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The classification of EEG signals using discretization-based entropy and the adaptive neuro-fuzzy inference system

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Abstract: A novel feature extraction called discretization-based entropy is proposed for use in the classification of EEG signals. To this end, EEG signals are decomposed into frequency subbands using the discrete wavelet transform (DWT), the coefficients of these subbands are discretized into the desired number of intervals using the discretization method, the entropy values of the discretized subbands are calculated using the Shannon entropy method, and these are then used as the inputs of the adaptive neuro-fuzzy inference system (ANFIS). The equal width discretization (EWD) and equal frequency discretization (EFD) methods are used for the discretization. In order to evaluate their performances in terms of classification accuracy, three different experiments are implemented using different combinations of healthy segments, epileptic seizure-free segments, and epileptic seizure segments. The experiments show that the EWD-based entropy approach achieves higher classification accuracy rates than the EFD-based entropy approach.

Key words: EEG signals, discrete wavelet transform (DWT), discretization-based entropy, adaptive neuro-fuzzy inference system (ANFIS)

1. Introduction

Epilepsy is a serious neurological disorder that affects 2%–3% of the world's population. Epileptic seizures caused by temporary excessive electrical discharges occurring in the brains of epilepsy patients lead to uncontrollable movements and trembling in the human body. In general, electroencephalography (EEG) signals are used in the analysis of these electrical discharges that result in disorders of the brain [1]. The visual detection of epileptic seizures and the visual diagnosis of epilepsy require the scanning of long EEG recordings, which is a very time-consuming process. Since a whole visual examination is often not possible, the automated systems based on artificial neural networks (ANNs) are used in the analysis of EEG signals. The adaptive neuro-fuzzy inference system (ANFIS) can be used as a classification tool for the rule-based analysis of EEG signals, since it is an adaptive network that is capable of learning and adjusting the fuzzy rules and fuzzy membership functions of the system from data by processing patterns [1–6].

Although EEG signals are nonstationary signals, most epilepsy diagnosis systems are based on the assumption that EEG signals have quasistationary characteristics in the time or frequency domain. In order to analyze such signals, time-frequency-based approaches are the most suitable tools, [2,4]. The discrete wavelet transform (DWT) is the most appropriate transform method for applications with nonstationary signals like

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EEG signals, since it provides both time and frequency views of the signals simultaneously [6–8]. Several studies noted that the classification accuracy of EEG signals depends entirely on the selection of optimum statistical parameters (such as maximum, minimum, standard variation, mean, entropy, and average power) in not only the time or frequency domain, but also in the time-frequency domain [9–17]. Since the entropy is a nonlinear measure and quantifies the degree of complexity in a time series, it helps to understand brain dynamics when it is used in the analysis of EEG signals [17]. Kannathal et al. investigated the performance of several entropy measures using a classifier in the detection of epileptic seizures, and proved that the entropy values of the epileptic EEG signals were lower compared to the entropy values of healthy EEG signals [15].

In order to extract basic characteristic features from EEG signals, the entropy values of frequency subbands of the signals are computed with an entropy method after the signals are rearranged using a discretization method. The equal width discretization (EWD) and equal frequency discretization (EFD) methods are well-known discretization methods that discretize the data points of a given signal into K ranges according to the discretization parameter K [18]. This paper proposes a novel approach called discretization-based entropy, and investigates its impacts in an ANFIS-based classification of EEG signals in terms of classification accuracy. Since entropy quantifies the degree of complexity in a time series, it helps in the classification of EEG signals and in understanding brain dynamics. In addition, using any discretization method, the data points of EEG signals can be divided into clusters or groups, and, in this way, hidden clusters of data points may be discovered, and therefore the analysis of the signals may become easier. To this end, EEG signals are decomposed into frequency subbands using the DWT method, the coefficients of frequency subbands are discretized into the desired number (K) of intervals using the EWD and EFD methods, the entropy values of these discretized coefficients are computed with the Shannon entropy method, and these are then used as inputs into the ANFIS in the classification of EEG signals related to different combinations of healthy segments, epileptic seizure-free segments, and epileptic seizure segments. Figure 1 shows the schematic structure of the proposed method.

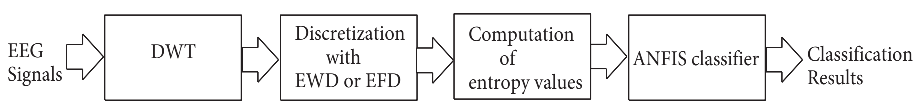

Figure 1. Schematic illustration of the proposed method.

