ORIGINAL SCIENTIFIC PAPER ORIGINALNI NAUČNI RAD ORIGINAL SCIENTIFIC PAPER

EPILEPSY DETECTION USING DWT BASED HURST EXPONENT AND SVM, K-NN CLASSIFIERS

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OTKRIVANJE EPILEPSIJE UPOTREBOM DTW BAZIRANE HURSTOVE EKSPONENCIJE I SVM, K-NN KLASIFIKATORA

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Received / Primljen: 07.05.2017. Accepted / Prihvaćen: 22.08.2017.

ABSTRACT

Epilepsy is a typical neurological issue which influence the focal sensory system and can make individuals have seizure. It can be surveyed by electroencephalogram (EEG). A wavelet based HURST EXPONENT strategy is displayed for the analysis of epilepsy. This strategy deals with the nonlinear analysis of EEG signals. Discrete wavelet transform is used to disintegrate the original EEG signal into specific subbands. The hurst exponent of different sub-bands is employed and then fed into two classifiers, namely SVM and KNN. The highest classification accuracy obtained in the presented work is 99% for healthy subject data versus epileptic data is obtained by SVM. However, the corresponding accuracy between normal subject data and epileptic data using SVM is obtained as 99% and 93% for the eyes open and eyes shut conditions, respectively. The detailed analysis of the methodology and results has been discussed in the paper.

Keywords: *Hurst exponent (HE), Support vector machine (SVM), Discrete wavelet transform (DWT), K- nearest neighbor (KNN)*

SAŽETAK

Epilepsija je tipični neurološki pormećaj pod uticajem fokalnog sanzornog sistema koji može da izyzove epi-napade kod obolelih. Može da se otkrije analizom elektroencefalograma (EEG). Razvijena je strategija analize epilepsije pomoću HURSTOVE EKSPONENCIJE zasnovane na malim talasima, koja se bavi nelinearnom analizom EEG zapisa. Koristi se diskretna transformacija malih talasa kako bi se originalni EEG zapis dezintegrisao na specifične podgrupe. Primenom Hurstove eksponscije na različite podgrupe svrstvaju se u odgovarajuće klasifikatore, pre svega SVM i KNN. Najveća tačnost klasifikacije je postignuta u navedenom radu i iznosi 99% za zdrave osobe u poređenju sa obolelim od epilepsije primenom SVM. Međutim, odgovarajuća preciznost za razlikovanje zdravih osoba od obolelih od epilepsije upotrebom SVM iznosi 99% i 93% u zavisnosti od toga da li su oči otvorene ili zatvorene. Detaljna analiza primenjenih metoda i dobijenih rezultata je prikazana u radu.

Ključne reči: *Hurstova eksponencija (HE), podrška vektor mašina (SWD), diskretna transformacija malih talasa (DWT), K-najbliži komšija (KNN)*

INTRODUCTION

Epilepsy is a standout amongst the most predominant neurological issues in people. It is described as repeating seizures in which strange electrical action in the mind causes the loss of awareness or an entire body shaking. Patients are unaware of the event of seizure because of the irregular way of such seizures which may expand the danger of physical damage. Surveys demonstrate that 4-5% of the aggregate total population has been experiencing epilepsy.

Electroencephalogram is one of the most important tools for examination of epilepsy. Electroencephalogram is the recorded portrayal of electrical action delivered by terminating of neuron inside the mind along the scalp. For recording of EEG, terminals will be glued at some key focuses on the patient's head. Anodes get the signs and will be recorded in a recording gadget through wires which are associated with terminals.

