SVM, the latest LIBSVM software package 3.22 version is applied with the radial base function (RBF) as the kernel function. The regularization parameter C and the kernel width g are selected according to the grid search method. In both ELM and SVM, fifty trials have been conducted with training and testing datasets randomly generated for each trial, where the size of training and testing datasets is equal. All of the parameters in our experiments are summarized specifically in Table 2.

Firstly, we reveal the practicability of proposed feature KRF for discriminating seizure and non-seizure EEGs as shown in Figs. 5 and 6. Figure 5 demonstrates the kernel radius corresponding to a non-seizure and seizure EEG

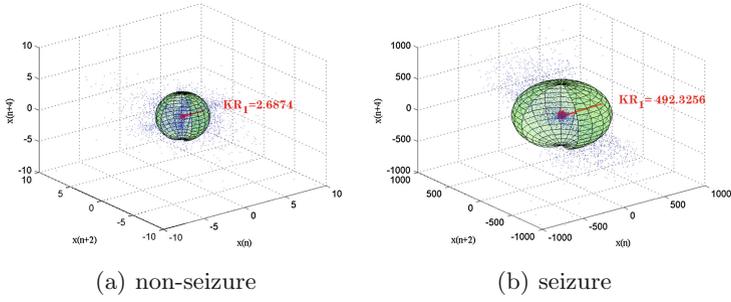


Fig. 5. The kernel radius corresponding to a non-seizure EEG and seizure EEG

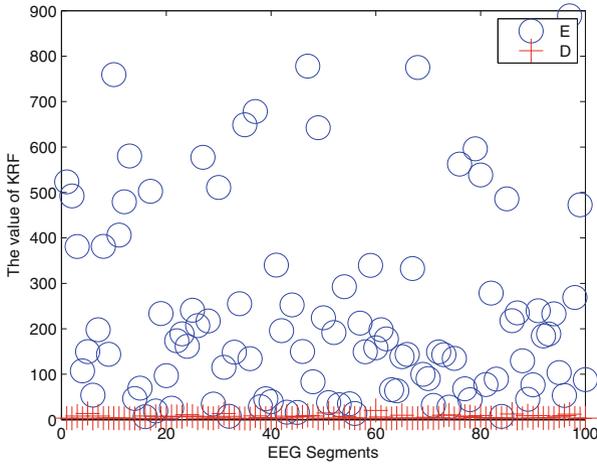


Fig. 6. The values of KRF corresponding to EEG segments of set D and set E

respectively. It is obvious that the kernel radius 2.6874 corresponding to non-seizure EEG is much smaller than the kernel radius 492.3256 corresponding to seizure EEG, which shows that the proposed feature KRF is able to differentiate seizure EEGs and non-seizure EEGs successfully. Such fact can also be illustrated in Fig. 6.

Next, a comparative study between ELM and SVM is done with the same feature KRF. Experiments results are shown in Table 3, which include accuracy, standard deviation of accuracy and training time. We can observe from Table 3 that the classification accuracy obtained by ELM is a little better than that obtained by SVM with much smaller standard variation. It means that a better and stabler performance of epileptic seizure detection can be achieved by using KRF and ELM. Meanwhile, ELM spends much less time than SVM.

Finally, we compare the proposed automated seizure detection method KRF-ELM with other existing methods where the same datasets (i.e., D and E) are applied in simulations. We can observe from Table 4 that the proposed method

Table 3. Performance comparison between ELM and SVM with the same feature KRF

Classifier	Time	Accuracy	Standard deviation
ELM	0.0022	96.64%	0.0180
SVM	7.93	96.00%	3.1

Table 4. A comparison between the proposed methods in this paper and the methodologies in other literatures

Authors	Year	Methods	CA(%)
Qi yuan et al. [19]	2012	Approximate entropy+ELM	88.00 ± 0.75%
	2012	Hurst exponent+ELM	88.00 ± 0.5%
	2012	DFA+ELM	82.00 ± 0.5%
Nicolaou et al. [11]	2012	Permutation entropy+SVM	83.13%
Zhu et al. [21]	2014	Degree and Strength of HVG+KNN	93%
Siuly et al. [14]	2011	Clustering+SVM	93.6%
Y. Kumar et al. [7]	2014	Fuzzy approximate entropy+SVM	95.85%
J.-L. Song et al. [15]	2016	lagged- <i>Poincaré</i> based feature+ELM	96.16%
This paper		KRF+ELM	96.64%

KRF-ELM performs better than others. Even for the best and the most recent results obtained in [15], the classification accuracy obtained by our method increases from 96.16% to 96.64%.

4 Conclusion

In this work, we proposed the kernel-radius-based feature extraction method, where the kernel radius of three-dimensional phase space representation (3D-PSR) of intrinsic mode functions (IMFs) is defined to be the feature, which is further applied to differentiate seizure EEGs from non-seizure EEGs in accordance with the following procedures. At the first step, the given EEG signal is decomposed into different numbers of intrinsic mode functions (IMFs) adaptively by empirical mode decomposition (EMD) method; At the second step, the 3D-PSR is reconstructed for each IMF according to the time delay method; At the third step, the kernel radius of the corresponding 3D-PSR is defined, which aims to characterize the concentration degree of all the points in 3D-PSR. Combining with ELM and SVM, performances of the proposed method are finally verified on the open EEG database from three aspects: (1) performance verification of the proposed feature KRF; (2) performance comparison between ELM and SVM with the same feature KRF; (3) performance comparison between the proposed seizure detection method KRF-ELM with other existing methods. All the experimental results have demonstrated that the proposed method does a good job in the automated seizure detection.