This paper demonstrates that the EWD and EFD-based entropy approaches can be an effective analysis tool for not only the detection of epileptic seizures, but also in the diagnosis of epilepsy.

2. Materials and methods

2.1. EEG dataset

In this study, publicly available EEG data are used [19]. These data are recorded by means of a 128-channel 12-bit EEG system with 173.5 samples per second. A total of 500 segments are grouped into five sets (A–E). Each segment is 23.6 s in duration. All sets are selected from EEG records after purifying artifacts caused by eye and muscle movements. Sets A (eyes open) and B (eyes closed) are recorded using the placement scheme of an international 10–20 electrode from five healthy subjects. Sets C and D are intracranial recordings obtained from five epilepsy patients measured in seizure-free intervals. For these recordings, the electrodes are placed on epileptic foci for set C and on the hippocampus of the opposite hemisphere for set D. Set E includes only epileptic seizure recordings of the same five epilepsy patients. Examples of EEG segments from sets A, B, C, D, and E are shown in Figure 2.

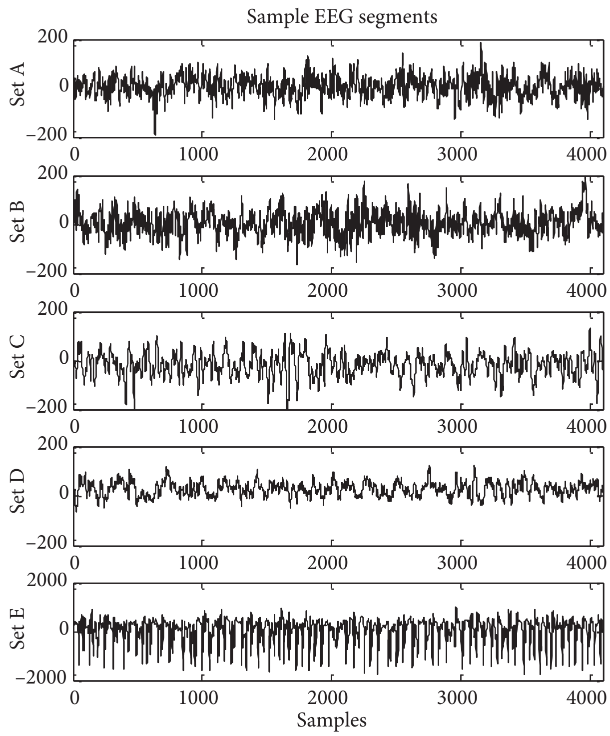

Figure 2. Sample EEG segments of sets A, B, C, D, and E.

2.2. Discrete wavelet transform (DWT)

DWT is an effective way of analyzing nonstationary EEG signals. This technique provides high-frequency resolution if the frequency is low, and high-time resolution if the frequency is high because it uses long time windows at low frequencies and short time windows at high frequencies [8,17]. DWT decomposes a signal into subbands by filtering of the time domain signal f using sequential high-pass and low-pass filters as shown in Figure 3.

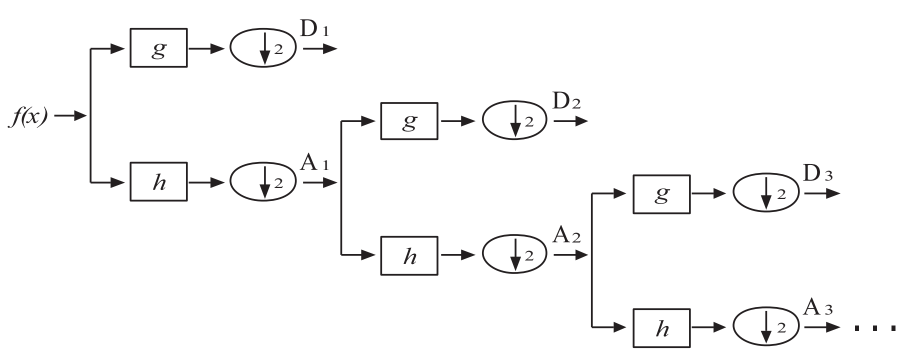

Figure 3. Subband decomposition of a signal using DWT.

