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Short Communication

EEG signals classification using the *K*-means clustering and a multilayer perceptron neural network model

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ABSTRACT

We introduced a multilayer perceptron neural network (MLPNN) based classification model as a diagnostic decision support mechanism in the epilepsy treatment. EEG signals were decomposed into frequency sub-bands using discrete wavelet transform (DWT). The wavelet coefficients were clustered using the *K*-means algorithm for each frequency sub-band. The probability distributions were computed according to distribution of wavelet coefficients to the clusters, and then used as inputs to the MLPNN model. We conducted five different experiments to evaluate the performance of the proposed model in the classifications of different mixtures of healthy segments, epileptic seizure free segments and epileptic seizure segments. We showed that the proposed model resulted in satisfactory classification accuracy rates.

1. Introduction

Epilepsy is a critical neurological disease stemming from temporary abnormal discharges of the brain electrical activity, leading to uncontrollable movements and tremblings. About 1% of the world population suffers from epilepsy (Adeli, Zhou, & Dadmehr, 2003). Therefore, the diagnosis of epilepsy allows the choice of medicine or surgical treatment (Ogulata, Sahin, & Erol, 2009). Since the electroencephalogram (EEG) records show the brain electrical activities, they can provide valuable insight into disorders of the brain activity. In this context, the EEG recordings measured in seizure-free intervals from the epilepsy patients are considered as important components for the diagnosis or prediction process (Adeli et al., 2003; Subasi, 2005a, 2007). Although the occurrence of epileptic seizures seems unpredictable (Subasi, 2007), more efforts are focused on the development of computational models for automatic detection of epileptic discharges, which then can be used to predict the onset of seizure (Adeli et al., 2003).

Artificial neural networks (ANNs) have been widely used in many biomedical signal analysis because they not only model the signal, but also make a decision to classify the signal (Subasi, 2007). Therefore, they provide an important support for the medical diagnostic decision. In a classification system with ANN, first step is related to the feature extraction from the raw data with minimal loss of important information by using numerous different methods such as frequency domain features, time-frequency features, wavelet transform (WT), leading to the extracted feature vectors (Hazarika, Chen, Tsoi, & Sergejew, 1997; Ubeyli, 2009a, 2009b). In the second step, some statistics over the vectors are used to reduce the dimensionality of these vectors. Final step is to apply the feature vectors as inputs to ANNs (Subasi, 2007; Ubeyli, 2009a, 2009b). Both the architecture of the ANN and the training algorithm play key roles to obtain satisfactory results from ANNs (Ubeyli, 2009b).

In order to analyze the EEG signals, ANN models with different architectures have been used such as multilayer perceptron neural network (MLPNN) (Alkan, Koklukaya, & Subasi, 2005; Subasi, 2005a, 2005b, 2007; Subasi & Ercelebi, 2005; Ubeyli, 2009), adaptive neuro-fuzzy inference system (ANFIS) (Guler & Ubeyli, 2005), radial basis function neural network (RBFNN) (Aslan, Bozdemir, Sahin, Ogulata, & Erol, 2008), recurrent neural network (RNN) (Petrosian, Prokhorov, Homan, Dashei, & Wunsch, 2000; Srinivasan, Eswaran, & Sriraam, 2005), learning quantization vector (LVQ) (Pradhan, Sadasivan, & Arunodaya, 1996), support vector machine (SVM) (Ubeyli, 2008) and mixture of experts (ME) model (Subasi, 2007). We recently proposed the probability distribution approach based on equal frequency discretization for the epileptic seizure detection (Orhan, Hekim, & Ozer, 2011). Most of these studies focus on the epilepsy by using the statistical features obtained from the sub-bands of EEG signals to analyze the epileptic activities.

