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ORIGINAL PAPER

A Radial Basis Function Neural Network Model for Classification of Epilepsy Using EEG Signals

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Abstract Epilepsy is a disorder of cortical excitability and still an important medical problem. The correct diagnosis of a patient's epilepsy syndrome clarifies the choice of drug treatment and also allows an accurate assessment of prognosis in many cases. The aim of this study is to evaluate epileptic patients and classify epilepsy groups such as partial and primary generalized epilepsy by using Radial Basis Function Neural Network (RBFNN) and Multilayer Perceptron Neural Network (MLPNNs). Four hundred eighteen patients with epilepsy diagnoses according to International League against Epilepsy (ILAE 1981) were included in this study. The correct classification of this data was performed by two expert neurologists before they were executed by neural networks. The neural networks were trained by the parameters obtained from the EEG signals and clinic properties of the patients. Experimental results show that the predictions of both neural network models are very satisfying for learning data sets. According to test results, RBFNN (total classification accuracy=95.2%) has classified more successfully when compared with MLPNN (total classification accuracy=89.2%). These results indicate that RBFNN model may be used in clinical studies as a decision support tool to confirm the classification of epilepsy groups after the model is developed.

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Introduction

Epilepsy is a disorder of cortical excitability and interictal electroencephalography (EEG) remains the most convenient and the least expensive way to demonstrate physiological manifestations of this disorder [1–3].

Epilepsy is classified as either generalized or partial with several subcategories in each class. In the management of patients with established epilepsy, the concept of epilepsy syndrome is based on age at onset, seizure type or types, EEG findings and etiology has been an important advancement [4]. The correct diagnosis of a patient's epilepsy syndrome clarifies the choice of drug treatment and also allows an accurate assessment of prognosis in many cases [3–5].

About 50% of the patients with epilepsy show interictal epileptiform discharge on EEG. Epileptiform activity is specific, but not sensitive for diagnosis of epilepsy as a cause of transient loss of consciousness or other paroxysmal event that is clinically likely to be epilepsy [1, 3, 6].

Artificial neural networks (ANNs) have been used extensively in many different problems in medicine [7–11]. ANNs have also been used for the detection of seizure activity [12–14]. The results of these studies on detection of seizure events in EEGs of epileptic patients showed that ANNs are capable of capturing qualitative information from an EEG with over 90% accuracy. Additionally, Walczak and Nowack [15] reported that ANNs were used for the diagnosis of epilepsy firstly. However, they did not obtain high categorization accuracy. Some authors also applied neural network and statistical recognition methods to EEG analysis [16–19]. Their results confirmed that the proposed models have potential in classifying the EEG signals.

Recently Radial Basis Function Neural Networks (RBFNNs) have been found to be very attractive for many problems. An important property of the RBFNNs is that they form a unifying link among many different research fields such as function approximation, regularization, noisy interpolation, pattern recognition, and medicine. The increasing popularity of the RBFNNs is partly due to their simple topological structure, their locally tuned neurons, and their ability to have a fast learning algorithm in comparison with other multilayer feed forward neural networks.

In this study, we both categorized the EEG findings and combined the clinic properties of the patients along with these EEG findings. We tested to what extent we could determine the epilepsy classification of the patients with the method of ANN using RBFNN and Multilayer Perceptron Neural Network (MLPNN) approaches.

Materials and methods

Collection and processing of data

Five hundred seventy-nine patients with epilepsy diagnoses according to International League against Epilepsy (ILAE 1981) are included in this study. The patients at the clinic of epilepsy outpatients of Cukurova University Medical School, Neurology Department between the years of 2002 and 2005 were examined and included in the study. The epilepsy diagnosis was based on the medical history, clinical findings, electrophysiological reports, radiological and biochemical analysis.

This study considers the categorization of sex, age of seizure onset groups, seizure types, the loss of consciousness in the course of seizure time and the properties of the first interictal EEG analysis of epileptic patients. In the classification belonging to age of seizure onset: the patients between 0 and 20 year olds were classified as group 1, between 21 and 60 year olds were classified as group 2, and 61 and over year olds were classified as group 3. The EEG records were detected by 12 channel Nihon-Kohden EEG machine. Each EEG record was done for 20 min, but the EEG of the activated sleep was recorded for 2 h. The patients who had pseudo seizures and EEG from out of our electrophysiology laboratory were excluded from the study. Eventually, we reevaluated 418 patients with their first EEGs and clinical properties. All the EEGs examined in this study were recorded after postictal period of seizure.