The high-pass filter g and the low-pass filter h are the discrete mother wavelet function and its mirror version, respectively. In the DWT method, the signals are filtered using these filters, and then sampled using the down-sampler. The down-sampled signals in the 1st level are 1st-level approximation coefficients A_1 and 1st-level detail coefficients D_1. Approximation and detail coefficients for each subsequent level are determined using the approximation coefficient from the previous level in the same way. Scaling function $\phi_{j,k}(x)$ representing the low-pass filter and wavelet function $\psi_{j,k}(x)$ representing the high-pass filter are described as:

$$\phi_{j,k}(x) = 2^{j/2}h(2^j x - k) \tag{1}$$

$$\psi_{j,k}(x) = 2^{j/2}g(2^j x - k), \tag{2}$$

where $x = 0, 1, 2, \ldots, M-1, j = 0, 1, 2, \ldots, J-1$, and $k = 0, 1, 2, \ldots, 2^j - 1. J$ is equal to $\log_2(M)$, and M is the length of an EEG segment [20]. k is the sampling rate, and j is the resolution, and they indicate the function positions and function widths on the x axis, respectively. The function heights depend on $2^{j/2}$ value. For $k = 0,\ 1,\ 2,\ \ldots,\ 2^j - 1$, the approximation coefficients $A_i(k)$ and detail coefficients $D_i(k)$ for the ith level are:

$$A_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x)\phi_{j,k}(x) \right\} \text{ and } D_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x)\psi_{j,k}(x) \right\} \tag{3}$$

The length of an EEG segment M is equal to 4097, and J can be computed by $log_2(M)$. In this case, J is equal to 12, and therefore the maximum decomposition in level L is chosen as 11.

In this paper, the DWT method with the wavelet of order 2 of Daubechies was used in the decomposition of EEG signals into frequency subbands, since it achieves good results in the classification of EEG signals [5,17]. The decomposition level providing the highest success of the ANFIS was investigated between 2 and 11, and the decomposition level was selected as 6 for all experiments. The approximate and the detail coefficients of a healthy EEG segment and an epileptic seizure segment are shown in Figures 4 and 5, respectively.

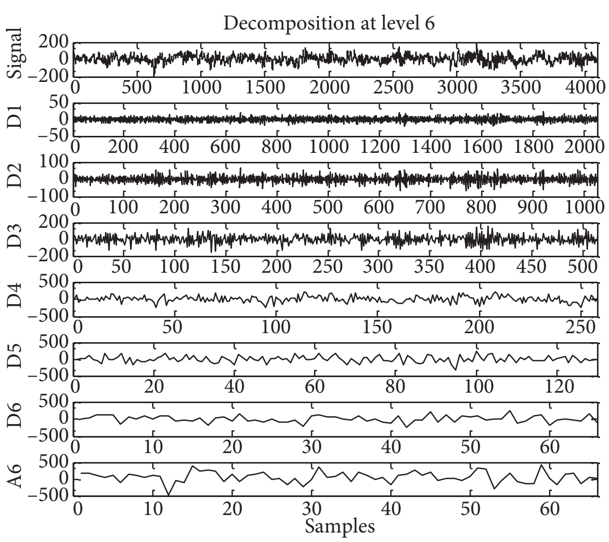

Figure 4. The approximate and detailed coefficients of a healthy segment taken from set A.

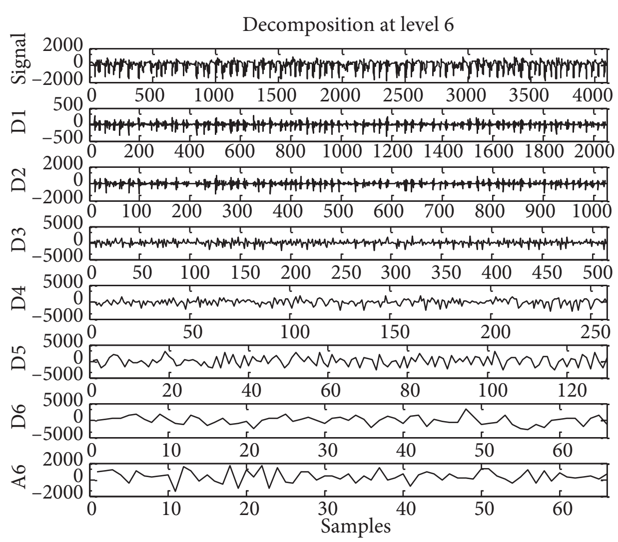

Figure 5. The approximate and detailed coefficients of an epileptic seizure segment taken from set E.