In order to extract associative features from EEG signals without any prior information, the signals can be grouped by a clustering algorithm. *K*-means is a well known clustering algorithm which requires no prior information about the associations of data points with clusters (Faraoun & Boukelif, 2007; Hekim & Orhan, 2011; Mwasiagi, Wang, & Huang, 2009; Orhan & Hekim, 2007; Orhan, Hekim, & Ibrikci, 2008; Ross, 2004). *K*-means algorithm groups

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the data points into K clusters according to the distance measure. But a literature survey leaves us with the impression that the K-means clustering algorithm has not been investigated in any detail related to the estimation of the MLPNN accuracy in the analysis of EEG signals. Therefore, our purpose in this paper is to investigate the impact of the K-means clustering algorithm on the MLPNN accuracy for the detection of epileptic events. For this aim, EEG signals are decomposed into sub-bands through the discrete wavelet transform (DWT). The wavelet coefficients are clustered by using K-means algorithm for each sub-band. The probability distributions are computed according to distribution of wavelet coefficients to the clusters, and then these distributions are used as inputs to MLPNN model (Fig. 1).

2. Material and methods

2.1. Data selection

We used the publicly available data in Andrzejak et al. (2001). The complete data consists of five sets (A, B, C, D, and E), each one containing 100 single-channel EEG segments of 23.6 s duration. The sets were selected from EEG records after purifying artifacts caused by eye and muscle movements. Sets A (eyes open) and B (eyes closed) were extracranially taken from five healthy subjects. Sets C, D, and E were intracranially taken from five epilepsy patients. While sets D and C contained the EEG activity measured in seizure-free intervals from epileptic hemisphere and the opposite hemisphere of the brain, respectively, set E only contained the seizure activity. In this study, we used all dataset (A, B, C, D and E) and conducted five different classifications. Sample EEG segments taken from sets A, B, C, D, and E are illustrated in Fig. 2.

2.2. Discrete wavelet transform

Discrete wavelet transform (DWT) is a spectral analysis technique used for analyzing non-stationary signals, and provides time-frequency representation of the signals. Since EEG signal contains non-stationary characteristics, DWT have been widely used for analyzing EEG signals (Adeli et al., 2003; Akay, 1997; Hazarika et al., 1997; Kiymik, Akin, & Subasi, 2004; Ocak, 2008, 2009; Soltani, 2002; Subasi, 2005a, 2005b, 2007; Ubeyli, 2009). DWT uses long time windows at low frequencies and short time windows at high frequencies, leading to good time–frequency localization.

DWT decomposes a signal into a set of sub-bands through consecutive high-pass and low-pass filtering of the time domain signal, f as shown in Fig. 3 (Subasi, 2007; Ubeyli; 2009a). The high-pass filter, g is the discrete mother wavelet while the low-pass filter, h is its mirror version (Ubeyli, 2009a). The down-sampled signals through first filters are called first level approximation, A1 and detail coefficients, D1. Then, approximation and detail coefficients of next level are obtained by using the approximation coefficient of the previous level. The number of decomposition levels is determined depending on the dominant frequency components of the signals (Adeli et al., 2003; Akay, 1997; Ocak, 2008; Soltani, 2002; Subasi, 2007).

Scaling function, $\phi_{j,k}(x)$ based on low pass filter and wavelet function, $\psi_{j,k}(x)$ based on high pass filter are defined as

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

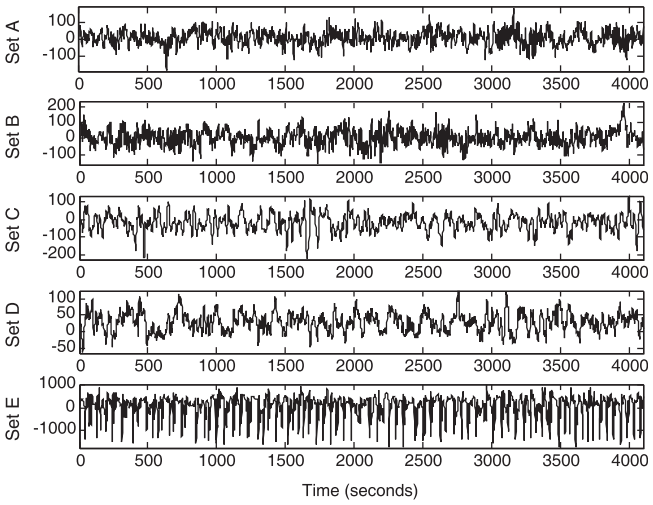

Fig. 2. Sample EEG segments from sets A, B, C, D, and E.