EEG signals contain a wide range of frequency components; this range is classified approximately in a number of frequency bands as follows: δ (0.5–4 Hz), (4–8 Hz), α (8–13 Hz), β (13–30 Hz). The δ, waves were accepted as abnormal activities, whereas α, β waves were accepted as normal. On the other hand, sharp, sharp and wave, spike, spike and wave activities were accepted as abnormal signals as well. While the frequency component of delta and theta activities as stated above is a limited application, the frequency of the other abnormal activities is not limited [20]. Two experienced neurologists in the clinical analysis of EEG signals inspected each record separately in the study to categorize signals. The EEGs of every patient were evaluated by using visual methods. The activity properties of EEG findings were classified in the direction of group 1: sharp and/or spikes; group 2: delta and/or theta, group 3: normal. During EEG, the physiological conditions of the patients were determined as either awake or sleep and the properties of rhythmicity of the abnormal activities were categorized as yes or no. The localization of abnormal activities was categorized; either they are focal (frontal, temporal, parietal, occipital or in more fields than one) or generalized or normal. On the other hand, abnormal activities were categorized from the point of hemispheric lateralization as right, left, diffuse and normal. We determined the frequency of abnormal waves (how many times a second these activities have been repeated), and duration of the abnormal signals (how long abnormal signals take during the EEG recording) on the EEG. On the other hand we checked the parameter of whether the loss of consciousness in the course of seizure time was being identified (yes/no/sometimes reported but not in all seizure).

MLPNN approach

The architecture of MLPNN may contain two or more layers. Each layer consists of units which receive their input from a layer directly below and send their output to units in a layer directly above the unit. The input node activation values x_i are multiplied by the strengths of the respective connection weights w_{ji} and summed at each hidden layer node. The weighted sum is then transmitted by an appropriate transfer function into the activation value of the hidden node, which becomes the input to the output layer nodes. The connections between the neurons are arranged by using a “learn” algorithm. There are many training algorithms used to train an MLPNN and a frequently used one is called backpropagation (BP) training algorithm [21–23]. Although the BP algorithm has been a significant milestone in neural network research area of interest, it has been known as an algorithm with a very poor convergence rate. Many attempts have been made to speed up the BP algorithm. A significant improvement on realization performance can be observed by using various second order approaches namely Newton’s method, conjugate gradient’s, or the Levenberg–Marquardt (LM) optimization technique [24–27]. LM can be thought of as a combination of the steepest descent and the Gauss-Newton method. In the last years, the LM method, directly taken from the Optimization field, has been increasing its popularity within the neural networks community. The difference between optimization and neural network applications of the method comes from the fact that in the latter there is usually a great deal of parameters to be estimated [28, 29].

RBFNN approach

Radial basis function networks are also feedforward, but have only one hidden layer. RBFNN is considered as a good candidate for approximation problems because of its faster learning capability compared with other feedforward networks. In traditional RBFNN, the Gaussian function and the least squares (LS) criterion are selected as the activation function of network and the objective function, respectively. A network adjusts iteratively parameters of each node by minimizing the LS criterion according to gradient descent algorithm. Since a neural network can accomplish a highly nonlinear mapping from input space to output space, the approximate curve generated by the network may be able to interpolate all training patterns. Like the more commonly used MLPNN, RBFNN comprises three layers of nodes but with the middle (hidden) layer being made up of Gaussian or asymmetric kernels. A number of kernels are positioned in the input space using one of a number of possible placement algorithms. As in MLP, the inputs to the network are nodes that simply pass each of the input signals to the middle layer kernels. The architecture consists of one hidden and one output layer. This shallow architecture has great advantage in terms of computing speed compared to multiple hidden layer nets [21, 22, 30, 31].

Development of neural networks

A commercial Microsoft Windows based ANN software package was used to set up the MLPNNs in the study. The types of neural network used in the study have been RBFNN and MLPNN. Levenberg–Marquardt has been used as learning rule. In order to carry out classifications, the networks have been trained with training patterns namely input and output parameters.

The input of the neural networks has ten nodes representing parameters, the age of seizure onset groups, sex, the activity properties of EEG findings, the physiological conditions of the patients during EEG, the existence of rhythmicity of the abnormal activities, the localization of abnormal signals, hemispheric lateralization, the frequency of abnormal waves, the duration of the abnormal signals and the loss of consciousness in the course of seizure time. Among these parameters, the duration of the abnormal signals and the frequency of abnormal waves are interval variables while the others are categorical variables. The coding of input parameters was shown in Table 1.

Results

Four hundred eighteen patients who had been diagnosed with epilepsy were included in this study. Two hundred twenty-nine (54.8%) of patients were female and 189 (45.2%) of them were male. According to the age of seizure onset groups, the patients was between 0 and 21 years in 237 patients (56.7%), between 21 and 60 years in 141 patients (33.7%) and older than 61 years in 40 (9.6%) of all patients. The seizures were classified as partial epilepsy in 339 patients (81.9%) and as primary generalized epilepsy in 79 patients (18.9%). The data set was summarized in Table 2.