As total visual examination of EEG signal is exceptionally troublesome, automatic detection is preferred. Fourier transform has been mostly utilized as a part of feature extraction of EEG signals. However as EEG signal is a non stationary signal, Fourier examination does not give precise outcomes. Most effective tool is wavelet transform. Better information can be extracted from the individual frequency sub signals rather than extracting it directly

UDK: 616.831-073 / Ser J Exp Clin Res 2018; 19 (4): 311-319
DOI: 10.1515/SJECR-2017-0043

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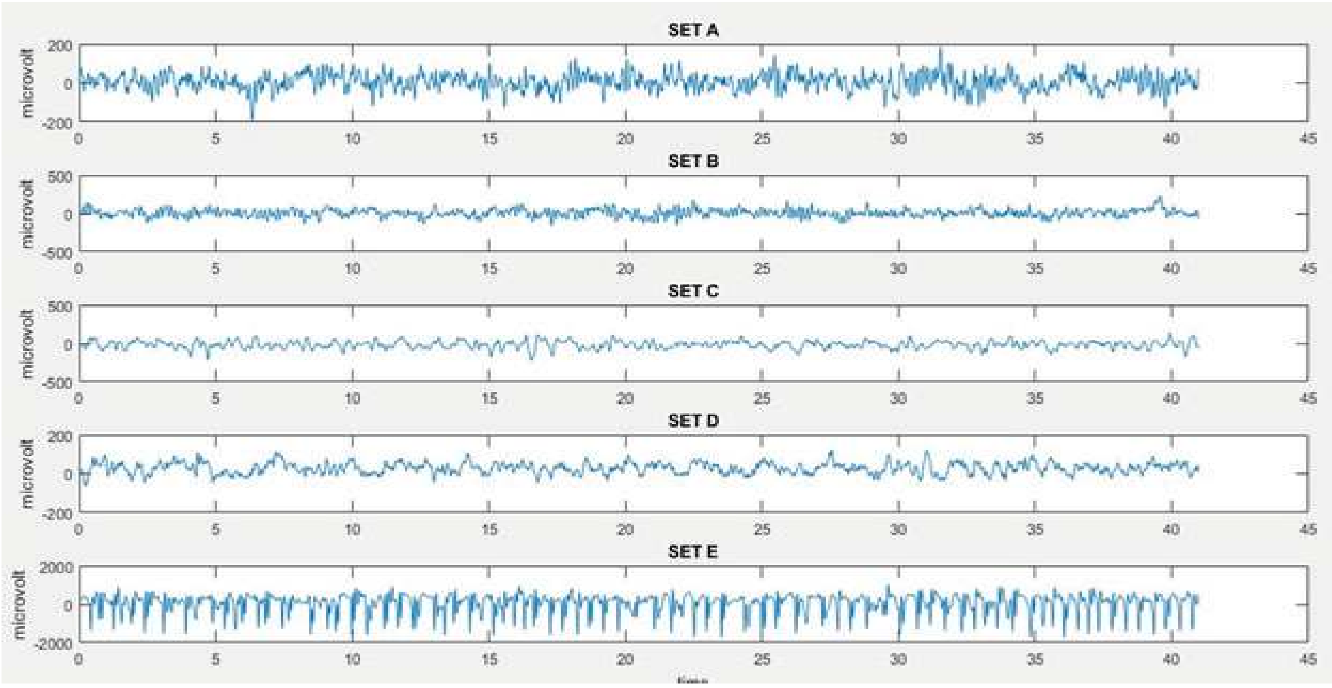

Fig. 1 Sample Plots of A-E Data Sets.

from the EEG signal. Also by using wavelet transform, it becomes easier to get the time and frequency information of a signal together, which makes it practical to obtain the transient components in EEG. Research works in recent studies can be categorized as time domain, frequency domain, time-frequency domain and nonlinear methods of analysis. Since the EEG signals are complex, nonlinear and non-stationary in general, time-frequency domain and non linear analysis methods are most broadly utilized in epilepsy detection. Nonlinear components, for example, time lag (TL), hurst exponent (HE), implanting dimension (ED), relationship dimension (CD) and biggest Lyapunov exponent (LLE) are extracted from the EEG and their each sub-band to describe and distinguish the epileptic seizure.

