CLASSIFICATION OF EEG SIGNALS' SPECTRUM WITH USING NEURAL NETWORKS

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***Abstract*:** In this study, our goal is to classify Electroencephalogram (EEG) waveform recorded by a computer-aided system at Dicle University Medical Research Hospital. Spectrum of these recordings have been analysed by using FFT. Therefore, the health states of patients have been classified into three groups, as normal, pathologic, and unspecified by using a neural network algorithm based on frequency characteristics of these signals. We would like to carry out further studies in order to make this method practically implement able in hospitals.

1. INTRODUCTION

Recorded representation of brain potentials is called electroencephalogram (EEG). It has been thought that, EEG signals involve a great deal of information about the functions of brain, and the mental activity of human.

Most of the electroencephalographers classify the EEG frequency rhythms (bands) approximately δ, θ, α, and β, below 4Hz, from 4Hz to 8Hz, from 8Hz to12Hz, and above 12Hz respectively. Therefore we can say that the frequency of the brain signals increases properly as the mental activity of the human increase. In addition we can say that the higher frequency components of EEG have lower amplitudes [5].

One of the important brain disorders is epilepsy. Today, a lot of people are suffering from this illness. In epilepsy, the waveforms that are called epileptic discharges, which have slower frequencies, and higher amplitudes, are observed. So we think that, analysing the spectral components of the EEG is very useful, and economical for the diagnosing of the epilepsy.

2. METHODS, AND MATERIALS

2.1. Obtaining The EEG Data Sets

In this study, a data acquisition and processing unit (PCI-MIO-16-E4) is used to record the EEG signals from patients, in Dicle University Neurology Clinic. Recordings have been made as 202 samples during 6 seconds. The acquisition unit has an12 bits analogue to digital converter (AD 7572, % 0.02 sensitivity, 0.014ms conversion time) to discritisize the EEG waveform [1,2]. One of the recorded epileptic EEG waveform is shown below in figure1.

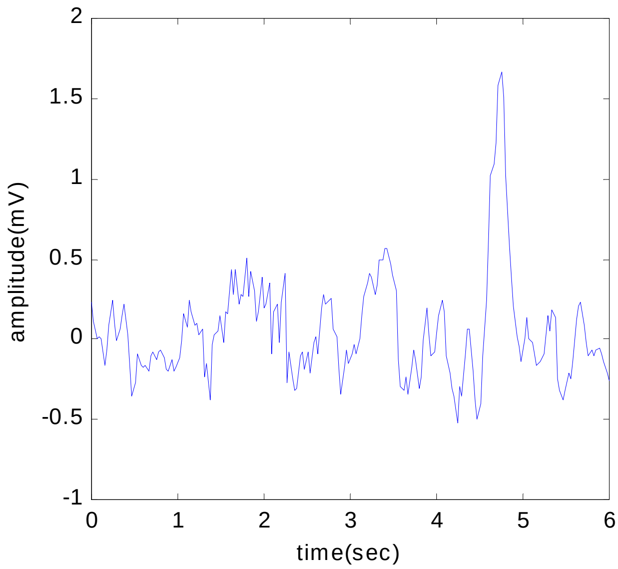


Fig. 1. Recorded epileptic EEG Signal

2.2. Spectral Transform and Filtering

Frequency analysis of a signal, involves the resolution of the signal into its frequency (sinusoidal) components. This means that you can separate the original signal into sub-spectral components, and you can interpret the signal easily.

One of the spectral analysis methods is discrete Fourier transform [7]. Thus;

$$X(k+1) = \sum_{n=0}^{N-1} x(n+1)\, W_n^{kn}$$

where $W_N = e^{-j(2\pi/N)}$, and N = length(x)

The discrete Fourier transform(dft) of the signal in figure 1 is shown below in figure 2.