The learning of the networks are executed by applying the input and output vectors. In this study, the output of the network is the epilepsy groups (partial and primary generalized epilepsy which are coded as 1 and 2, respectively). In using the neural networks, the neural networks were trained with the training set, cross validated with the cross validation set and checked with the test set.

Table 1 Coding of input parameters used in training and testing

Parameter	Value/range	Code
Age of seizure onset groups	0–20	1
	21–60	2
	61-↑	3
Sex	Male	0
	Female	1
Physiological conditions during EEG	Awake	0
	Sleep	1
Existence of rhythmicity of the abnormal activities	Yes	0
	No	1
Localization	Local discharge	1
	Generalize discharge	2
	Normal	3
Hemispheric lateralization	Right	1
	Left	2
	Diffuse	3
	Normal	4
Activity properties of EEG findings	Group 1: Sharp and/or spikes	1
	Group 2: Delta and/or theta	2
	Group3: Normal	3
The loss of consciousness	Yes	0
In the course of seizure time	No	1
	Sometimes reported but not in all seizure	2

Table 2 Demographic and disease properties of the patients

	Number	Percent
Sex		
Female	229	54.8
Male	189	45.2
Total	418	
Age groups		
0–20	237	56.7
21–60	141	33.7
61–↑	40	9.6
Epilepsy groups		
Partial epilepsy	339	81.9
Primary generalized epilepsy	79	18.9

The cross validating stopping rule was used for terminating training in this research. When the error in the cross validation increased, the training was stopped because the point of the best generalization was reached. The MLPNN model for classifying epilepsy groups was developed using the 167 training examples, while the remaining 251 examples were used for testing of the model. For obtaining a better generalization 33 training examples were selected randomly to be used as a cross validation set.

After the training stage of both neural network models, RBFNN has a record of more successful training with less error as shown in Fig. 1 and Table 3. Correlation coefficient of 0.95 for RBFNN indicates that there is a strong correlation between classifications made by the expert neurologists and the neural network classifications.

Prediction performance of a neural network may be evaluated examining the table that is called as confusion matrix. To analyze the output data that is obtained from the application, sensitivity (true positive ratio) and total classification accuracy are calculated by using confusion matrix. Sensitivity for each subgroup is expressed as the ratio of number of correctly classified cases within the subgroup over the total number of cases in that subgroup. Total classification accuracy shows the overall performance of a neural network over all cases. Observed values for these two performance statistics are summarized in Table 4 and 5 for MLPNN and RBFNN, respectively.

The second and third columns of Table 4 represent confusion matrix obtained by MLPNN. According to confusion matrix, nine out of 47 primary generalized epilepsy samples were classified incorrectly by the MLPNN as partial epilepsy and 18 out of 204 partial epilepsy samples were classified as primary generalized epilepsy. The values of the statistical parameters are given in the fourth column of Table 4. The MLPNN classified partial and primary generalized epilepsy with the accuracy of 91.1% and 80.8%, respectively. Furthermore, MLPNN succeeded in classifying the epilepsy groups with the total classification accuracy of 89.2%.

Similarly, the classification success of RBFNN is evaluated in detail by examining the table called the confusion matrix. According to confusion matrix, five out of 47 primary generalized epilepsy samples were classified incorrectly by the RBFNN as partial epilepsy and seven out of 204 partial epilepsy samples were classified as primary generalized epilepsy. The RBFNN classified partial and primary generalized epilepsy with the accuracy of 96.5%