Nonlinear investigation is another prominent research strategy which could better reflect the attributes of the EEG signals. The utilization of Hurst exponent (HE) has been demonstrated to accomplish great accuracy in recognizing seizures. Also, entropies like estimated entropy (ApEn) and test entropy (SampEn) are broadly connected to uncover the shrouded complexities existing in the EEG time arrangement. In this paper, the HE is introduced to characterize the EEG signals in terms of the stronger relative consistency and less dependence on data length.

DATA

The complete database used in this study consists of five sets denoted as A-E, each containing 100 samples. These datasets are explained in Table 1. The signals were recorded with the 128-channel amplifier system and digitized at 173.61 samples per second using 12 bit resolution. Sets C and D is an interictal data and is recorded when the patient in pre-ictal state. Set E, which is called ictal data, contains signals recorded during the epileptic seizure. Fig. 1 depicts the sample of EEG signals for each of the five sets.

METHODS

In this study, DWT is used to decompose the original EEG signal into six sub-band signals using fifth level decomposition. Complexity of this EEG signal is simplified by extracting Hurst Exponent values from each sub-band signal. For classification, SVM and KNN classifiers are used. The block diagram of the proposed approach is shown in figure below fig 2.

Discrete Wavelet Transform

Since EEG signal is a non-stationary signal, Fourier Transform cannot be used as it can better analyse stationary signals but not non-stationary signals. It provides the signal which is localized only in frequency domain. Also, it

Fig 2 Block diagram of proposed approach

does not provide multi-resolution analysis. Moreover, window size is not available. These drawbacks are overcome in Wavelet transform. Wavelet change is an exceptionally helpful approach used on a signal for time–frequency representation since it utilizes the variable size of windows. Long time and short time windows are utilized to get a low and high frequency resolution data respectively. In this way, WT gives specific frequency data and time data at low frequencies and high frequencies, individually. Continuous wavelet transform (CWT) and discrete wavelet transform (DWT) are the two types of a wavelet transform. If x (t) is the input raw signal then CWT of a signal is

$$SENSITIVITY\ (SEN) = \frac{true\ positives}{true\ positives + false\ negatives} \times 100\%$$

where a is the scaling parameter and b is the shifting parameter. Now it is a difficult task to find the wavelet coefficient at each scale so the scaling and shifting parameters are converted to powers of two. DWT is defined as

$$DWT(j,k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t)\Psi\left(\frac{t-2^j k}{2^j}\right) dt$$

First of all, input signal is made to pass through a low pass and high pass filter and output from this is referred as approximation coeffiecient (A1) and detailed coefficient (D1) of first level. Similarly, all the coefficients of five levels are extracted as D1, D2, D3, D4, D5, A5. At each level of decomposition, filtering is used to double the frequency resolution and down-sampling is used to half the time resolution. While analyzing a signal, the most important parameter to be considered is the number of decomposition levels, which in this case is chosen to be five. Since above 40 hz, the frequency components may not contain useful information so only fifth level decomposition is done.

Hurst Exponent

At the surface of brain, the response is created in the form of wavelets. A desired feature is extracted in the form of wavelets which is called as feature extraction. Hurst exponent is extracted from these wavelets only.

Hurst type (HE) is an established parameter which is utilized as a part of this case for nonlinear analysis. In a time series, this parameter is used to quantify the correlation of points.

- HE < 0.5 indicates that the sequences are long range anti-correlations and anti-persistent
- HE > 0.5 indicates the sequences with long range correlations.

The presence or absence of long-range dependence and its degree in a time series is assessed through HE. During interruption of seizures, HE is very much useful in identifying deviations from the normal pattern of brain activity. Commonly, HE can be estimated using rescaled range analysis (R/S) of which the equation is defined below

$$HE = \frac{log(R/S)}{\log T}$$

Where R is the difference between the maximum and minimum of deviation and S represents the standard deviation of the time series. T denotes the duration of the sample data (11).

Support vector machine (SVM)

For binary classification tasks in machine learning and for high dimensional feature vectors SVM is a very well known tool due to its accuracy and capability to deal with a large number of predictors. For multi-class classification process, SVM gives much better results. SVM constructs $M(M-1)/2$ binary sub-classifiers, where M is the number of classes. To separate a pair of classes, each binary sub-classifier is trained and a prediction is made by the majority voting technique.