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

where $x = 0, 1, 2, \ldots, M-1$, $j = 0, 1, 2, \ldots, J-1$, $k = 0, 1, 2, \ldots, 2^j - 1$, J equals to $log_2(M)$ and M is the length of the signal and chosen as 2^J (Gonzalez & Woods, 2002).

Sampling rate k and the resolution j specify the positions and the widths on the x-axis of functions, respectively. The heights (or amplitudes) of functions depend on $2^{j/2}$ value (Gonzalez & Woods, 2002). Approximation coefficients $A_i(k)$ and detail coefficients $D_i(k)$ in ith level are described as

$$A_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x) \cdot \varphi_{j,k}(x) \right\} \text{ and } D_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x) \cdot \psi_{j,k}(x) \right\} \quad \text{for } k = 0, 1, 2, \ldots, 2^j - 1 \tag{3}$$

Because the length of EEG segments, M equals to 4097, if J is computed by $log_2(M)$, it is found as 12. Thus, the maximal value of decomposition level L is 11. Figs. 4–6 show approximate and detailed coefficients of EEG segments taken from the healthy subject with open eyes (set A), the epileptogenic zone (set D) and epileptic patient (set E), respectively.

2.3. The probability distributions using K-means clustering

Wavelet coefficients were obtained for each segment by decomposing the EEG signals into sub-bands using the DWT, resulting in the extracted feature vectors. Some basic statistics over the vectors are used to reduce the dimensionality of these vectors, such as average power, mean, entropy and standard deviation of the wavelet coefficients in each sub-band (Ocak, 2009; Subasi, 2007; Ubeyli, 2009a, 2009b). In this study, instead of using basic statistics, we used the clustering approach for the wavelet coefficients in each sub-band by using K-means algorithm. The probability distributions are computed according to distribution of wavelet coefficients to the clusters.

A clustering method divides a dataset into groups according to similarities or dissimilarities among the patterns. K-means algorithm is one of the simplest and well known clustering algorithms

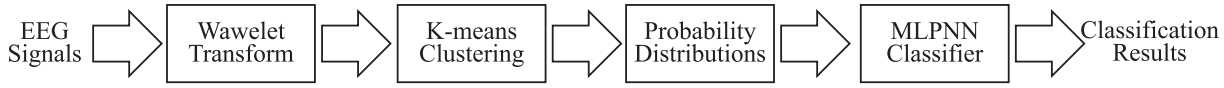

Fig. 1. Schematic illustration of the proposed method.

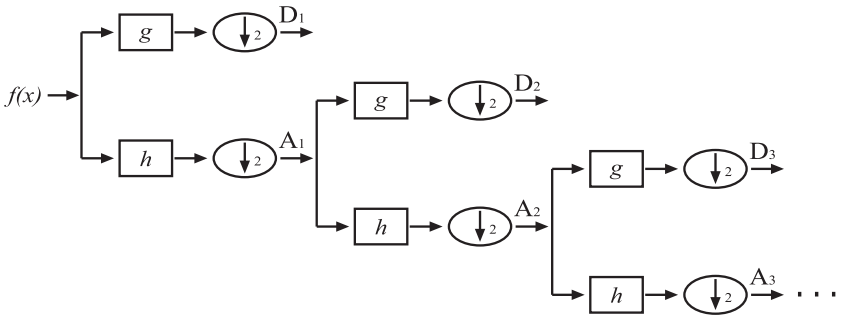

Fig. 3. Sub-band decomposition of a signal by using DWT.

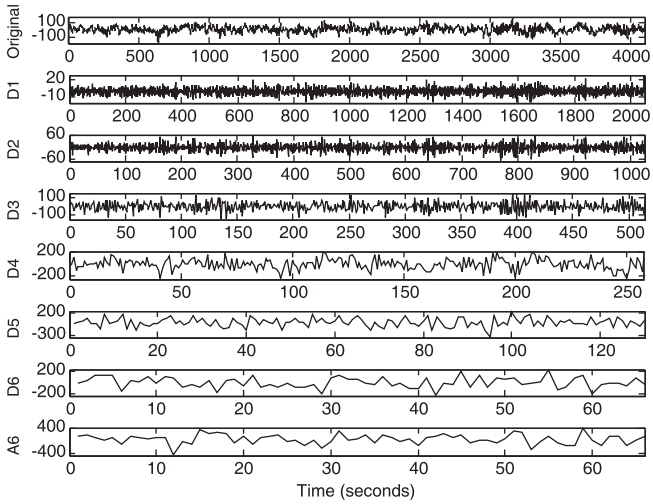

Fig. 4. Approximate and detailed coefficients of a sample EEG segment taken from healthy subject with open eyes (set A).