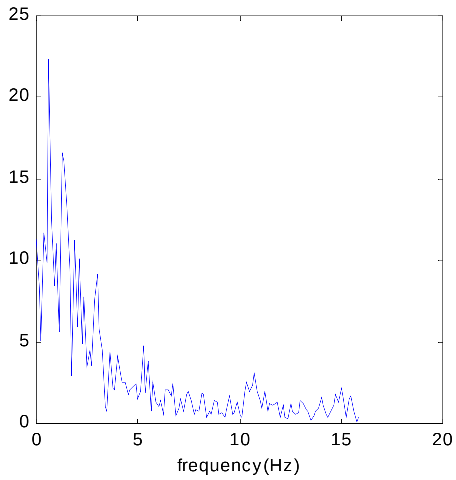


Fig. 2. The dft of the EEG signal

As mentioned above, EEG signals have four major sub-frequency bands which are δ, θ, α, and β waves. To obtain this situation, filtering should be done.

One of the filtering methods is butterworth filtering. Butterworth filters are defined by two parameters; the filter order, N, and The cut-off frequency,Ω_c. The magnitude response is given as

$$|H(\Omega)|^2 = \frac{1}{1+(\Omega/\Omega_c)^{2N}}$$

By using some simple transformations, the digital butterworth filters are obtained from analogue filters easily. If the system response of analogue butterworth filter is shown below

$$H(s) = \frac{B(s)}{A(s)} = \frac{b(1)s^n + b(2)s^{n-1} + \cdots + b(n+1)}{s^n + a(2)s^{n-1} + \cdots + a(n+1)}$$

Then, the bilinear transformation maps the *s*-plane into the *z*-plane by

$$H(z) = H(s)\Big|_{s = 2f_s\frac{z-1}{z+1}}$$

This transformation maps the $j\Omega$ axis (from Ω = - :to +:) repeatedly around the unit circle (exp($j\varpi$), from $\varpi = -\pi$ to π) by

$$\omega = 2\tan^{-1}\left(\frac{\Omega}{2f_s}\right)$$

where, ϖ, and Ω represent the digital, and analog frequencies[8].

2.3. Artificial Neural Network

In today artificial neural networks have a great importance. Because of their capability in making decisions after learning the event like human. And also, scientists use the artificial neural networks in many fields such as signal processing, control, pattern recognition, medicine, speech recognition, and business.

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements.

We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

One of the neural network training methods is error back propagation learning method, and there are many variations of the error back propagation-learning algorithm. The simplest implementation of back propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly – the negative of the gradient. One iteration of this algorithm can be written

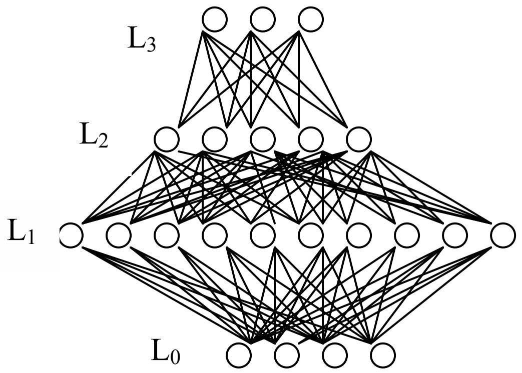
$$\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha_k \gamma_k$$

where $\mathbf{x}_k$ is a vector of current weights and biases, $\mathbf{g}_k$ is the current gradient, and α_k is the learning rate[6].

3.EXPERIMENTAL STUDY

According to our study, to get the δ, θ, α, and β sub-spectral bands, EEG waveforms are filtered. There are four pass-band filters, which have 1.5-4Hz, 4-8Hz, 8-12Hz, and 12-16Hz boundary frequencies. After filtering, Fourier transforms of the spectral components have been taken.

To adapt these signals as the inputs of the artificial neural networks, their averages are taken. Then these averages are applied to the inputs of the net. Neural network has been consisted of four layers (Input layer, first hidden layer, second hidden layer, and the output layer has 4,10,5,and 3 neurons respectively). The schematic of the neural network is shown in figure 3.



