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DSP Based ECG Abnormality Classification using Artificial Neural Network

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ABSTRACT--- Monitoring of electrocardiogram during normal activity becomes standard procedure for ECG abnormality. The paper presents processing system based on a DSP Processor TMS 320C6711 for classification of various abnormality. The proposed system is developed on the basis of applications of supervised structure of Artificial Neural Network (ANN) using Fourier transform and windowed Fourier Transform for ECG abnormality . For this, Multilayer Perceptron (MLP) network is used to maximize accuracy under the constraints of minimum network dimension so that its hardware implementation further requires minimum number of components to satisfy real time constraints and low power consumption.

KEYWORDS--- Fourier transform , Windowed Fourier transform , DSP processor

1 INTRODUCTION

Electrocardiography has been used for many years as a key, non-invasive method in the diagnosis and early detection of coronary heart disease, which is the leading cause of mortality in Western countries. In 1993, it was estimated that more than 100 million standard ECG are recorded yearly in the European Community (EC) for routine diagnostic and screening purposes at an estimated cost of more than 1.2 billion ECU per year. Almost all newer electrocardiographs nowadays use digital recording, interpretation and communication techniques.

The new generation devices is capable of analyzing and interpreting ECG Signal in real time [5].Analysis of ECG signal is important when studying the automatic Nervous system because it helps in evaluating the equilibrium between sympathetic and parasympathetic branch of nervous system increases the heat rhythm ,resulting in shorter Beat intervals .The parasympathetic branch decelerates the heart rhythm resulting in longer beat interval. Heart rate variability can be measured based on beat interval which are more easily observed as RR intervals. However the manual measurement of RR intervals from ECG tapes is time consuming and it is difficult to calculate all parameters from HRV analysis so certain software algorithm is implemented by some method and download this is in DSP processor for ECG abnormality.

In this work offline analysis of various ECG records from MIT-BIH database is carried out by Fourier transform and windowed Fourier transform. Then for particular records training and testing is done by ANN .After testing it for a particular target whatever weight matrix is result is downloaded in DSP processor.

Waveform description:-

The ECG waveform as shown in Fig1 basically consists of P, Q, R, S & T waves, the details of which are discussed below:

P-Wave: The slow moving depolarization of the artia which begins at the sinuartrial node (SA-node), produces the P-wave.

Q-Wave: The Q wave is produced because of the excitation stimulus provided by the Purkinje fibers, which takes place after the delaying of the signal in the atrio ventricular node.

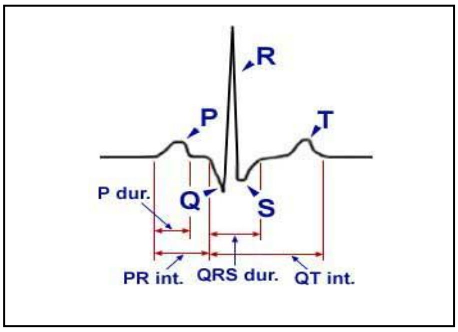

Fig 1: Normal ECG Waveform description

R-Wave: The rapid depolarization of the ventricular muscle is depicted as a large, fast moving vector, which begins producing the R-wave.

S-Wave: When the excitation spreads and moves towards the base of the ventricles. The last phase of ventricular depolarization results & causes the production of the S-wave.

T-Wave: The T-wave is produced due to the repolarization of the ventricles.

QRS Complex: The QRS complex is the combined result of the repolarization of the atria & the depolarization of the ventricles, which occur almost simultaneously.

PQ interval: The PQ interval represents the time during which the excitation wave is delayed I the gibers near the AV node. The PQ interval is also called as the PR interval as the Q wave is sometimes absent.

QT interval: Contraction of the ventricle lasts almost from the beginning of the Q wave to the end of the T wave. This interval represents the QT interval.

PR interval: The PR interval is the electrocardiography representation of the delay in electrical activation of the ventricles after sino-atrial nodal discharge. This interval is mainly a result of slow conduction through the atrio-ventricular node.

2 Neural Network

Artificial Neural Networks are parallel computational models comprised of densely interconnected adaptive processing units. A very important feature of these networks is their adaptive nature (learning by example).