2.3. EWD- and EFD-based entropy approaches

The discretization process divides a continuous signal into a few intervals on the amplitude axis, and the patterns of signals are assigned to the intervals on the amplitude axis. In effect, a discretization method aims to divide the data points of the signal into clusters [18]. In this way, hidden clusters related to the data points of the signal may be discovered using discretization methods, and therefore the examination of the signals may become easier. The discretization methods are very important signal preprocessing approaches for pattern recognition. The simplest discretization methods are EWD and EFD. The EWD method separates the signal into K equal width intervals, while the other divides the signal into K intervals where the number of patterns belonging to each interval is equal.

The EWD method equally divides the continuous-valued signal into K intervals between the minimum and maximum amplitude [18]. These intervals have the width of:

$$W = \frac{v_{\max} - v_{\min}}{K}, \tag{4}$$

where, v_{min} is the minimum amplitude, and v_{max} is the maximum amplitude of the signal. K is a predefined parameter. The cut-points of the amplitude axis become:

$$v_{\min} + W, v_{\min} + 2W, ..., v_{\min} + (K-1)W \tag{5}$$

The EFD method places the same number of patterns into intervals. Assume that the signal has N patterns and this signal will be separated into K intervals. In this case, each interval between the cut-points c_i will have N/K patterns [21].

In this study, the frequency subbands obtained from the EEG signals using the DWT method were discretized using EWD and EFD methods, and then the entropy values of the discretized frequency subbands were computed by the following Shannon entropy:

$$H(i) = -\sum_i p_i \log p_i, \tag{6}$$

where $p_i = n_i/N$ in the EWD-based approach, $p_i = c_i$ in the EFD-based approach, N is the length of an EEG segment, n_i is the number of patterns belonging to the ith interval, and c_i is the cut-points. Figure 6 shows the entropy values computed using the EWD- based approach for sets A and E, where set A is the first 100 and set E is the second 100.

As seen in Figure 6, the entropy values of D2, D3, and D4 subbands illustrate the difference between healthy and epileptic segments. The difference makes classification easier.

2.4. Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS is an adaptive system that combines the advantages of the learning capabilities of ANNs and the mapping capabilities of the fuzzy inference system (FIS) by associating input and output spaces. In the ANFIS model, fuzzy rules can be extracted from the training dataset and a rule base can be built consisting of these rules in an adaptive manner. Two fuzzy *if-then* rules of the ANFIS with a first-order Sugeno model [22] are described as:

Rule 1 : If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2 : If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i is the output within the fuzzy region expressed by the fuzzy rule, and parameters p_i, q_i, and r_i are the parameters obtained during the training process. Figure 7 shows the ANFIS model with two rules, where circle and square symbols indicate fixed and adaptive nodes, respectively [5].

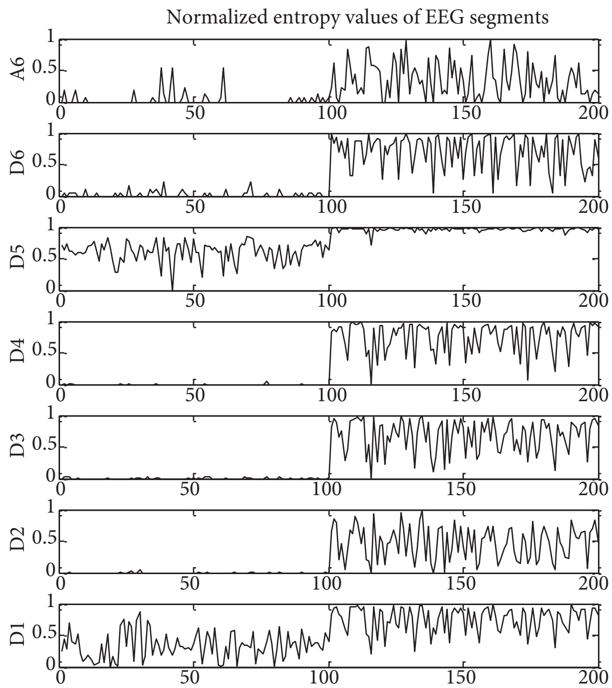

Figure 6. The entropy values computed using the EWD-based approach for sets A and E.

