Detection of Disease using EEG Signal Based on PSO and NN Classifier

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Abstract - Electroencephalogram (EEG) is used routinely for diagnosis of diseases occurring in the brain. It is a very useful clinical tool in the classification of epileptic seizures and the diagnosis of epilepsy. In this study, epilepsy diagnosis has been investigated using EEG records. For this purpose, an artificial neural network (ANN), widely used and known as an active classification technique, is applied. The particle swarm optimization (PSO) method, which does not need gradient calculation, derivative information, or any solution of differential equations, is preferred as the training algorithm for the ANN. A PSO-based neural network (PSONN) model is diversified according to PSO versions, and 7 PSO-based neural network models are described. Among these models, PSONN3 and PSONN4 are determined to be appropriate models for epilepsy diagnosis due to having the better classification accuracy. The training methods-based PSO versions are compared with the back propagation algorithm, which is a traditional method. In addition, different numbers of neurons, iterations/generations, and swarm sizes have been considered and tried. Results obtained from the models are evaluated, interpreted, and compared with the results of earlier works done with the same dataset in the literature.

Keywords - Artificial neural networks, back propagation algorithm, electroencephalogram, epilepsy diagnosis, particle swarm optimization**.**

I. INTRODUCTION

Epilepsy is a major disease occurring in the brain. Wave forms contained in electroencephalograms (EEGs) recorded during the occurrence of epileptic seizures are similar to wave forms of some other brain disorders. Thus, epilepsy cannot be recognized easily [1]. EEG signals as shown in Figure 1 are not periodic; their phase, amplitude, and frequency change constantly. The changing forms of EEG signals are complex and difficult to interpret and define [2,3]. Therefore, a doctor making a diagnosis should be a good observer and have considerable experience. In recent years, recognition and diagnostic studies of EEG signals using artificial intelligence methods have been studied quite extensively. Artificial neural networks (ANNs), one of the artificial intelligence methods, are widely used in the classification of EEG signals because of their fast response in analyzing many samples of EEG signals in a second [4]. In addition to these methods, heuristic optimization algorithms are used to increase the success and/or the speed of these methods. Particle swarm optimization (PSO) as a heuristic optimization method has been successfully applied to train ANNs. It has been proposed to update network weights because of its easy implementation and realization, the small number of parameters to be set, and capability for treatment with real numbers, not derivative information [5]. The related works in the literature are presented as follows in descending order of the year published.

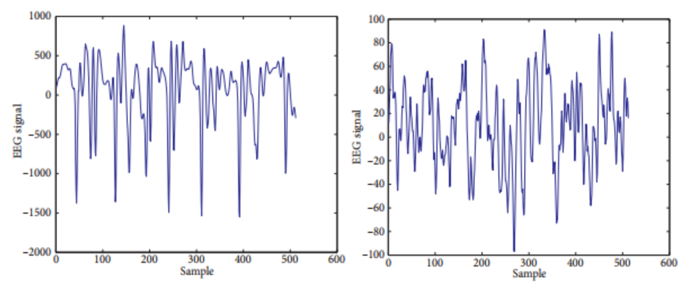


Fig.1 Examples samples a)eleceptic signal b)healthy person signal

This work aimed to diagnose epilepsy from EEG records quickly and accurately using PSO-based ANN models and to determine the best classifier among the PSO-based ANN models. For these purposes, EEG signals received from healthy and epileptic volunteers were normalized and then used to train and test different versions of PSONN models and improve the performance of these models. Following this introductory section, the rest of the paper is organized as follows: in the next section, materials and methods used in this study and the procedures used to train the ANN with the back propagation and PSO algorithms are explained. In Section 3, experimental studies are presented and the performances of the PSONNs and backpropagation neural network (BPNN) are compared. In the final section, the results are summarized and conclusions are drawn

II. RELATED PROBLEMS

EEG dataset EEGs are used for diagnosing diseases occurring in the brain, especially epilepsy. In this study, publicly accessible EEG data, defined in [17], were used. The data consist of 5 sets. Set A and Set B include data received from healthy (nonepileptic) volunteers while their eyes were open and closed, respectively. Activities measured in intervals without seizures are in Set C and Set D, and only epileptic seizure activity is in Set E [15,17]. All EEG signals were recorded with the same 128-channel amplifier system using an average common reference. The data were digitized at 173.61 samples per second using 12-bit resolution. Band-pass filter settings were 0.53 and 40 Hz (12 dB/octave) [15]..