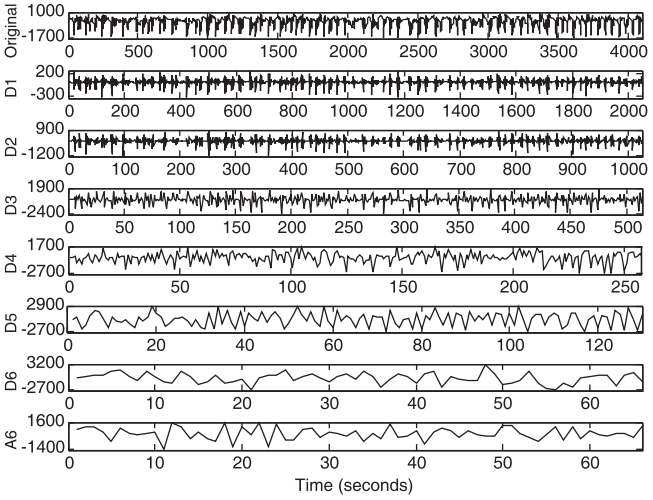

Fig. 6. Approximate and detailed coefficients of a sample EEG segment taken from epilepsy patients during seizure activity (set E).

(Hekim & Orhan, 2007; Ross, 2004; Faraoun & Boukelif, 2007; Mwasiagi et al., 2009; Orhan & Hekim, 2007; Orhan et al., 2008). This algorithm determines the cluster centers and the elements belonging to them by minimizing the squared error based objective function. The aim of the algorithm is to locate the cluster centers as much as possible far away from each other and to associate each data point to the nearest cluster center. Euclidean distance is usually used as the dissimilarity measure in *K*-means algorithm. The objective function *J* is described as follows:

$$J = \sum_{i=1}^{K} \left(\sum_{k} \|x_k - c_i\|^2 \right) \tag{4}$$

where K is the number of clusters, c_i is the centers of clusters, and x_k is kth data point in ith cluster. A data point belongs to a cluster whose center is the closest to that data point. Thus, the clusters are represented by binary membership matrix U. The elements of matrix U are determined as follows:

$$u_{ij} = \begin{cases} 1 & \text{if } \|x_j - c_i\|^2 \leqslant \|x_j - c_t\|^2, \ \forall t \neq i \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where u_{ij} shows that jth data point belongs to ith cluster, or not. Each cluster center c_i minimizing the objective function J is defined as follows:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij} x_j}{\sum_{j=1}^{N} u_{ij}} \tag{6}$$

where N is the number of data points. The algorithm is composed of the following steps (Orhan et al., 2008):

1. Select K data points as the cluster centers for initialization.
2. Compute the membership matrix U according to Eq. (5).
3. Calculate the objective function J according to Eq. (4).
4. Update the positions of the cluster centers according to Eq. (6).
5. Go to Step 2 until the cluster centers no longer move.

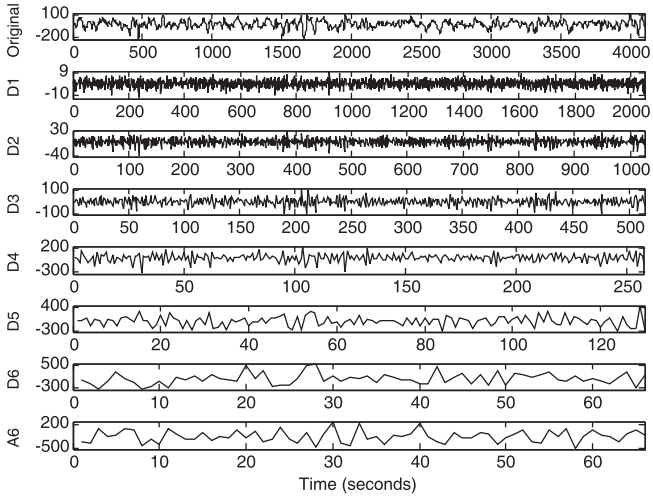

Fig. 5. Approximate and detailed coefficients of a sample EEG segment taken from the epileptogenic zone of epilepsy patient during seizure-free interval (set D).