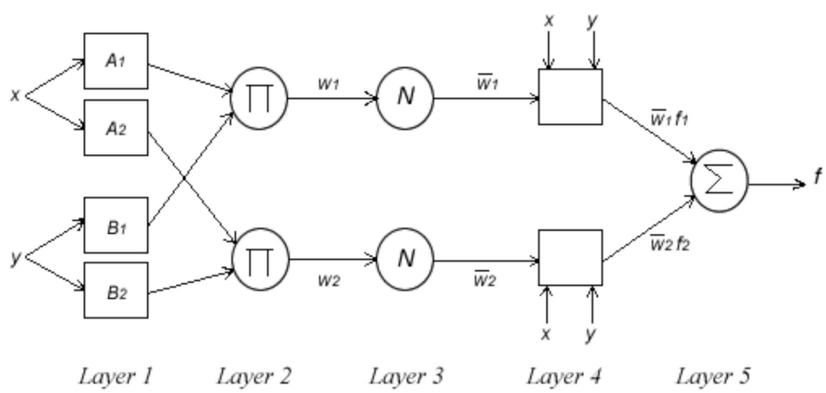

Figure 7. A sample ANFIS structure.

The 1st layer is referred to as the fuzzification layer. Each adaptive node in this layer generates fuzzy membership grades. The outputs of this layer are described as:

$$O_{i1} = \mu A_i(x) \tag{7}$$

$$O_{i1} = \mu B_{i-2}(y) \tag{8}$$

The output of each node is computed using the membership functions given in Eqs. (7) and (8). In general, the ANFIS model uses a generalized Bell activation function as the membership function in order to fuzzify the input values, where A_i and B_i are the linguistic labels represented by membership functions μA_i and μB_i, respectively.

In the 2nd layer, each node refers to the rules and their numbers created by the Sugeno FIS. The output of each rule is the product of membership degrees from the previous layer:

$$O_{i2} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{9}$$

In the 3rd layer, each node accepts all outputs of nodes from the rule layer (the previous layer), and calculates the normalized firing strength of each rule as follows:

$$O_{i3} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{10}$$

In the 4th layer, the weighted consequent value of each rule is computed by multiplying the normalized firing strength and a 1st-order polynomial. The output value of the ith node in this layer is:

$$O_{i4} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \tag{11}$$

where $\bar{w}_i$ is the ith node output coming from the preceding nodes. Parameters p_i, q_i, and r_i are the linear combination coefficients and are the parameter sets in the consequent part of the Sugeno fuzzy model.

The 5th layer has only one single node, and this fixed node computes the total output by summing the incoming signals:

$$f = \sum_i \bar{w}_i f_i = \frac{\sum_i \bar{w}_i(p_i x + q_i y + r_i)}{\sum_i w_i} \tag{12}$$

In general, a hybrid learning algorithm is used for training the ANFIS model [5,6]. This algorithm adjusts the parameters $\{a_i,\ b_i,\ c_i\}$ and $\{p_i,\ q_i,\ r_i\}$ to construct the ANFIS output equivalent to the training dataset in the manner of forward and backward passes. In forward passes, the least squares method is utilized to improve the consequent parameters with the fixed premise parameters. When obtaining the optimum consequent parameters, the backward pass starts to set the premise parameters of the fuzzy sets according to the gradient descent method. The standard back-propagation algorithm is used for adapting the premise parameters [5].

2.5. Validity criterion

In order to comment on the performances of the classification experiments, the following statistical measures were used [23,24]:

True Positive (TP): the number of true positive decisions

True Negative (TN): the number of true negative decisions

False Positive (FP): the number of false positive decisions

False Negative (FN): the number of false negative decisions

Sensitivity is the capacity to find epilepsy patients among real epilepsy patients, and it is the ratio of TP decisions to actual positive cases (TP+FN). Specificity is the capacity to find healthy subjects among real healthy subjects, and it is the ratio of TN decisions to actual negative cases (TN+FP). The total correct classification (TCC) is the ratio of correctly classified decisions (TN+TP) to all cases (TN+FN+TP+FP).