In this work, we have used Set A and Set E. The dataset was prepared with 1600 segments (800 segments for each class, epileptic and healthy) and 512 samples for each segment. The dataset was preprocessed using statistical features, which are the minimum, maximum, mean, and standard deviation of each sample; thus, the number of samples in each segment was reduced to 4. The new dataset was normalized in the range of [0, 1] using Eq. (1):

$$X_s^{norm} = \frac{X_s - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

whereXs is the value of the sth (s = 1, 2, ..., 1600) segment to be normalized and Xmax andXmin are the maximum and minimum values of the data.

Neural network learned by backpropagation

Backpropagation [18] is generally used to train multilayer ANNs. A multilayer backpropagation network includes an input layer, at least one hidden layer, and an output layer. The backpropagation algorithm is a supervised learning method and aims to optimize weights and biases between the input layer and the output layer depending on the output error of the network. The input vector is given to the input layer and reaches the final output layer after passing through hidden layers. Each neuron in the network transmits the result to all neurons of the next layer after receiving the arithmetical addition of the weighted signal from the previous layer's neurons, depending on the activation function.

The ANN's training by backpropagation operates consistently in both forward computing and backward computing, as given in Figure 2, where X1 and X2 are inputs and C1, C2, and C3 are output vectors of the layers. W1 and W2 are weight matrices; W3 is a weight vector; θ 1, θ 2, and θ 3 are bias vectors; and E1, E2, and E3 bias inputs are chosen as 1. NET1, NET2, and NET3 are net input vectors for the related layer. Sigmoid activation function (φ) is preferred for all neurons. φ' is the derivative of the activation function. δ 1, δ 2, and δ 3 are local gradient vectors.

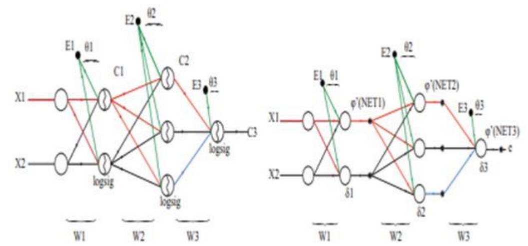


Fig.2 (a) Forward computing schematic structure, (b) Backward computing schematic structure (transpose network)

Discrete Wavelet Transform

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. The DWT decomposes an input image into four components labeled as LL, HL, LH and HH [9]. The first letter corresponds to applying either a low pass frequency operation or high pass frequency operation to the rows, and the second letter refers to the filter applied to the columns. The lowest resolution level LL consists of the approximation part of the original image. The remaining three resolution levels consist of the detail parts and give the vertical high (LH), horizontal high (HL) and high (HH) frequencies. Figure 3 shows three-level wavelet decomposition of an image.

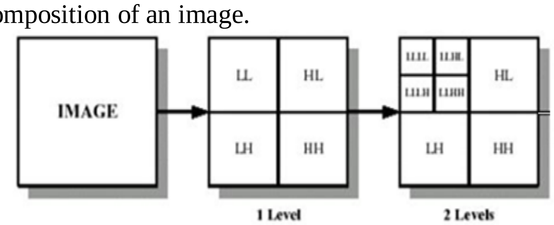


Fig.3 Wavelet-based texture analysis in retina

Neural network learned by PSO

PSO, one of the population-based heuristic optimization methods, was first developed by Kennedy and Eberhart in 1995 [19], inspired by social behavior in flocks of birds or schools of fish while finding food. The PSO algorithm is initialized with a group of random particles (candidate solutions for the problem) and then searches for an optimal solution by updating its individuals. In each generation, each particle is updated based on 2 special particles: pbest is the personal best solution of each particle found so far, and gbest. is the global best solution found so far by any particle in the swarm (population) [20,21]. Figure 3 shows the updating procedure of a particle by vectorial representation.