After clustering the wavelet coefficients of each sub-band of EEG signals by *K*-means algorithm, the probability of belonging of wavelet coefficients to *i*th cluster for each sub-band of *j*th EEG segment is calculated as follows:

$$P_{ij} = \frac{|S_{ij}|}{|S_j|}, \quad i = 1, \ldots, K \text{ and } j = 1, \ldots, n \tag{7}$$

where, $|S_{ij}|$ is the number of wavelet coefficients of *j*th EEG segment belonging to *i*th cluster, $|S_j|$ is the number of wavelet coefficients of *j*th EEG segment, and *n* is the number of EEG segments. Fig. 7 shows the probability distributions according to the clusters of sub-bands of two EEG segments taken from ABCD class, and E class for $L = 2$ and $K = 6$.

2.4. Multilayer perceptron neural network (MLPNN)

Multilayer perceptron neural networks (MLPNNs) are the most commonly used feedforward neural networks due to their fast operation, ease of implementation, and smaller training set requirements (Kocyigit, Alkan, & Erol, 2008; Subasi, 2007; Ubeyli 2009a). The MLPNN consists of three sequential layers: input, hidden and output layers (Fig. 8). The hidden layer processes and transmits the input information to the output layer. A MLPNN model with insufficient or excessive number of neurons in the hidden layer most likely causes the problems of bad generalization and overfitting. There is no analytical method for determining the number of neurons in the hidden layer. Therefore, it is only found by trial and error (Hazarika et al., 1997; Ogulata et al., 2009; Subasi & Ercelebi, 2005; Haykin, 2008). In the study, we used a MLPNN model with single hidden layer of 5 hidden neurons.

Each neuron *j* in the hidden layer sums its input signals x_i impinging onto it after multiplying them by their respective connection weights w_{ji}. The output of each neuron is described as follows:

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{8}$$

where *f* is an activation function using the weighted summations of the inputs. An activation function can be a simple threshold, sigmoid, or hyperbolic tangent function (Hazarika et al., 1997; Ogulata et al., 2009; Subasi & Ercelebi, 2005). In this study, a hyperbolic tangent function was used as the activation function.

The sum of squared differences between the desired and actual values of the output neurons *E* is defined as follows (Subasi, 2007; Ubeyli, 2009a):

$$E = \frac{1}{2} \sum_j (y_{dj} - y_j)^2 \tag{9}$$

where y_{dj} is the desired value of output neuron *j* and y_j is the actual output of that neuron. Each w_{ji} weight is adjusted to minimize the value *E* depending on the training algorithm adopted (Basheer & Hajmeer, 2000; Haykin, 2008; Subasi, 2007; Ubeyli, 2009a). In this context, the backpropagation algorithm is widely used as a primary part of an ANN model. However, since the backpropagation has some constraints such as slow convergence (Ubeyli, 2009a) or not be able to find the global minimum of the error function (Subasi, 2007), a number of variations for the backpropagation were proposed. Therefore, in this study we used the backpropagation supported by the Levenberg–Marquardt (LM) algorithm (Hazarika et al., 1997; Ogulata et al., 2009; Subasi and Ercelebi, 2005).