3. Results and discussion

In this study, MATLAB 2011b was used as the computation tool. In order to classify EEG signals, all EEG segments were decomposed into frequency subbands by using the DWT with Daubechies wavelet of order 2 for level 6, the obtained coefficients of each frequency subband were discretized into the desired number of intervals using the EWD and EFD methods, the entropy values of the discretized subbands were calculated using Shannon entropy, and these were then used as the inputs of the ANFIS classifier. In order to demonstrate the usefulness of the proposed approach in the classification of EEG signals, three different experiments were implemented. In order to validate the classifier in each experiment, according to a 2-fold cross validation, the EEG data were separated into two datasets: the training dataset and the testing dataset. These datasets were randomly selected from EEG segments in the ratios of 50%. Two-fold cross validation is the simplest type of k-fold cross validation, which is also called the holdout method. In this method, for each fold, data points are randomly assigned to two sets d_0 and d_1 so that both sets are of equal size. After that, the classifier is trained on d_0 and tested on d_1, followed by training on d_1 and testing on d_0. This has the advantage that both the training and testing sets are large, and each data point is used for both training and validation on each fold. In all experiments, a 1st-order Sugeno FIS model was selected for the ANFIS classifiers. A subtractive clustering method was used for finding the cluster centers within the training datasets, the base of the fuzzy rules of the ANFIS classifiers was designed using the generalized bell-shaped membership function, and these classifiers were trained with a hybrid learning algorithm during 100 epochs. Each experiment was repeated for different values of the discretization parameter K, and the ones providing the highest TCC ratio were selected as the optimal discretization parameters for those experiments. In all experiments, the features obtained using the EWD- and EFD-based entropy approaches were used as the inputs of the ANFIS classifiers, and the outputs of the ANFIS classifiers were evaluated by the threshold value of 0.5. In addition, in order to illustrate the contribution of the proposed EWD- and EFD-based entropy approaches to classifiers, all experiments were implemented using the same classifier without any discretization method. The classification successes of classifiers decreased in all experiments, significantly. The details and TCC results of the experiments are provided as follows:

A–E classification (the detection of epileptic seizure segments): For both EWD and EFD-based entropy approaches, the training dataset for the ANFIS classifiers was constructed by randomly selecting 50 segments from eyes-open healthy segments (set A) and 50 segments from epileptic seizure segments (set E), and these training datasets were used for training the ANFIS classifiers. The other 50 segments from set A and 50 segments from set E were used for testing the classifiers. Both of the ANFIS classifiers with EWD and EFD-based entropy approaches achieved a TCC accuracy of 100% with the MSE ratios of 0.00064 and 0.0069, respectively. In both approaches, there was not any misclassification, as seen in Table 1. On the other hand, when this experiment was implemented without any discretization method, the TCC accuracy of the ANFIS classifier was 97% with the MSE ratios of 0.03, and there was a total of three misclassifications, as seen in Table 2.

Table 1. The confusion matrix of A–E classification with EWD and EFD-based entropy approaches.

Class	Set A	Set E
Set A	50	0
Set E	0	50

Table 2. The confusion matrix of A–E classification without any discretization method.

Class	Set A	Set E
Set A	50	3
Set E	0	47

AB–CD classification (the diagnosis of epilepsy without using epileptic seizure segments): For both EWD and EFD-based entropy approaches, the training dataset for the ANFIS classifiers was constructed by randomly selecting 100 segments from healthy segments (set AB) and 100 segments from epilepsy segments without seizures (set CD), and these training datasets were used for training the ANFIS classifiers. After that, the other 100 segments from set AB and 100 segments from set CD were used for testing the classifiers. The ANFIS classifier with the EWD-based entropy approach achieved a TCC accuracy of 96.50% with the MSE ratio of 0.0407, while the TCC accuracy of the ANFIS classifier with the EFD-based entropy approach was 91.50% with the MSE ratio of 0.0816. In EWD and EFD-based approaches, the classifiers misclassified a total of 8 and 17 segments, as shown in Tables 3 and 4, respectively. On the other hand, when this experiment was implemented without any discretization method, the TCC accuracy of the ANFIS classifier was 92% with the MSE ratios of 0.08, and there were a total of 16 misclassifications, as seen in Table 5.

Table 3. The confusion matrix of AB–CD classification with the EWD-based entropy approach.

Class	Set AB	Set CD
Set AB	95	2
Set CD	5	98

Table 4. The confusion matrix of AB–CD classification with the EFD-based entropy approach.

Class	Set AB	Set CD
Set AB	91	8
Set CD	9	92

Table 5. The confusion matrix of AB–CD classification without any discretization method.