The SVMs tend to find an optimal hyper-plane in high dimensional feature space in order to maximize the distance between this hyper-plane and the nearest data point of each class. SVM classifiers gives much better results as compared to other classifiers. Standard optimization software can be used to find optimum parameters. General quadratic programming software will often fail for large sample sizes and to solve the optimization special-purpose optimizers need to be used. (25–29).

K-nearest neighbor (KNN)

It is a simple machine learning algorithm. A majority vote of neighbors is used to classify an object, with the object being assigned to the class most common amongst its k- nearest neighbors. K is a positive integer whose value is typically small. k = 1 implies that the object is assigned to the class of its nearest neighbor. To avoid tied votes in binary classification problems, k should be an odd number.

Assume each sample of our dataset has n attributes and an n dimensional vector: x = (x1, x2. . . xn) is formed by combining these attributes. These attributes are independent variables. The problem that we have to solve is that we have a new sample where x=u. We want to find the class of this sample. In the event, if we knew the function f, we could compute v= f (u) to classify this sample. But in this case we don't know about f.

The thought in k Nearest Neighbor strategies is to distinguish k samples in the training set whose autonomous factors x are like u, and to utilize these k tests to characterize this new specimen into a class. On the off chance that all we are set up to accept is that f is a smooth function, a sensible thought is to search for samples in training data that are close to it and after that to figure out from the estimations of y for these samples .When we discuss neighbors we are inferring that there is a separation that we can compute between samples in view of the autonomous factors. For the minute we will concern ourselves to the most prominent measure of separation: Euclidean separation (7).

We observe that the sort of separation utilized has little impact on accuracy. We actualized the k-neares neighbor calculation on dimensionally lessened information. As we probably am aware dimensional diminishment lessens the connection between elements. We attribute the dimensional lessening to be the explanation behind unaffected characterization precision with separation sort.

Statistical parameters

To evaluate the performance of the classifier, two different parameters are employed, namely sensitivity and accuracy. Mathematically, these parameters are defined as,

$$SENSITIVITY\ (SEN) = \frac{true\ positives}{true\ positives + false\ negatives} \times 100\%$$

$$ACCURACY\ (A) = \frac{correct\ cllasified\ patterns}{total\ patterns} \times 100\%$$

RESULTS

DWT technique was used to decompose all the 500 epochs of normal, interictal and epileptic (ictal) EEG data sets. The sub-bands were divided as follows: A5 (0–2.70 Hz), D1 (43.4–86.8 Hz), D2 (21.7–43.4 Hz), D3 (10.85–21.7 Hz), D4 (5.43–10.85 Hz) and D5 (2.70–5.43 Hz). Fig 3 represents decomposition of a sample dataset A into different sub-bands.

The approximation and detail coefficients of all sub bands of the entire 500 EEG epochs were used to calculate HE values. For five data sets A-E the value of HE for entire 500 epochs are plotted in figure 4,5 and 6. Data set A and B have higher HE value as compared to data set E, this proves that the data set E is in more ordered form than the data sets A and B. Similarly the data sets C and D tends to have higher HE values than the data set E and lesser than data sets A and B. Hence we can conclude that data sets C and D are more ordered than the data sets A and B and are less regular than E.

Tabulation of average HE values for wavelet coefficients of the six sub bands (D1 to D5 and A5) of data sets A,B,C,D and E is given in table 2. We can come to a conclusion that epileptic EEG i.e. set E is more regular or less complex as compared to normal i.e. set A and B and data sets representing interictal periods i.e. sets C and D. We also observed that the complexity of data sets C and A is almost similar, when recorded for normal subjects. Conversely , the complexity of data set E is lower than the complexity of data set D, when recorded from epileptic patient throughout the ictal period.