The general neural model is shown in Fig Single R element input vector .Here the individual element input x1,x2,……xn and multiply by weight w1,w2,….wn. The neuron has bias b ,which is summed with weight input to form net input n. Then this sum, n, is argument of transfer function f

$n=x1w1+x2w2+……..+xnwn+b \quad a=f(n)$

The transfer functions calculate layers output from its net input. A particular transfer function is chosen to specify some specification of the problem that the neuron is attempting to solve. Three most commonly used functions are:

1. Hardlim function: It sets the output of neuron to 0 if the function argument is less than zero or 1 if its argument is greater than or equal to zero.
2. Purelin function: The output of a linear transfer function is equal to its input.
3. Logsigmod function: It is commonly used in multiplayer networks that are trained using back propagation algorithm, in part because this function is differentiable.
4. Tan-Sigmoid Function: The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks may use the tan-sigmoid transfer function tansig.

Supervised Learning

In supervised learning we assume that at each instant of time, when the input is applied the desired response d of the system is provided by the teacher. This is illustrated in figure 2 below. The distance p[d,o] between the actual and desired response serves as an error measure and is used to correct network parameters externally. Since we assume adjustable weights the teacher may implement a reward and punishment scheme to adapt the network's weight matrix W. A set of input and output patterns called a training set is required for this learning mode.

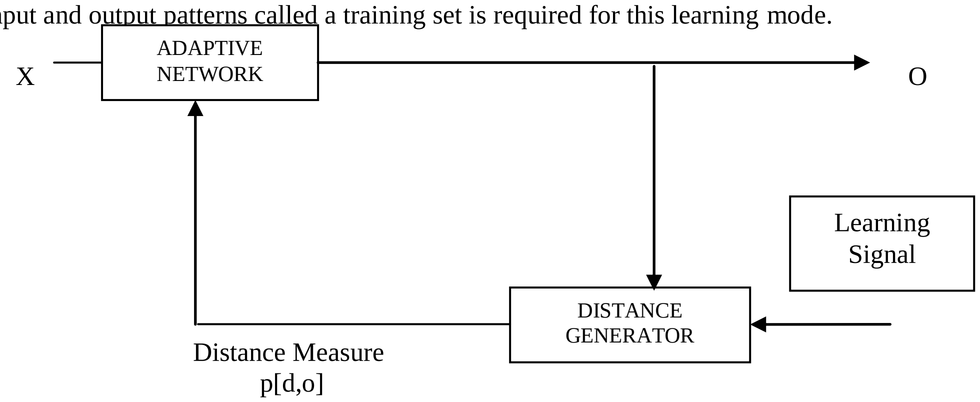

Fig 2. Supervised Learning

Unsupervised Learning:

In learning without supervision, the desired response is not behavior. Since no information is available as to correctness or incorrectness of responses, learning must be accomplished based on observations of responses to inputs that we have marginal or no knowledge about. Suitable weight self-adaptation mechanisms have to be embedded in the trained network, because no external instructions regarding potential clusters are available. Unsupervised learning is sometimes called learning without a teacher. This terminology is not appropriate because learning without a teacher is not possible. The goals have to be set even in an unsupervised mode. This is illustrated in figure 3 below

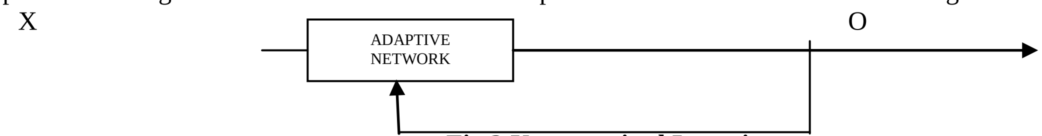

Fig 3 Unsupervised Learning

A multilayer N/W consist of I/P layer ,hidden layer and O/P layer The N/W can be train by two style 1 in incremental training the weight and biases of N/W are updated each time on I/p is presented to N/W .In batch training weight and biases are only updated after all of the I/P are presented.

3 Transform domain for ECG abnormality detection:-

The normal and abnormal ECG signals are grouped into separate groups first. An effective method of classification of ECG signals is devised. The Fourier Transform (FT), Windowed Fourier Transform are used for abnormality detection. The details of each of these methods are discussed.