The algorithm’s pseudo code is the following for each particle do initialize the particle with random value send for Do for each particle do Calculate fitness value of the particle if fitness value of the current particle < fitness value of the pbest particle then update the pbest particle end if end for gbest = the particle whose fitness value is equal to min(fitness values of all particles) for each particle do update velocity and position of the current particle end for while stop criterion (maximum generation number or target fitness value of the gbest particle) is provided The vk ij and xk ij variables in Figure 3 are respectively the j th velocity component and the j th (j = 1, 2, ..., D) position component of the ith (i = 1, 2, 3, . . . , N) particle at generation k . N is the number of particles in the swarm. D is the dimension size of the search space.

Experimental studies

In this work, an EEG dataset with data from both epileptic and healthy people was used. The dataset was preprocessed using statistical values (minimum, maximum, mean, and standard deviation) to give as inputs for diagnosing systems, and so the number of samples was reduced. The dataset was then normalized in the range of [0, 1] to increase the performance of the neural network.

The dataset was divided into 2 subsets for training and testing of the networks. There are 1200 segments (600 epileptic and 600 healthy) and 400 segments (200 epileptic and 200 healthy) of EEG data in the training and test datasets, respectively. The training dataset was used to train the PSONNs and BPNN. Each network consists of an input layer, a hidden layer, and an output layer, as shown in Figure 5. X1, X2, X3, and X4 are inputs obtained from statistical values as depicted above; Y is the output. The desired output value is 0 for healthy and 1 for epileptic. W1 and W2 are connection weight matrices; θ 1 and θ 2 are bias vectors. Threshold inputs are used in the layers; their values are chosen as 1. Sigmoid activation function was preferred.

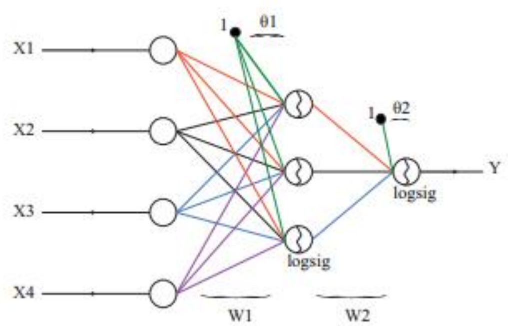


Fig:4 schematic architecture of neural network

To determine the best classifier network model and architecture, the number of particles, maximum generation, and neurons in the hidden layer were investigated by trial and error for each model. As a result of the experimental evaluations, the most suitable values of these parameters were determined to be 30, 200, and 3, respectively [23].

The optimal threshold value has to be determined to minimize false negatives (FNs) while maintaining false positives (FPs) within a reasonably low limit [26]. Thus, the appropriate FN and FP values were obtained when the classification threshold value was chosen as 0.4 in both training and testing. If the output value is lower than this value, the output signifies that the patient is healthy; if higher, the patient is epileptic.

Initialization values of α and w in Eq. (6) were chosen as 0.975 and 0.9, respectively [27]. w max and wmin were 0.9 and 0.4 [28]. c 1 and c 2 constants were 2.1 and equal to each other. Limitations V min and Vmax were selected as –0.1 and 0.1, respectively. These values provided fast convergence to the target. Sensitivity, specificity, and accuracy are widely preferred statistics in determining the performance of a classifier. Sensitivity is the estimation rate of data belonging to epileptic patients, specificity is the estimation rate of data belonging to healthy people, and accuracy is the true classification rate [29]. Eqs. (15), (16), and (17) are used to calculate these statistical numbers.

Accuracy:- Accuracy is also used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. among the total number of cases examined. To make the context clear by the semantics, it is often referred to as the "rand accuracy. It is a parameter of the test.it shows in the command window..

Acc=(Tp+Tn)/(Tp+Tn+Fp+Fn)

Sensitivity:-In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease (true positive rate).