Class	Set AB	Set CD
Set AB	91	7
Set CD	9	93

AB–CDE classification (the diagnosis of epilepsy): For both EWD and EFD-based entropy approaches, the training dataset for the ANFIS classifiers was constructed by randomly selecting 100 segments from healthy segments (set AB) and 150 segments from epilepsy segments both with and without seizures (set CDE), and these training datasets were used for training the ANFIS classifiers. After that, the other 100 segments from set AB and 150 segments from set CDE were used for testing the classifiers. The ANFIS classifier with the EWD-based entropy approach achieved a TCC accuracy of 96.80% with the MSE ratio of 0.0335, while the TCC accuracy of the ANFIS classifier with the EFD-based entropy approach was 94.80% with the MSE ratio of 0.0533. In EWD and EFD-based approaches, the classifiers misclassified a total of 8 and 13 segments as shown in Tables 6 and 7, respectively. On the other hand, when this experiment was implemented without any discretization method, the TCC accuracy of the ANFIS classifier was 79.20% with the MSE ratios of 0.208, and there were a total of 52 misclassifications, as seen in Table 8.

Table 6. The confusion matrix of AB–CDE classification with the EWD-based entropy approach.

Class	Set AB	Set CDE
Set AB	96	4
Set CDE	4	146

Table 7. The confusion matrix of AB–CDE classification with the EFD-based entropy approach.

Class	Set AB	Set CDE
Set AB	92	5
Set CDE	8	145

Table 8. The confusion matrix of AB–CDE classification without any discretization method.

Class	Set AB	Set CDE
Set AB	97	49
Set CDE	3	101

For all experiments, the classification accuracy, specificity, sensitivity, number of rules, number of inputs, and the discretization parameter are illustrated in Tables 9–11.

As seen in Tables 9–11, the ANFIS classifiers with both EWD and EFD-based approaches classified healthy segments with open eyes (set A) and epileptic seizure segments (set E) with a TCC accuracy of 100% while the success of the same classification implemented without any discretization was 97%. In the same A–E classification experiment, Subasi [6], Umut et al. [21,23], Altunay et al. [25], and Kocyigit et al. [26] achieved TCC accuracies of 94%, 99.23%, 100%, 90%, and 94.25% with ANFIS classifier-based basic statistics, an ANN classifier using probability distribution based on equal frequency discretization, K-means clustering based on an ANN classifier, a linear prediction filter, and an ANN classifier model with the independent component analysis, respectively.

Table 9. The results of the experiments implemented using the EWD-based entropy approach.

	Experiments	TCC accuracy (%)	Specificity (%)	Sensitivity (%)	Number of rules	Number of inputs	K
1.	A–E	100	100	100	4	7	2
2.	AB–CD	96.50	95	98	8	7	18
3.	AB–CDE	96.80	96	97.33	8	7	18

Table 10. The results of the experiments implemented using the EFD-based entropy approach.

	Experiments	TCC accuracy (%)	Specificity (%)	Sensitivity (%)	Number of rules	Number of inputs	K
1.	A–E	100	100	100	2	7	3
2.	AB–CD	91.50	91	92	2	7	2
3.	AB–CDE	94.80	92	96.67	3	7	2

Table 11. The results of the experiments implemented using only entropy values without any discretization method.

	Experiments	TCC accuracy (%)	Specificity (%)	Sensitivity (%)	Number of rules	Number of inputs
1.	A–E	97	94	100	2	7
2.	AB–CD	92	91	93	2	7
3.	AB–CDE	79.20	67.33	97	2	7

ANFIS classifiers using EWD and EFD-based entropy approaches achieved 96.50% and 91.50% accuracy in the classifications of healthy segments with open eyes or not (set AB) and epileptic seizure-free segments (set CD), and 96.80% and 94.40% in the classification of healthy segments with open eyes or not (set AB) and epileptic seizure-free and epileptic seizure segments (set CDE), respectively. On the other hand, the success of the same classification implemented without any discretization was 92% and 79.20% for these experiments, respectively. Moreover, as seen in Tables 9–11, the experiment of A–E classification is much easier than the others, but the experiments of AB–CD and AB–CDE classifications are very difficult. Therefore, K values are much bigger, and the numbers of rules are much higher than the others for these experiments. The classification accuracy of experiment of AB–CDE is a little better than the experiment of AB–CD classification, although the classification of AB–CDE is intuitively more difficult than the classification of AB–CD. Figures 8 and 9 show the ROC curves of the implemented experiments.