3.1 Fourier transform

Each ECG segment is analyzed by Fast Fourier Transform (FFT) , of 256 points. Due to the symmetry of the FT, 128 points are considered . the absolute value of this spectrum is found out. To avoid effect of Gibb's phenomenon the absolute values of (2:128) FFT points are taken into considerations. The plot of these values for xe2 and xe4 are shown in fig 5. It is observed that (2:33) components have significant values out of (2:128) components. So training sets and testing sets for ANN are prepared from (2:33) components only.

The signals are of two groups viz. normal and abnormal ECG. First the ANN is fed with few sets of FTT (2:33) components derived from the normal ECGs. The target value for ANN output is set for 0.9. The ANN is trained with sum squared error goal, of 0.01. similarly the ANN is fed with few sets of FFT (2:33) components derived from the abnormal ECGS. The target value for ANN output is set for 0.1. the ANN is trained with sum squared error goal of 0.01.

The ANN designed is of feed forward type with one input layer, two hidden layers and one output layer. The neurons used ar 32,16,8 and 1 respectively with log-sigmoid functions. The results of training such a network are shown in fig 6.

It is observed that the system needs more time to train and the detection that the system needs more time to train and the detection accuracy is poor. This is because of two reasons.

(1) The input set size is 32.
(2) ECG is a non stationary signal and transforms like FT, Discrete Cosine Transform (DCT) etc are suitable for stationary signals.

3.2 Windowed Fourier Transform:-

To reduce the size of input of ANN from 32 (which is in FT case), Windowed Fourier Transform is used. In this system since each ECG segment is of 256 samples, four windows, each of 64 samples, are used. There is no overlap in the windows. The window function used is Hamming window.

Each ECG segment is normalized to maximum magnitude of 1 and QRS complex is adjusted at sample number 100. This is done so as to bring uniformity in all ECG segments. The Windowed FT obtained is 64 points, and due to symmetry of FT 32 points are considered. Thus the absolute magnitude of windowed FT components of each signal is represented by a set of 32 rows each of 4 columns.

These components are represented on the Time-Frequency axis and are shown in fig. the dark shades of color indicate higher magnitude. Again to avoid Gibb's phenomenon the first two rows are not considered for preparing training, testing sets for ANN. The training, testing sets are prepared as

Four rows i.e. row numbers 3 to of a set of sixteen values. The signals are ECG(Heart fail). First the ANN is fed with 6 consisting few sets of windowed FFT components (third row as a set of four values) derived from the normal ECGs. The target value for ANN output is set for 0of two groups viz. normal and abnormal ECG. The signals are of two groups viz. normal and abnormal.9. the ANN is trained with sum squared error goal of 0.01. similarly the ANN is fed with few sets of windowed FFT components (third row as a set of four values) derived from the abnormal ECGs. The target value for ANN output is set for 0.1. The ANN is trained with sum squared erro goal of 0.01. similarly training is given to another ANN that has training and testing sets prepared from windowed FFT components (third row to sixth row, a set of 16 values) both for normal and abnormal ECG. The ANN designed for a set of sixteen values, is of feed-forward type with 16,8,1 (i.e. 16 neurons in input layer, 8 in hidden layer, 1 in output layer) with linear and log-sigmoid functions respectively .Both ANN worked very well and the sum squared error goal was achieved in a maximum of 4 epochs only. This ANN system gives around 90% detection accuracy.

4 Experimental set up OR DSP development system

Standard 3 lead or 12 lead system is being extensively used for recording of ECG signal. The ECG is stochastic signal .The frequency of interest in ECG signal for clinical use varies from 0.05 to 100HZ.tThe signal is generally sampled at 500HZ[1].The QRS waves are create around 20 to 30 Hz and P and T waves well below this freq band.

Fig 4 shows block diagram of DSP based system. In the real world all phenomena are analog (sound, light ,heat electricity, magnetism).in order to process them with a computer the measuring system uses transducers to convert the analog levels into electrical signals. The ADC converts these electrical signals into digital values what are processed with DSP which execute specific algorithm. The result then convert into analog from and display this result on computer PC screen.