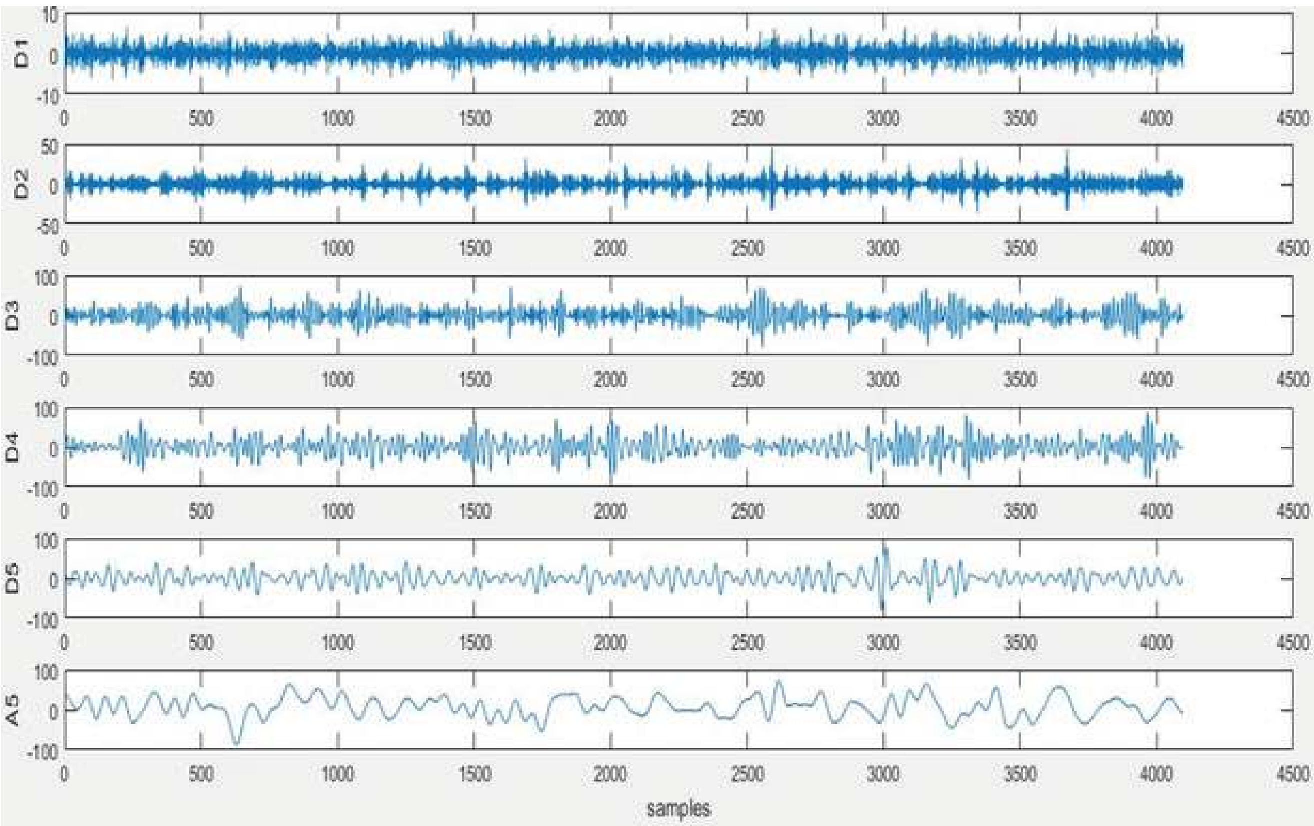

Fig 3 Decomposition of Set A into sub-bands

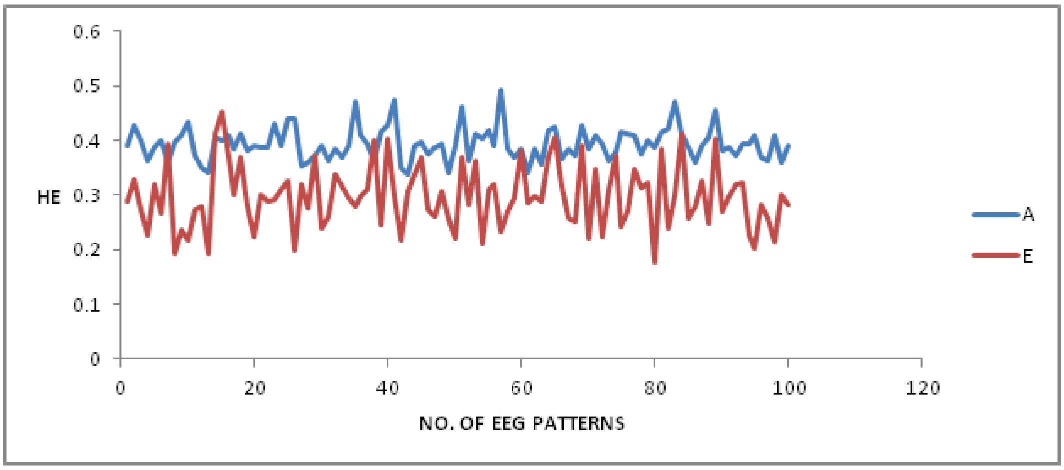

Fig 4 DWT based HE values