3. Results and discussion

EEG signals were decomposed into sub-bands by using the DWT with Daubechies wavelet of order 2 (db2) because it yields good

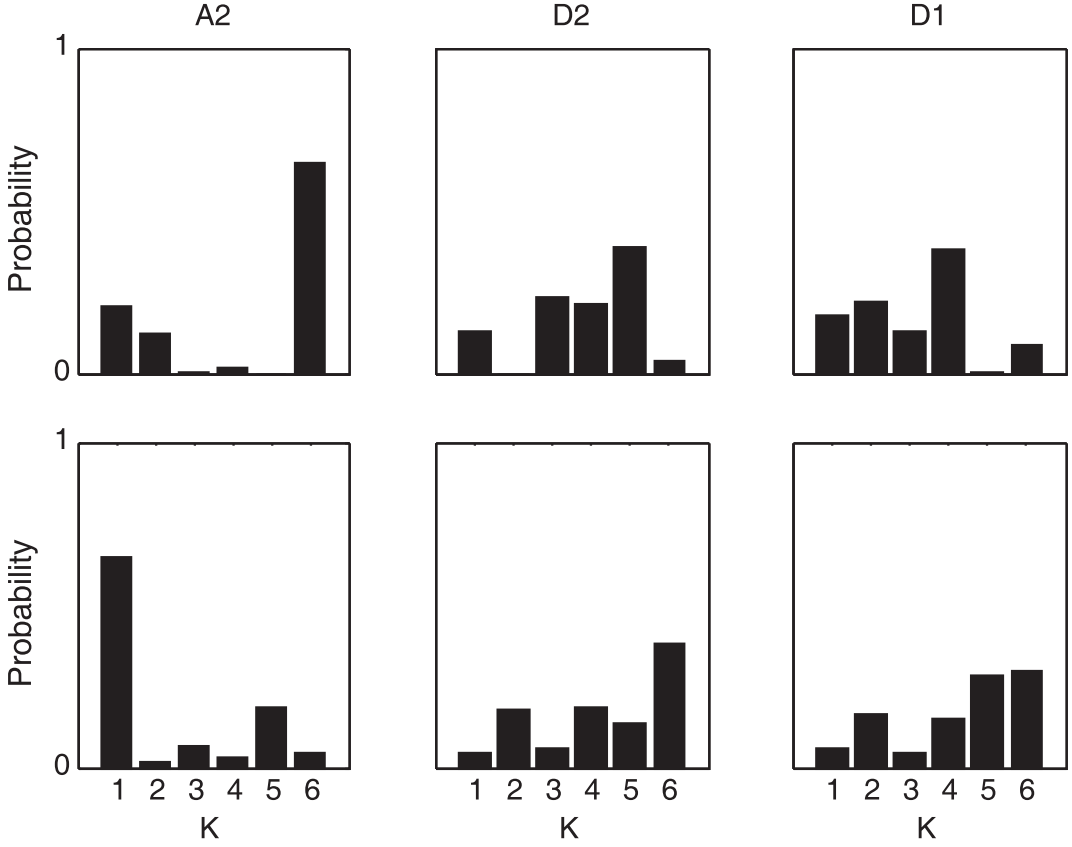

Fig. 7. The probability distributions of sub-bands of two EEG segments taken from ABCD class (top panel), and E class (bottom panel).