Acknowledgement. This work was supported by the National Natural Science Foundation of China under Grant 61473223.

References

1. Acharya, U.R., Molinari, F., Subbhuraam, V.S., Chattopadhyay, S.: Automated diagnosis of epileptic EEG using entropies. *Biomed. Signal Process. Control* **7**, 401–408 (2012)
2. Chen, L.L., Zhang, J., Zou, J.Z., Zhao, C.J., Wang, G.S.: A frame work on wavelet-based nonlinear features and extreme learning machine for epileptic seizure detection. *Biomed. Signal Process. Control* **10**, 1–10 (2014)
3. Correa, A.G., Orosco, L., Diez, P., Laciari, E.: Automatic detection of epileptic seizures in longterm EEG records. *Comput. Biol. Med.* **57**, 66–73 (2015)
4. Takens, F.: Detecting strange attractors in turbulence. In: Rand, D., Young, L.-S. (eds.) *Dynamical Systems and Turbulence*, Warwick 1980. LNM, vol. 898, pp. 366–381. Springer, Heidelberg (1981). doi:[10.1007/BFb0091924](https://doi.org/10.1007/BFb0091924)
5. Huang, N.E., Zheng, S., Long, S.R., Wu, M.C.: The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc. R. Soc. London Ser. A Math. Phys. Eng. Sci.* **454**, 903–995 (1998)
6. Song, J.-L., Zhang, R.: Automated detection of epileptic EEGs using a novel fusion feature and extreme learning machine. *Neurocomputing* **175**, 383–391 (2016)
7. Kumar, Y., Dewal, M.L., Anand, R.S.: Epileptic seizuredetection using DWT based fuzzy approximate entropy and support vector machine. *Neurocomputing* **133**, 271–279 (2014)
8. Li, S.F., Zhong, W.D., Yuan, Q., Geng, S.J., Cai, D.M.: Feature extraction and recognition of ictal EEG using EMD and SVM. *Comput. Biol. Med.* **43**, 807–816 (2013)
9. Niknazar, M., Mousavi, S.R.: A new dissimilarity index of EEG signals for epileptic seizure detection. In: *Control and Signal Processing*, pp. 1–5 (2010)
10. Niknazar, M., Mousavi, S.R., Shamsollahi, M., Vahdat, B.V., Sayyah, M., Motaghi, S., Dehghani, A., Noorbakhsh, S.: Application of a dissimilarity index of EEG and its sub-bands on prediction of induced epileptic seizures from rat’s EEG signals. *IRBM* **33**, 298–307 (2012)
11. Nicolaou, N., Georgiou, J.: Detection of epileptic electroencephalogram based on permutation entropy and support vector machines. *Expert Syst. Appl.* **39**, 202–209 (2012)
12. Ouyang, G., Li, X.L., Guan, X.P.: Use of fuzzy similarity index for epileptic seizure prediction. In: *The 5th World Congress on Intelligent Control and Automation*, Hang Zhou, China, vol. 6, pp. 5351–5355 (2004)
13. Quyen, M.L.V., Mattinerie, J., Navarro, V., Boon, P., DHave, M., Adam, C.: Anticipation of epileptic seizures from standard EEG recordings. *Lancet* **357**, 183–188 (2001)
14. Siuly, Y., Wen, P.P.: Clustering technique-based least square support vector machine for EEG signal classification. *Comput. Meth. Prog. Biomed* **104**, 358–372 (2011)
15. Song, J.L., Zhang, R.: Application of extreme learning machine to epileptic seizure detection based on lagged poincare plots. *Multidimension. Syst. Signal Process.* **28**, 945–959 (2017)

16. Song, Y., Crowcroft, J., Zhang, J.: Automated epileptic seizure detection in EEGs based on optimized sample entropy and extreme learning machine. *J. Neurosci. Methods* **210**, 132–146 (2012)
17. Tito, M., Cabrerizo, M., Ayala, M., Barreto, A., Miller, I., Jayakar, P., Adjouadi, M.: Classification of electroencephalographic seizure recordings into ictal and interictal files using correlation sum. *Comput. Biol. Med.* **39**, 604–614 (2009)
18. Übeyli, E.D., Güler, I.: Detection of electrocardiographic changes in partial epileptic patients using lyapunov exponents with multilayer perceptron neural networks. *Eng. Appl. Artif. Intell.* **17**, 567–576 (2004)
19. Yuan, Q., Zhou, W., Li, S., Cai, D.: Epileptic EEG classification based on extreme learning machine and nonlinear features. *Epilepsy Res.* **96**, 29–38 (2011)
20. Zhang, Y.L., Zhou, W.D., Yuan, S.S., Yuan, Q.: Seizure detection method based on fractal dimension and gradient boosting. *Epilepsy Behav.* **43**, 30–38 (2015)
21. Zhu, G., Li, Y., Wen, P.: Epileptic seizure detection in eegs signals using a fast weighted horizontal visibility algorithm. *Comput. Biol. Med.* **115**, 64–75 (2014)



<http://www.springer.com/978-3-319-69181-7>

Health Information Science

6th International Conference, HIS 2017, Moscow,

Russia, October 7-9, 2017, Proceedings

Siuly, S.; Huang, Z.; Aickelin, U.; Zhou, R.; Wang, H.;

Zhang, Y.; Klimenko, S. (Eds.)

2017, X, 183 p. 58 illus., Softcover

ISBN: 978-3-319-69181-7