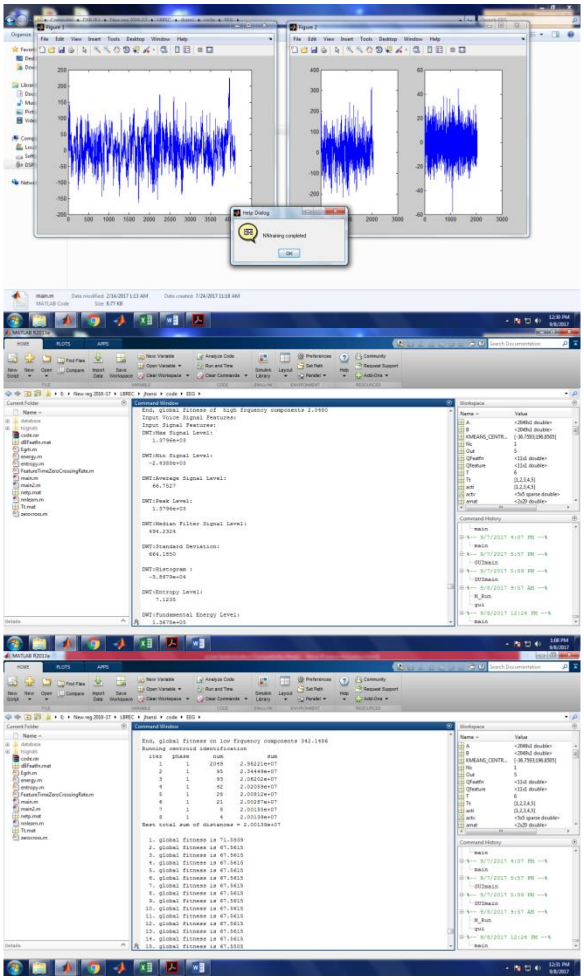
Sensitivity =Tp/(Tp+Fn).

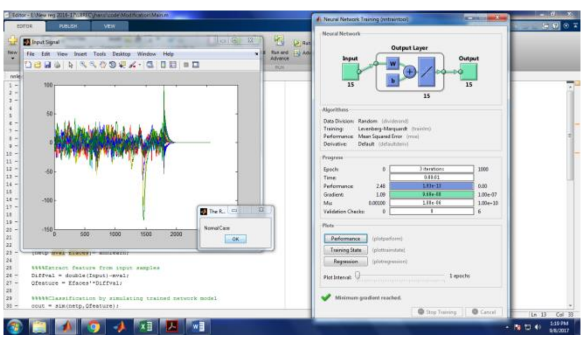
Specificity:-Whereas test specificity is the ability of the test to correctly identify those without the disease (true negative rate).

Specificity =Tn/(Tn+Fp).

In the above equations, TP (true positive) is the total number of epileptic patients diagnosed with epilepsy, TN (true negative) is the total number of normal patients diagnosed as healthy, FP is the total number of epileptic patients diagnosed as healthy, and FN is the total number of normal patients diagnosed with epilepsy.

Output image:-





III. CONCLUSION

In this work, versions of PSO and the back propagation algorithm were used for the training of ANNs in order to diagnose epilepsy. The results the developed networks (PSONNs and BPNN) were given in Table 2. It can be seen in Table 2 that the percentages of training success for PSONN3 and PSONN4 were about 99.67% and 98.75%, respectively. The percentage of test success for both of them was 100%.

The results of sensitivity analysis of these PSONN models in the training and test datasets were 1. The percentages of training and test success for the BPNN were 99.83% and 90.75%, respectively. The results of sensitivity analysis of BPNN were low in both the training and test datasets. Thus, it can be said that PSO is quite suitable for the training of ANNs, and the developed PSONN models are more successful ANN models for epilepsy diagnosis. The classification accuracy rates of this study and other classifiers are given in Table 3 for the same dataset. As seen, the best reported result is 99.45%. In addition, PSONN3, developed in this study, has the best classification ability to diagnose epilepsy (Table 3). Furthermore, it can be said that the proposed ANN structure and its training process includes (and needs) fewer complex calculations than its counterparts in the literature. Generally, computing load and the required amount of memory change linearly depending on the number of particles and neurons on layers. When the number of particles increases, the success of the network increases, but training of the network slows down and required memory demands increase. The neural network models considered here for epilepsy diagnosis can be adapted for different medical diagnosis problems. An application of this study will be helpful to neurologists for epilepsy diagnosis.

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