EKG Signal Recognition with Neural Network

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Abstract: *The paper is a description of the way in which one pattern recognition application was built. The aim of the application is to diagnose a number of 15 heart diseases by using the EKG signal with the help of neural networks.*

All the steps of the application (recording the signal, filtering the signal, the resulting prototype) are briefly detailed, insisting on the problems that appeared in each of the steps and on the way they were solved.

Throughout this paper, we will describe how the EKG signal was initially filtered, how each of the three constituents of the signal (the P wave, the QRS complex and the T wave) has been recognized and interpreted by a neural network; in the end, the three interpretations of the constituents and other data have been analyzed by using a neural network which established a diagnosis.

The application described in this paper is called EKGByte and it was used for testing certain diagnosis. The results achieved with the help of this program are encouraging and they open new possibilities of study for the future.

Keywords: *neural network, pattern recognition, EKG signal*

1 Introduction

The use of neural networks in medicine is concentrated mainly on classification purposes. The most successful use of neural networks in clinical medicine is image analysis and analysis of wave forms - ECG or EEG pattern recognition and classification and partly also clinical diagnosis and prognosis [1].

EKG signal is a bioelectric heart activity measured in a number of places on the skin (the number of electrodes is equal to 3 in the presented work). The measured signals are digitized and stored on hard disk of a computer.

The aim of the described paper is to create a computer program that tries to diagnose 15 different heart diseases by analyzing and classifying the EKG signal with the help of neural networks.

Throughout this paper, we will describe how the EKG signal was initially filtered, how each of the three constituents of the signal (the P wave, the QRS complex and the T wave) has been recognized and interpreted by a neural network; in the end, the three interpretations of the constituents and other data have been analyzed by using a neural network which established a diagnosis.

The program can make the doctors' work easier by giving a fast diagnosis and by helping them to make a decision.

The second part of the paper deals with some theoretic aspects about the pattern recognition with neural network. These aspects are used in the third part of the paper, in which, all the steps of processing the information are briefly presented as well as the way these steps have been implemented in application. Each step will present the problems met in the implementation and it will explain, if necessary, the reason for choosing a method or another. This is the most interesting part of the paper due to the complexity of the application which required many techniques from different fields. The results of this program will be presented in part four. We must add that this program was rarely used and it was used only on experimental sets of data. It hasn't been made yet a statistics that can show the aspects concerning the performance of the program, this thing being possible only through an agreement with an institution that could supply large amounts of data necessary in this kind of process. The ways of development and the conclusions will be presented in the last section.

2 Pattern recognition with neural network

2.1 What is pattern recognition?

Pattern recognition is concerned with making decisions from complex patterns of information. Usual there is a predefined set of classes of patterns which might be presented, and the goal is to classify a future pattern as one of these classes. Such tasks are called *classification* or *supervised pattern recognition*. Clearly someone had to determine the classes in the first place, and seeking groupings of patterns is called *cluster analysis* or *unsupervised* pattern recognition [2].

2.2 What is neural network?

An *artificial neural network* is a model that emulates the biologic neural network. A neural artificial network is made up of thousands of artificial neurons; elements of non-linear processing that operate in parallel.

The main characteristics of the neural networks are the same with those of the human brain that is:

- capacity of learning
- capacity of generalizing

If trained adequately, the artificial neural networks would be capable of giving correct answers even for the set-entries different from those they have already been used to, as long as they don't differ too much. This generalization is made automatically as a result of their structure and not as a result of human intelligence which is included in a program as in the expert systems.

2.3 What kind of neural network it's good to use in that field?

Error back propagation (BP) neural network is one of neural networks most in common use.

3 How works the application?

3.1 Recording the EKG signal.

For recording the electro-cardiogram we use a special machine called electrocardiograph. A system of electrodes attached to the electrocardiograph form a derivation. Depending on the electrodes involved in taking over the signal, more derivations are obtained. In our application, only three of the twelve derivations possible have been used, namely: DI, DII and DIII. The EKG signal has been taken over with the help of three electrodes situated on all the positions resulting from the Einhoven's triangle. So, by moving the three electrodes, the three derivations were obtained. The electric signal received was taken over by an electronic device which transformed it from an electric signal into a digital signal. Finally, the electric signal was transformed into a multitude of samples. The signal composed of samples was sent to the computer through the parallel interface where from it was read by a special program [3] and it was recorded in a file. The EKG signal was introduced in the ECGByte as a multitude of samples, each sample having certain amplitude.