of sub-band (D1) for data sets (A and E)

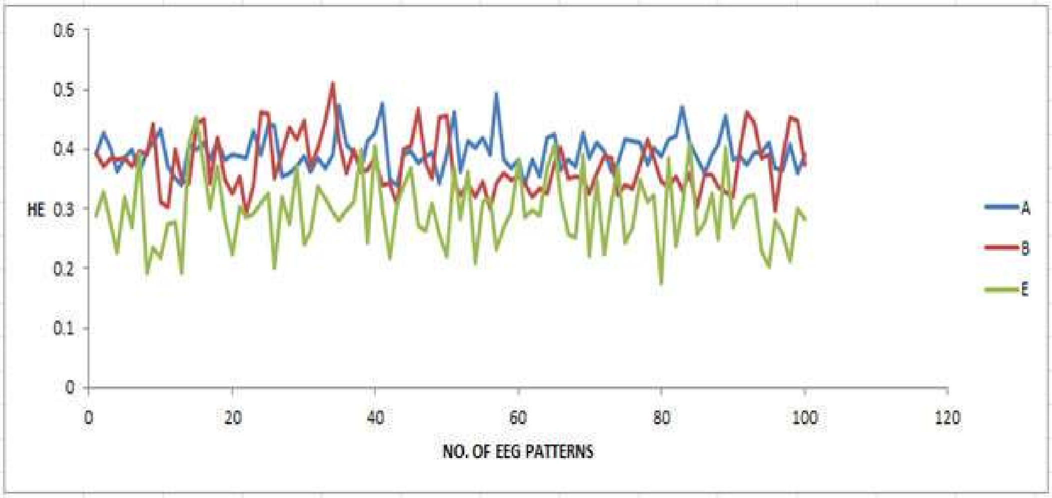

Fig 5 DWT based HE values of sub-band (D1) for data sets (A,B and E)