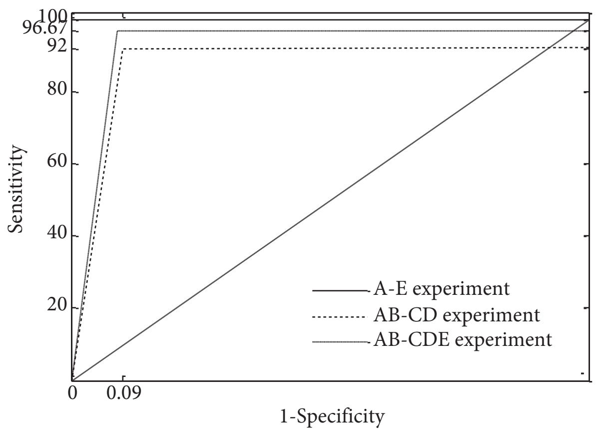

Figure 8. The ROC analysis of the experiments with EWD-based entropy.

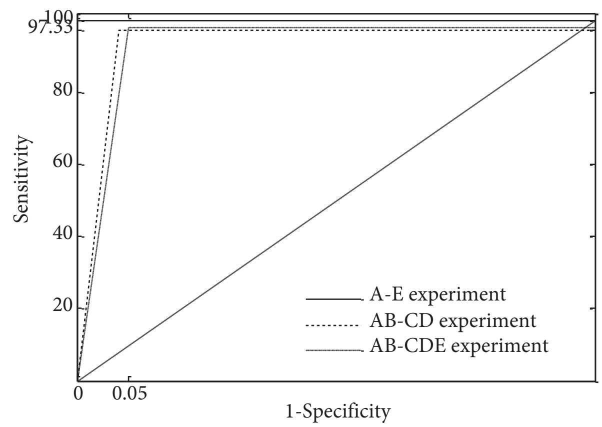

Figure 9. The ROC analysis of the experiments with EFD-based entropy.

As seen in Figures 8 and 9, according to the ROC analysis, both EWD- and EFD-based approaches showed 100% success in the detection of epileptic seizures. As a result, these approaches can be considered a capable tool in order to detect epileptic seizures from EEG signals. The large areas under the ROC curves demonstrate that the classifiers have high specificity and sensitivity. These results confirm the experimental results given in Tables 9 and 10. In conclusion, these results show that the EWD- and EFD-based approaches provide the highest TCC accuracy in the detection of healthy EEG segments and epileptic seizure EEG segments. However, as a result of this study, the EWD-based approach achieves slightly higher classification accuracy rates than the EFD-based approach.

In order to see the ANFIS classifier, all experiments were re-implemented using a multilayer perceptron neural network (MLPNN) classifier, which is well known as an ANN model instead of an ANFIS classifier. The used MLPNN classifiers had one hidden layer of 20 hidden neurons, its activation function was selected as hyperbolic tangent function, and it was trained by the most widely used Levenberg–Marquardt back-propagation algorithm in all experiments. The successes of the ANFIS classifiers with EWD-based entropy approaches were 100%, 96.50%, and 96.80% for A–E, AB–CD, and AB–CDE experiments, while the successes of MLPNN classifiers were 98%, 96%, and 92.80% for the same experiments, respectively. The ANFIS classifiers with EFD-based entropy approaches achieved successes of 100%, 91.50%, and 94.80% in those experiments. In conclusion, these results show that our approaches achieved high TCC accuracies for both classifiers of ANFIS and MLPNN.

4. Conclusions

This paper proposes an ANFIS classifier with the discretization-based entropy approach in order to classify EEG signals, which plays a significant role in dealing with the detection of epileptic seizures and the diagnosis of epilepsy from EEG signals. To this end, EEG signals were decomposed into frequency subbands using the DWT, each subband was discretized into the desired number of intervals using the EWD and EFD methods, the entropy value of each discretized subband was calculated using the Shannon entropy method, and the obtained entropy values were used as the input of the ANFIS classifiers. Three different classification experiments were implemented by using the ANFIS classifiers to evaluate the efficiency of EWD and EFD approaches in the classifications of sets A and E, sets AB and CD, and finally sets AB and CDE. The obtained results were satisfactory in terms of classification accuracies for all experiments. However, the proposed approaches provided the highest TCC accuracy in the detection of healthy EEG segments and epileptic seizure EEG segments. As another result of the study, the EWD-based approach achieved higher classification accuracies rates than the EFD-based approach.

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