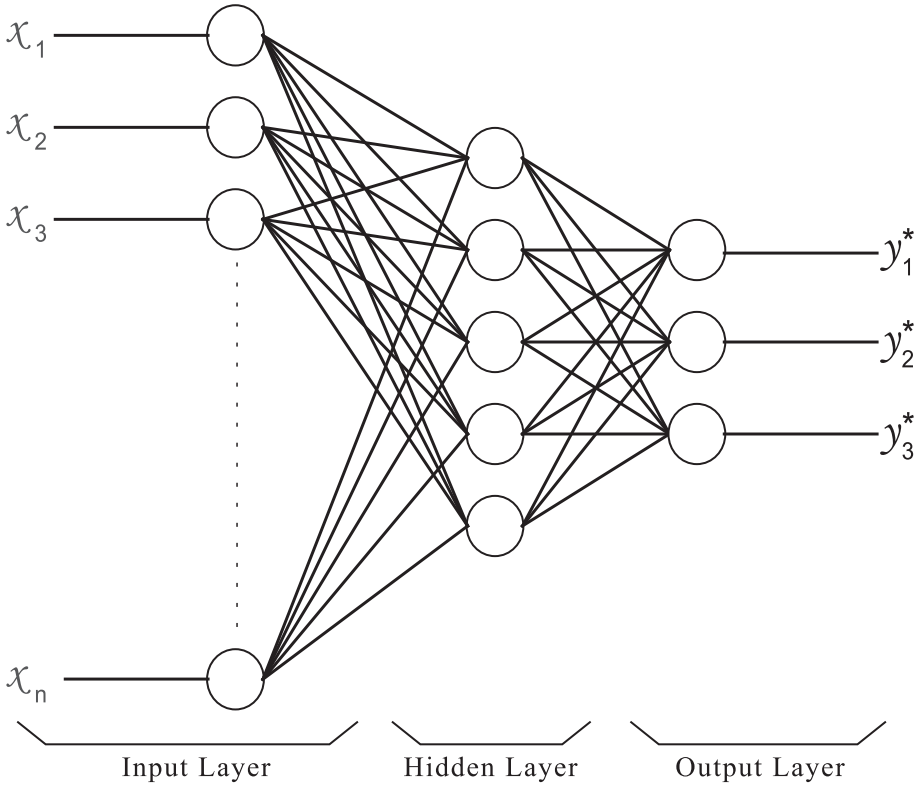

Fig. 8. The structure of the MLPNN model used in the study.

results in classification of the EEG segments (Ubeyli, 2009a). Wavelet coefficients obtained from EEG segments with 4097 samples were clustered by *K*-means algorithm, and then the probability distributions of each sub-band for EEG segments were computed. These probability distributions were used as inputs to the MLPNN model. Five different experiments were implemented by the MLPNN model. Each experiment was repeated 5000 times for different values of *L* and *K*, and then, the ones providing the highest total correct classification ratio were selected for the model. In order to prevent the model from the overfitting, repeated random sub-sampling cross validation was used. This validation method randomly selects data points for the sets of training, test and validation. The model was trained by the training data. Predictive accuracy of the model was calculated by using the validation data. When predictive accuracy started decreasing, the training was stopped because of reaching to the best general solution. Total classification accuracy was computed by using the test data. We used the following statistical measures to evaluate the performance of the classification (Kocyigit et al., 2008; Subasi, 2007; Ubeyli, 2009a, 2009b):

Specificity: number of true negative decisions (TN)/number of actually negative cases (TN + FP);
Sensitivity: number of true positive decisions (TP)/number of actually positive cases (TP+FN);
Total classification accuracy: number of correct decisions (TN + TP)/number of cases (TN + FN + TP + FP).

Table 1
The confusion matrix for the Experiment 1.

Class	ABCD	E
ABCD	199	1
E	0	50

Table 2
The confusion matrix for the Experiment 2.

Class	A	E
A	50	0
E	0	50

Table 3
The confusion matrix for the Experiment 3.

Class	AB	CDE
AB	99	1
CDE	2	148

Table 4
The confusion matrix for the Experiment 4.

Class	AB	CD	E
AB	97	2	1
CD	3	94	3
E	1	1	48

Table 5
The confusion matrix for the Experiment 5.

Class	A	D	E
A	48	1	1
D	1	48	1
E	0	1	49

Table 6
The classification results for five different experiments.

Experiment type	Total classification accuracy (%)	Specificity (%)	Sensitivity (%)	*L*	*K*	The number of inputs
1. ABCD-E	99.60	98.04	100	2	6	18
2. A-E	100	100	100	1	2	4
3. AB-CDE	98.80	99.33	98.02	6	8	56
4. AB-CD-E	95.60	97.93	92.38	6	8	56
		96.03	94.95			
		98.96	84.21			
5. A-D-E	96.67	97.98	94.12	6	8	56
		97.98	94.12			
		98.97	92.45			

In what follows, we provide the details and the classification accuracies of five different experiments.

Experiment 1: The aim of this experiment is the diagnosis of epileptic seizure. For the test set, 200 vectors from ABCD class (healthy subjects and epilepsy patients in seizure-free intervals) and 50 vectors from E class (epilepsy patients with epileptic seizure) were used for the classification. Table 1 shows the confusion matrix of the classification. The classifier misclassified only one case as shown in Table 1.