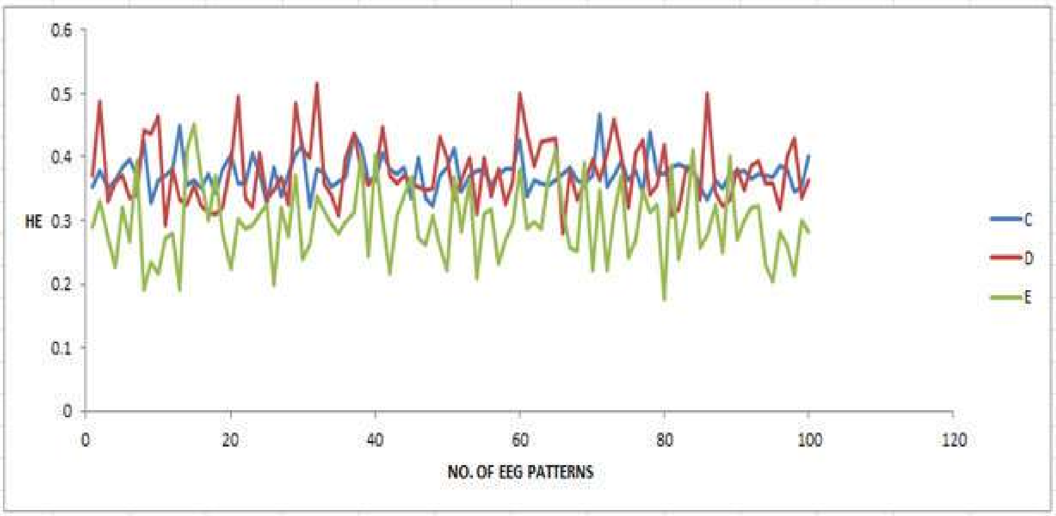

Fig 6 DWT based HE values of sub-band (D1) for data sets (C,D and E)

A significabt difference was found between the DWT based HE values of different sub bands of all the data sets , this fact is very much evident from data in table 1. The differences in these values is used to formulate feature vector of an entire band (0-86.8 Hz) of EEG signal. The SVM and KNN classifiers thus uses these six features as an input in or-

Table 1: Statistical parameters of SVM and k-NN

	SVM			KNN		
Sets	Accuracy (%)	Sensitivity (%)	Elapsed Time (sec)	Accuracy (%)	Sensitivity (%)	Elapsed Time (Sec)
A-E	99.00	100.00	0.0184	98.00	98.00	1.2885
B-E	95.00	95.91	0.0208	95.00	94.00	0.7638
C-E	99.00	100.00	0.0018	98.00	96.00	0.7695
D-E	93.00	97.77	0.0022	91.00	94.00	0.7587
BCD-E	91.50	85.10	0.0038	95.00	90.00	0.7883
AB-E	94.67	88.89	0.0007	95.33	92.00	0.9628
AC-E	97.33	94.23	0.0007	98.00	96.00	0.8158
AD-E	93.33	90.00	0.0006	93.33	94.00	0.7489
BC-E	93.33	93.47	0.0008	96.00	92.00	0.7444
BD-E	89.33	88.63	0.0007	93.33	90.00	0.7616
CD-E	94.00	88.67	0.0008	94.00	94.00	0.7541
ABC-E	95.50	93.61	0.0008	96.50	92.00	0.7522
ACD-E	95.00	85.71	0.0008	95.00	94.00	0.7521
ABD-E	92.50	85.71	0.0008	94.50	90.00	0.7592
ABCD-E	93.20	81.13	0.0171	95.60	90.00	0.67422

der to further classify the EEG as healthy,interictal and ictal. The following cases have been taken up for consideration.

While processing class 0 is allotted value 1 and class 2 is allotted as 1 in the target vector , for all the cases.Implementation of SVM is done using MATLAB software version 7.8.0 (R2016a). The input feature vector thus obtained is divided randomly into training data set and testing data set. For training the SVM the training data set is used, whereas the accuracy and effectiveness of the trained SVM for given EEG signal is determined using the training set. Similar procedure is carried out for classification using KNN classifier.

The input data matrix which is prepared from the HE values has 100 rows and 6 columns in this work. In this matrix each row represents one observation and its column is one feature. In the same way, the feature vectors of sets B, C, D and E have 100 observations each. Present binary classifier task comprise of 200 observation of six features for case 1 to case 4, 300 observation with six features for case 5 to case 11, 400 observation with six features for case 12 to case 14 and 500 observation with six features for case 15. For testing of classifier 50% of input data set is used and remaining 50% is used for training.

Comparison with existing state-of-art work

The work done by various researchers in this field of epilepsy detectionis tabulated in Table 2. We have drawn here a comparison between the results obtained in other methods and our proposed approach. For making the results more realistic only the methods using same data sets and similar cases is incorporated.