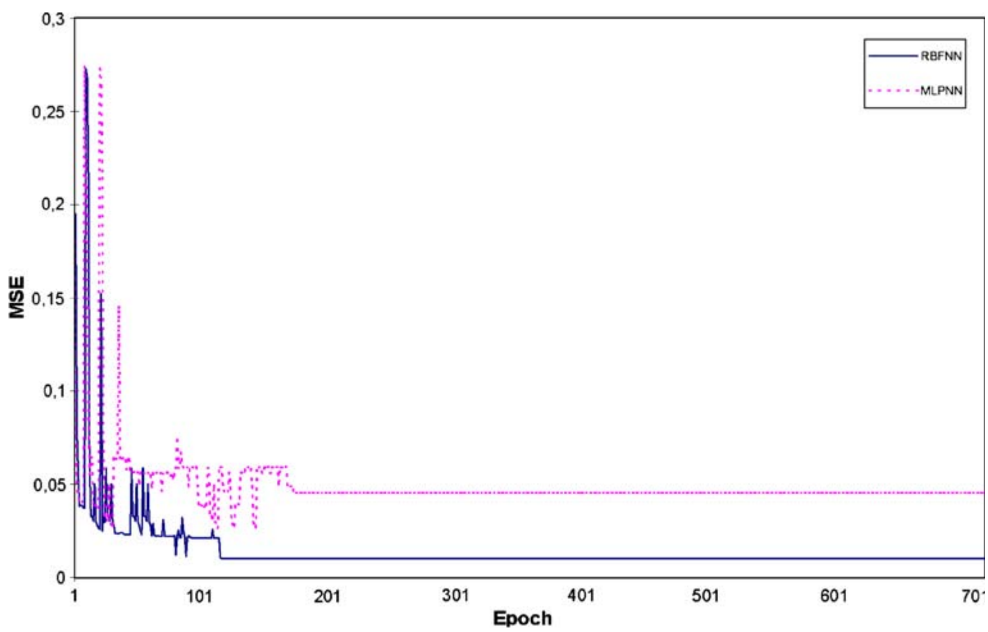

Fig. 1 RBFNN showing a record of more successful training with less error

Table 3 Performance sizes of RBFNN and MLPNN

Performance	RBFNN	MLPNN
MSE	0.015	0.0637
Min. abs. error	0.0023	0.0046
Max. abs. error	0.3562	0.4452
R	0.95	0.92

MSE Mean square error, *R* correlation coefficient

Table 5 Confusion matrix and statistical parameters for epilepsy groups obtained by RBFNN

	Result (PE)	Result (PGE)	Sensitivity (%)
Result (PE)	197	5	96.5%
Result (PGE)	7	42	89.3%
Total	204	47	95.2%

PE Partial epilepsy, *PGE* Primary generalized epilepsy

and 89.3%, respectively. The total classification accuracy for RBFNN (95.2%) is greater than for MLPNN.

Discussion

This study shows that the EEG findings may be classified by using neural networks and the diagnosis of epilepsy. The aim of this classification system is to establish medical diagnosis rapidly.

EEG findings enhance the multi-axial diagnosis of epilepsy in terms of whether the seizure disorder is partial or generalized. As other laboratory tests, it should be used in conjunction with clinical data. However, partial and generalized seizure disorders show some overlap both clinical and EEG manifestation. The conceptual classification of seizures as partial or primary generalized epilepsy is important and clinically useful because the knowledge of an individual patient's epilepsy group allows the assessment of prognosis and the choice of the most effective antiepileptic drug.

On the other hand, EEG has relatively low sensitivity in epilepsy ranging from 25% to 56%. Specificity is better, but it varies between 78 and 98% [3]. As most authors suggest, only interictal epileptiform discharge (IED) are associated with seizure disorder [3, 5, 6].

The category of partial seizures was found as one of the most controversial aspects of the ILAE classification [5]. In this study, we found that seizures were classified as partial epilepsy in 339 (81.9%) of all patients whereas primary generalized epilepsy in 79 (18.9%) of all patients (Table 2). This distribution is not uniform as our epilepsy clinic treats mostly adult patients. The patients who were diagnosed with partial epilepsy were classified as having simple partial for 32 patients (7.7%), complex partial for 179 patients (42.8%), and secondary generalized epilepsy for 128 patients (30.6%). The ratio of secondary generalized epilepsy appears to be very high since symptomatic epilepsy group is as large as other partial epilepsy groups in our epilepsy clinic.

Table 4 Confusion matrix and statistical parameters for epilepsy groups obtained by MLPNN

	Result (PE)	Result (PGE)	Sensitivity (%)
Result (PE)	186	9	91.1
Result (PGE)	18	38	80.8
Total	204	47	89.2

PE Partial epilepsy, *PGE* primary generalized epilepsy

Most of the studies done earlier focused on the epileptic seizure detection and the classification of EEG signals through ANN using some of EEG properties. In this study, the neural network is trained by the parameters obtained from not only the EEG signals, but also the demographic properties of patients and the parameter of the loss of consciousness in the course of seizure. The aim of this study is to classify the epilepsy groups using MLPNN and RBFNN according to these parameters. To achieve this aim, the demographic properties, the loss of consciousness in the course of seizure and the first EEGs of 418 patients were evaluated and applied to neural network as independent variables. Subsequently, the RBFNN and MLPNN were used to classify epilepsy groups. To get better generalization, our data set was divided into three sub-datasets and in using the neural networks, the MLPNN and RBFNN were trained with the training set, cross validated with the cross validation set and checked with the test set. The correct classification of this data that had been classified by expert neurologists before was executed by MLPNN and RBFNN.

According to the statistical parameters and confusion matrix including test data results, the MLPNN succeeded in classifying epilepsy groups with the accuracy of 89.2% (Table 4). On the other hand, the RBFNN classified the groups of epilepsy with the accuracy of 95.2% according to statistical parameters and confusion matrix (Table 5). RBFNN outperforms MLPNN when compared all statistics.

When the confusion matrixes and statistics are examined, the neural network systems have obtained acceptable classification success. The classification performance of both models for epilepsy groups have been found satisfactory and we think that RBFNN model can be used in clinical studies as a decision support tool to confirm the classification of epilepsy groups after the model is developed.

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