Fig 4 Block Diagram OF DSP

Different technique have been used to extract the parameters from ECG signals. In the freq domain the discrete Fourier transform is most popular technique. It is simple and fast but only suitable for stationed signals owing to its lack of tier resolution

5 Implementation

5.1 **Data characterstics**

1 Load the data sheet of normal and abnormal ECG on Microsoft excel.

2 Select these normal and abnormal ECG values as input to and select 0.9 and 0.1 as target for normal and abnormal ECG.

5.2 Neural Network Developed

i. 60 Percent of data. is tagged as training and 40 percent is tagged as testing using matlab.

ii. Multi Layer neural network is developed using two hidden layers and one input and one output layer.

iii. Here we decide the neurons is hidden layer first we kept 1 st hidden layer constant and varies the neurons in 2 nd hidden layer. Then kept 2nd hidden layer constant as varies neurons in 1st hidden layer.

iv. After testing we get the weight matrix store this in excel.

5**.3 DSP kit create**

1Crate new project filename.pjt

2 To create a source file type the code, save and give file name.

3 Add source file to project. .file name.c

4 Add C6701.lib library files

5 Add hello.cmd files which common for all the programs

6 compile program

7 Rebuild it which will create output file having extension project name.ECG

8 Load the program to DSK and go to debug and press run

8 Apply ECG signal I/P to audio jack and observer O/P on pc or any display.

6 Results

6.1 .Fast Fourier Transform: -

The peak amplitudes for FFT of abnormal signals are greater than that of normal signals .Also the frequencies for normal signals are greater than for abnormal signals .is shown in fig 5

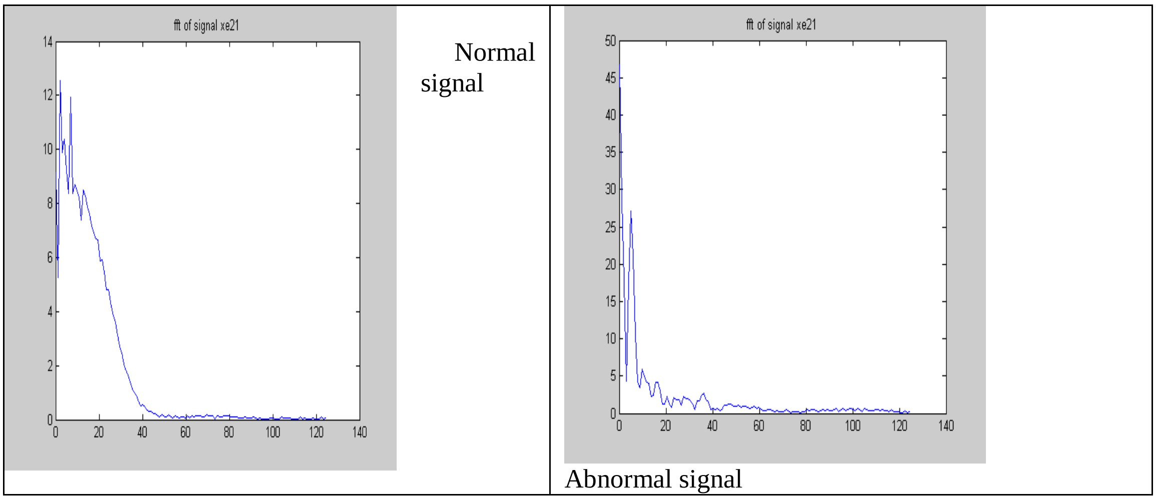

Fig 5 FFT of normal and abnormal signal

3.FFT TRAINING:-

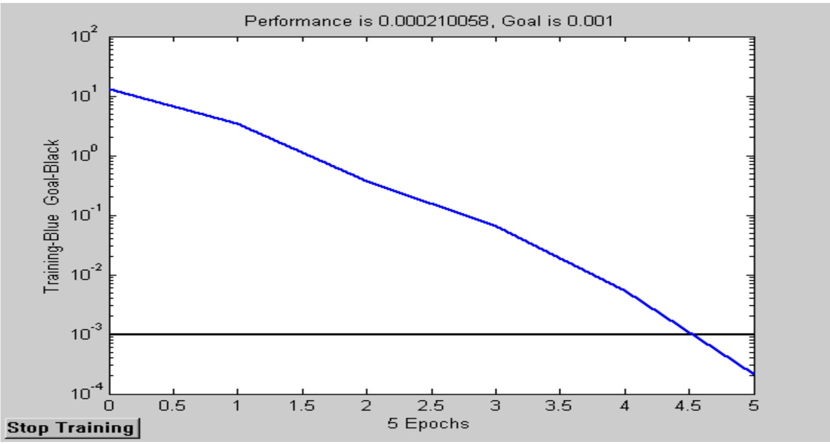

Fig 6 Training of a network

6.2 .Windowed FFT

The components for two signals :normal and heart fail are as shown in fig 7 and training of network is shown in fig 8 .