3.2 Filtering the EKG signal.

In the analysis of a particular EKG, we do not know the previous form of the waves of the most important events; consequently, general filters must be used. The characteristics of these filters should be based on the characteristics of a representative set of EKGs.

Knowing that the EKG signal is a signal whose band width is of 1 KHz maximum, we obtained the filtering of the signal by using a FIR signal (Finite Impulse Response).

The main method we followed was to project a FIR filter so that the amplitude of the signal obtained through the application of the transfer function to approximate good amplitude of the response signal. Using a finite Fourier series, the best transfer function is:

$$H(z) = \sum_{i=0}^{N} h_i z^{-i} \tag{1}$$

, where C_n are the coefficients of the Fourier series, which will be calculated so that the transfer function H(z) to approximate the best transfer function. The filter's coefficients are h_i, where $h_0 = C_Q$, $h_1 = C_{Q-1}$, …. , $h_{Q-1} = C_1$, $h_Q = C_0$, $h_{Q+1} = C_1$, …. , $h_{2Q-1} = C_{-Q+1}$ and $h_{2Q} = C_{-Q}$. The final impulse is symmetrical with h_Q, with $C_n = C_{-n}$. The order of the filter is N+1 or 2Q + 1.

The coefficients of the FIR filter can be calculated using the following formula for a down filter:

$$C_n = \int_0^{\nu_1} H_d(\nu)\cos(n\pi\nu)d\nu = \frac{\sin(n\pi\nu_1)}{n\pi} \tag{2}$$

In the ECGByte program we used a down filter in real time whose cutting frequency $\nu1$ is of 1 KHz. The filter has a variable number of coefficients, depending on the user's preference.

After calculating the filter's coefficients, there follows the filtering of the EKG signal made in two steps:

First: the filter used is a real time filter; consequently, for calculating each sample, we have to know a number of previous samples, number which is equal with the number of coefficients of the filter. Initially none of the samples has been processed by the filter, so, the first samples were identically copied.

Second: parts of the signal are now introduced in the filter, each of these parts having the length equal with the number of coefficients of the filter.

3.3 Recognizing the components of the EKG signal.

The EKG signal is composed of the P wave, the QRS complex and the T [4] wave. Each of these three components has its own specific forms and characteristics. Consequently, the recognition of each of the three components in the EKG signal is quite difficult.

Initially the EKG signal is represented as a sequence of samples of variable length. From this sequence we must select a characteristic period for diagnosis. The samples are normalized in amplitude so that the maximum to be of approximately 2mV.

This value will be reached only by the R wave and we can analyze the signal by following the next stages:

Detecting the R waves

We mentioned above that in the QRS complex we could reach the maximum of amplitude. This characteristic makes possible the division in periods of the EKG signal. The fact that in the derivations: DI, DII, DIII the QRS complex is always present, strengthens the rule of division of the signal in periods taking into consideration the R wave. Similarly, for the derivations DI, DII, DIII there are not abnormalities of the type: there are constituents in the signal whose amplitude is higher than the R wave. We can detect the position of the R waves for each cardiac cycle using an iterative technique of searching: we try to surpass the threshold value of (~1.1 mV) on the entire signal and we obtain compact groups of samples. From these compact groups of samples, we choose only the maximum corresponding to the R wave.

Statistic analysis of the length of the cardiac cycles

This stage helps to forming the medium length of the signal's periods and to discovering new cycles of signal that do not correspond to this medium length. Some of the abnormalities that can appear are:
- Incomplete periods of signal because of the recordings
- Impossible identification of all the R waves
- Possible short abnormalities in the functioning of the heart

Now we exclude from the EKG signal all the periods that do not correspond to the medium length of a period of signal. This thing is done by not taking into consideration the first and the last maximum which could belong to some incomplete periods and which wouldn't be R waves.

Finding the maximum interval that contains the useful information for each cycle, taking into consideration the R wave position

Knowing the R wave position in the EKG signal, we can determine the beginning of the period. This is possible due to the fact that at the beginning of an EKG period, the signal has the amplitude equal to the value of the isoelectric line. On an EKG, a cardiac cycle begins at (1/3) RR (a third part from the duration of the cycle) before the R wave and ends at (2/3) RR (two thirds from the duration of the cycle) after the R wave.