L_0=input layer(4 neuron)
L_1=first hidden layer(10 neuron)
L_2= second hidden layer(5 neuron)
L_3=output layer(3 neuron)

Fig.3. Neural Network Model

In addition, Momentum constant, and learning rate has been chosen as 0.9, and 0.1 respectively. Training of the neural network is made with respect to the mean square error parameter (mse). After 1115 iterations the mse parameter has been found as 0.00989093. The figure of mse versus number of iteration is shown in figure 4 below.

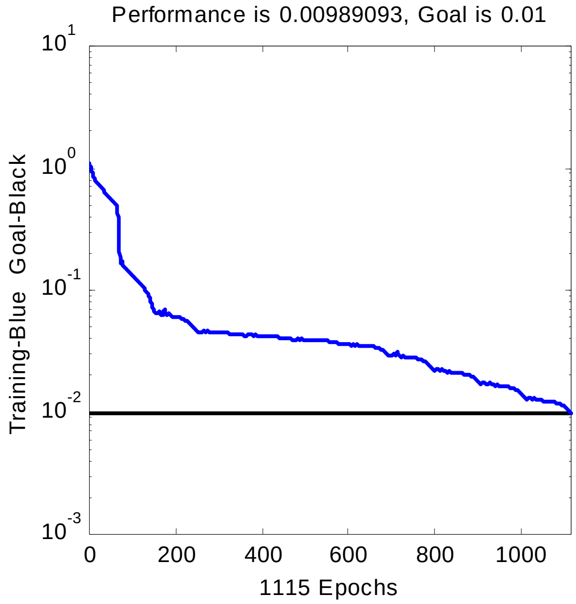


Fig. 4. Error versus iteration number

4. CONCLUSION AND RESULTS

In the world, a lot of people are suffering from epilepsy. From this point the diagnosing of this illness should be done carefully. For the absolute diagnose, the mistakes that have been done by the doctors should be decreased to minimal case. In our study we want to develop a new diagnosing technique for the epilepsy by using the modern signal processing methods and the neural networks, the decision mechanism should be computerized. Therefore the outputs of the neural networks can helped the neurologists, when they diagnose the epilepsy.

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NEYRON ŞƏBƏKƏLƏRDƏN İSTİFADƏ EDƏRƏK ELEKTROENSEFALOQRAMMA SİQNALLARININ SPEKTRİNİN KLASSİFİKASİYASI

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Təqdim olunan iş Dəclə Universitetinin Tibbi Tədqiqatlar Mərkəzində avtomatlandırılmış sistem vasitəsilə qeydə alınmış elektroensefaloqramma dalğasının formasının klassifikasiyasına həsr olunmuşdur. Bu siqnalların spektri Furye çevirmələrin tətbiq etməklə təhlil olunmuşdur. Alınan siqnalların tezlik xarakteristikalarına əsaslanan neyron şəbəkələrin alqoritmindən istifadə edərək sağlamlıq vəziyyəti üç kateqoriyaya bölünmüşdür: normal, patoloji və qeyri-müəyyən. Güman edirik ki, sonrakı tədqiqatlar bu metodun xəstələri müalicə etmək üçün tətbiq olunmasına imkan yaradacaq.

КЛАССИФИКАЦИЯ СПЕКТРА СИГНАЛОВ ЭЛЕКТРОЭНЦЕФАЛОГРАММЫ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННЫХ СЕТЕЙ

АКЫН М., КЫЙМЫК М.К., АРСЕРИМ М.А.

Данная работа посвящена классификации формы волны электроэнцефалограммы, зарегистрированной автоматизированной системой в Центре Медицинских Исследований Университета Дичле. Спектр этих сигналов был проанализирован с использованием Фурье - преобразований. Используя алгоритмы нейронных сетей, основанные на частотных характеристиках полученных сигналов, состояния здоровья пациентов были разбиты на три категории: на нормальные, патологические и неопределенные. Мы надеемся, что дальнейшие исследования позволят практически использовать данный метод для лечения больных.