For case 1 and case 3, the classification accuracy obtained from our work 99% (using SVM) is one of the best presented for these data sets. Tzallas et al.'s (38) work also represent this result by using the method of time-frequency analysis combined with ANN.

For case 2 and case 4, the accuracy obtained after classification process is 95%, 93% (using SVM) are the best presented. Nicolaou et al. (23) also looked upon these cases and reported their accuracy as 82.8%and 79.94% respectively. His method comprises using permutation entropy with SVM for the same data sets.

For case 12, the accuracy obtained after classification process is 95% (using both SVM and KNN). This particular case was also presented in Guo et al.'s (41) work , which were obtained by using the line length features centered on multi resolution decomposition combined with ANN.

Case 6 to Case 12 and case 15 is presented in our work for the first time and has given satisfactory results. As already mentioned the approach used by us involves using wavelet analysis (using DWT) for EEG signal decomposition combined with extracting HE (for all six sub bands) and using SVM and KNN classifiers for the classification process.

CONCLUSION

Manual detection of epileptic seizure is a very costly and time consuming process. In this work hurst exponent has been employed which simplifies automatic seizure detection process. Fifth leveldecomposition of EEG signals has been performed to decomposethe signal into different sub-bands by DWT to obtain the detail wavelet coefficients ($D1$–$D5$) and approximate wavelet coefficients ($A5$). The HE values are calculated from $D1$–$D5$ and $A5$ which provides the best detec tion rates. The 99% classification accuracy is obtained using SVM for cases 1 and 3 and 98% accuracy is obtained using KNN classifier. It can be concluded that using DWT based

Table 2: Comparison of classification accuracy obtained by proposed method and others existing methods

RESEARCHERS	YEAR	METHODS	CASES	ACCURACY (%)
Nigam and Graupe (35)	2004	Non linear preprocessing filter – diagnostic neural network	A-E	97.20
Srinivasan et al. (20)	2005	Time and frequency domain features – recurrent neural network	A-E	98.66
Kannathal et al. (36)	2005	Entropy measures – adaptive neuro-fuzzy inference system	A-E	92.22
Polat and Günes (37)	2007	Fast Fourier transform – decision tree	A-E	98.72
Subasi (34)	2007	Discrete wavelet transform – mixture of expert model	A-E	95.00
Guo et al. (19)	2009	Discrete wavelet transform – relative wavelet energy-MLPNNA	A-E	95.20
Ocak (18)	2009	Discrete wavelet transform – approximate entropy (ApEn)	A-E	99.60
Subasi et al (40)	2010	DWT – PCA, ICA, LDA and SVM	A-E	98.75 (PCA)
Guo et al. (41)	2010	Line length feature – ANN	A-E ACD-E ABCD-E	99.60 97.75 97.77
Guo et al (43)	2011	GP-based feature extraction – KNN classifier	A-E	99.20
Nicolaou et al. (23)	2012		A-E B-E C-E D-E	93.55 82.88 88.00 79.94
Akbarzadeh-T and Naghibi-Sistani	2013	Discrete wavelet transform – Hurst exponent and Lyapunov exponent	A-E B-E	96.90 96.50
Kaya et al.	2014	1-D local binary patterns + BayesNet	A-E	95.50
Riaz et al.	2015	Empirical mode decomposition based temporal and spectral features + SVM	A-E	93.00
Mingyang Li , Wanzhong Chen , Tao Zhang	2016	Double density discrete wavelet transform- Hurst exponent and fuzzy entropy	A-E	100
Present reporting		Discrete wavelet transform- Hurst exponent (SVM)	A-E B-E C-E D-E BCD-E AB-E AC-E AD-E BC-E BD-E CD-E ABC-E ACD-E ABD-E ABCD-E	99.00 95.00 99.00 93.00 91.50 94.67 97.33 93.33 93.33 89.33 94.00 95.50 95.00 92.50 93.20

Hurst exponent method using SVM clasiifier gives more satisfactory results as compared to other methods. The presented method may prove to be a useful tool in epilepsy detection.

DECLARATION

The authors declare no conflict of interest

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