Forming the expanded prototype

All the cycles remained valid until this moment help to form the expanded prototype. The expanded prototype becomes an "average" of all the periods of the signal. At this stage, we calculate a minimal period and then, we determine the distance (the mean square error) between this average period and each cardiac cycle (the first and the last have been excluded since the average period has been determined); if this distance is higher than a certain critical threshold (considered as the average of the mean square errors), then the interval tested is excluded and it isn't taken into consideration in the calculation of the prototype.

The expanded prototype of the cardiac wave is calculated as the average of the cycles remained after the exclusion stage. The expanded prototype obtained represents a period of the EKG signal.

Locating the area containing significant information (locating the limit points of the isoelectric line)

The complete diastole (the area between the end of the T wave and the beginning of the P wave) does not contain significant information about the disease, consequently, we don't have to take it into account. We are trying to find all the constituents of the EKG signal. Finding a constituent means locating the beginning and the end of the constituent in the expanded prototype.

In order to estimate the position of the limit, we make a linear approximation of the signal on segments (by replacing the arcs with the cords), each segment from the approximation corresponding to a group of M samples. Let's consider f(i) to be the EKG sample and z(i) to be the linear approximation as in:

$$z(i) = A \cdot i + B \tag{3}$$

For the method used in this paper we can have:

$$A = \frac{f(i+M) - f(i)}{M}, B = f(i) - A \cdot i \tag{4}$$

Experimentally, we observed that the best value for M is 15.

The location of the isoelectric line corresponds to the area from the diastole called "bio-electrical quietude", situated between the end of the T wave and the beginning of the P wave. The EKG signals contain neuromuscular noises, perturbations determined by the polarization of the electrodes and other electrical interferences (harmonics of the frequency of 50 Hz); consequently, locating the isoelectric line is a non-trivial problem. We defined the area corresponding to the isoelectric line as the multitude of linear regions adjacent to M samples with an inclination lesser than a threshold.

At the end of these stages, we obtain the EKG signal divided into three constituents: the P wave, the QRS complex, the T wave. A neural network will process all these constituents.

3.4 Processing the constituents of the EKG signal

The constituents that have been obtained will be processed; a neural network will analyze each constituent. The constituency of these networks is identical to the constituency of the network of diagnosing and it can be represented as in Figure 1.

The activation function of the neurons situated on the entrance layer is a linear function whose values can be between [-1, 1].

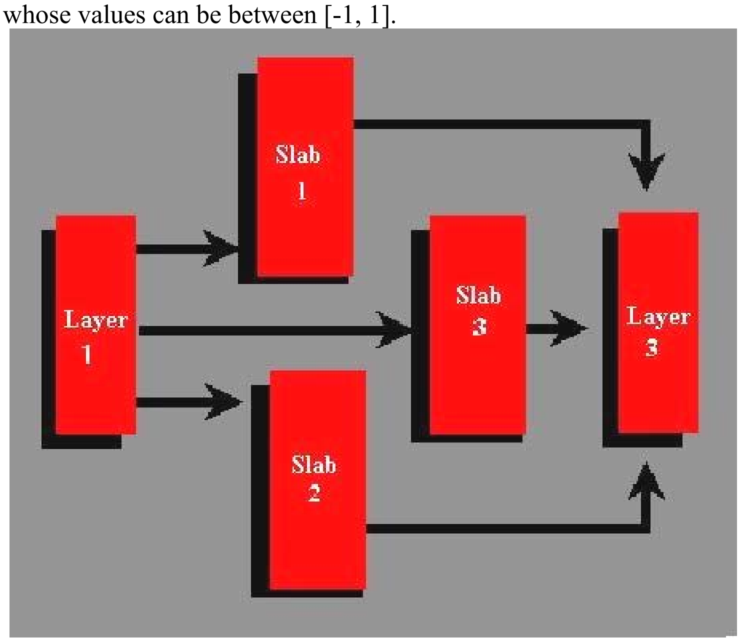

Figure 1 Neural network architecture

The hidden layer is a composed of 3 slab. The functions of activation of the neurons situated on the hidden layer differ. Consequently, we have:

- the Gaussian function for slab 1
- the tangent hyperbolic function for slab 2
- the complementary Gaussian function for slab 3

These functions and the fact that the hidden layer has been divided into 3 slabs determine a quick detection of the events in the pattern recognition process.