Experiment 2: The aim of this experiment is the diagnosis of epileptic seizure. For the test set, 50 vectors from A class (healthy subjects with eyes open) and 50 vectors from E class (epilepsy patients with epileptic seizure) were used for the classification. Table 2 shows the confusion matrix of the classification. There is no any misclassification as shown in Table 2.

Experiment 3: The aim of this experiment is the diagnosis of epilepsy. For the test set, 100 vectors from AB class (healthy subjects) and 150 vectors from CDE class (all epilepsy patients) were used for the classification. Table 3 shows the confusion matrix of the classification. The classifier misclassified only three cases as shown in Table 3.

Experiment 4: The aim of this experiment is the classification of AB, CD and E sets. For the test set, 100 vectors from AB class (healthy subjects) 100 vectors from CD class (epilepsy patients in seizure-free intervals) and 50 vectors from E class (epilepsy patients with epileptic seizure) were used for the classification. Table 4 shows the confusion matrix of the classification. According to the confusion matrix, three healthy subjects were classified incorrectly as an epileptic patient, whereas four epileptic patients were classified as a normal subject. In addition, three epilepsy patients in seizure-free intervals were classified as epilepsy patients with epileptic seizure, whereas only one epilepsy patient with epileptic seizure was classified as an epilepsy patient in seizure-free intervals.

Experiment 5: The aim of this experiment is the classification of A, D and E sets. For the test set, 50 vectors from A class (healthy subjects with open eyes) 50 vectors from D class (epilepsy patients in seizure-free intervals measured from the epileptic hemispheres of brains) and 50 vectors from E class (epilepsy patients with epileptic seizure) were used for the classification. Table 5 shows the confusion matrix of the classification. According to the confusion matrix, 2 healthy subjects were classified incorrectly as an epileptic patient, whereas only one epileptic patient was classified as a normal subject. In addition, one epilepsy patient in seizure-free intervals measured from the epileptic hemispheres of brain was classified as an epilepsy patient with epileptic seizure, and vice versa.

The classification statistics, decomposition level (*L*), the number of clusters (*K*), and the number of the inputs used for five different experiments of the MLPNN model are given in Table 6. As seen in Table 6, the proposed model classified healthy segments and epileptic seizure segments with the accuracy of 100%. Subasi (2007) found that ME and MLPNN models classified healthy segments and epileptic seizure segments with the accuracy of 94.5% and 93.2%, respectively. Kocyigit et al. (2008) classified healthy segments and epileptic seizure segments with the sensitivity of 98% and the specificity of 90.5% with a MLPNN classifier based on the independent component analysis. On the other hand, our model also classified 'healthy and seizure free' segments and epileptic seizure segments with the accuracy of 99.6% while it classified healthy segments and 'epileptic seizure free and epileptic seizure' segments with the accuracy of 98.8%. Our results together with those indicate that our model provides the highest accuracy in the classification of healthy segments and epileptic seizure segments.

We also provided detailed classifications of healthy segments, epileptic seizure free segments and epileptic seizure segments. The proposed model classified healthy segments with open eyes, seizure free epileptogenic zone segments and epileptic seizure segments with the accuracy of 96.67%, whereas Ubeyli (2009a) found that the combined neural network and the stand-alone MLPNN network performed that classification with the accuracy of 94.83% and 84.83%, respectively. Our model also classified healthy segments, seizure free segments and epileptic seizure segments with the accuracy of 95.60%.

4. Conclusion

In this study, we used a MLPNN-based classification model to classify EEG signals. EEG signals were decomposed into sub-bands through the DWT. Instead of using basic statistics over the wavelet coefficients, we used the clustering approach for the wavelet coefficients in each sub-band by using K-means algorithm. The probability distributions were computed according to distribution of wavelet coefficients to the clusters, and then these distributions were used as inputs to MLPNN model. We performed five different experiments to obtain the performance of the proposed model in the classifications of healthy segments and epileptic seizure segments, 'healthy and seizure free' segments and epileptic seizure segments, healthy segments and 'epileptic seizure free and epileptic seizure' segments, and finally healthy segments, epileptic seizure free segments and epileptic seizure segments. We showed that the proposed model resulted in satisfactory classification accuracies. Therefore, we suggest that it can be used as a diagnostic decision support mechanism in the epilepsy treatment.

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