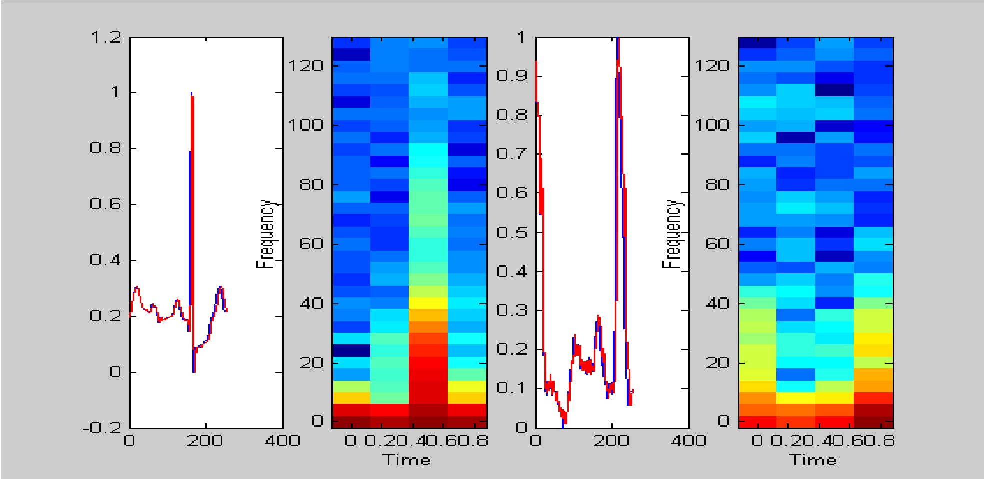

Fig 7 Windowed FFT of normal and abnormal signal

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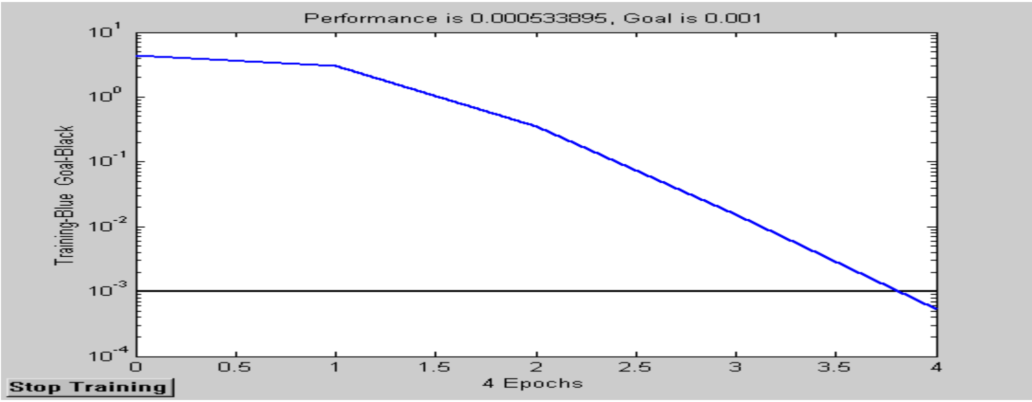

Fig 8 Training of a network

From the above plots we observe that our neural network is trained for FFT for desired goal with 5 epochs with sum squared error of 0.001.At the same time for windowed training goal is reached after 4 epochs only. Spectrogram gives the important information about frequency,magnitude,attenuation and time components. From spectrogram plot it is very clear that the abnormal signal do vary in components mentioned above.

7 Conclusion

The DSP system receives digital values based on sample of ECG signal and process this value with weights loaded in DSP processor and classify abnormality.The ANN designed with windowed Fourier Transform method gives reliable performance as compared with Fourier transform with reduced input The number of epchos in windowed Fourier Transform is less compared with Fourier Transform which reduces the processing time.So in combination of DSP with neural network algorithm is well suited for our complex task of on line classification of ECG signal.With the parallel work of bluetooth for WBAN[ ],there will be possibility to connect system to a central monitoring system.

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