The 3 slabs give different "interpretations" of the data. Combining the 3 outputs of the slabs, we will achieve a better prediction of the output layer.

The function of activation of the neurons situated on the output layer is the logistic functions.

Each neural network has at its input a set of samples and at the output; it supplies a number whose value is described in the following table:

Constituent	Property	Output Value
P wave	Ordinary	10 ÷ 29
	Mitral	30 ÷ 39

	Isoelectric	0 ÷ 9
QRS complex	Q > 0,40 s	10 ÷ 19
	S large and profound	30 ÷ 39
	S more than R	40 ÷ 49
	ST drift	20 ÷ 29
	Normal	0 ÷ 9
T wave	High and sharp	10 ÷ 19
	Normal	0 ÷ 9

The number of samples necessary for each constituent to be processed is the following:

- the P wave needs 25 samples
- the QRS complex needs 31 samples
- the T wave needs 71 samples

These samples are inputs in the neural networks. In order to make an adequate processing, the neural networks need training.

For the P wave we have the following configuration: input layer (25 neurons), hidden layer (3 blocks containing 6 neurons each), output layer (1 neuron).

For the QRS complex we have the following configuration: input layer (31 neurons), hidden layer (3 blocks containing 8 neurons each), and output layer (3 neurons).

For the T wave we have the following configuration: input layer (71 neurons), hidden layer (3 blocks containing 14 neurons each), output layer (1 neuron).

3.5 Neural network of diagnosing

The structure of the neural network of diagnosing is presented in figure 1.

The input layer is composed of 11 neurons whom value is presented as follows.

The input neurons:

- P wave in D1 – the exit of the P wave processing network
- QRS complex in D1 – the exit of the QRS wave processing network
- QRS complex in D2 – the exit of the QRS wave processing network
- QRS complex in D3 – the exit of the QRS wave processing network
- T wave in D1 – the exit of the T wave processing network
- Frequency – the heart contraction rate (is calculated)
- If the signal’s periods are equal – the analysis of the length of the EKG signal cycles (variable calculated)

- PR distance – the distance between the beginning of the P wave and the beginning of the R wave (variable calculated)
- Number of P waves in D1 – how many P waves we have in a period
- Distance between P and QRS – distance between the end of the P wave and the beginning of the Q wave (variable calculated)
- The R wave's amplitude in D1 – the R wave's amplitude

The hidden layer is a composed of 3 slab. Each slab has in its constituency 7 neurons.

The output layer is composed of 15 neurons. Each neuron has been associated to a diagnosis. Next, we will present a list with the 15 diagnosis.

The output nodes:
- The sinusal tachycardia
- The sinusal bradycardia
- The atrial extra systole
- The nodal paroxistic tachycardia
- AV1 block
- AV2 block
- Wolff-Parkinson-White syndrome
- Stroke
- Inferior stroke
- Anterior hemiblock
- Posterior hemiblock
- Emphysema
- Right axillaries deviation
- Pulmonary embolism
- Moderate hyperkaliemia

4 Experiments and results

We must add that this program was rarely used and it was used only on experimental sets of data. It hasn't been made yet a statistics that can show the aspects concerning the performance of the program, this thing being possible only through an agreement with an institution that could supply large amounts of data necessary in this kind of process.

However, the percentage of successful diagnosing on sets of experimental data was of 80%

Conclusions

This paper analyzed the problem of EKG signal recognition with neuronal network and its application succeeded in diagnosing 15 cardiac diseases.

The program can make the doctors' work easier by giving a fast diagnosis and by helping them to make a decision. The diagnosis is given only by taking into account specialized medical information that is obtained through analyzing the signal.

The program can run on any kind of computer with Windows Operating System and at least 200 MHz Pentium processor.

Possibilities of development could be:

- Increasing the number of diagnoses achieved by adding new nodes to the neural network
- Adding the possibility of printing the EKG processed signals
- The possibility of picking information from more derivations (6 or 12 derivations)

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