A NEW APPROACH FOR THE PATTERN RECOGNITION AND CLASSIFICATION OF ECG SIGNAL

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ABSTRACT

Electrocardiogram (ECG) reflects activity of the central of the blood circulatory system, i.e. the heart. An ECG signal can provide us with a great deal of information on the normal and pathological physiology of heart activity. Thus, ECG is an important non-invasive clinical tool for the diagnosis of heart diseases.

According to the medical definition the most important information in the ECG signal is concentrated in the P wave, QRS complex and T wave. These data include positions and/or magnitudes of the QRS interval, PR interval, QT interval, ST interval, PR segment, and ST segment (see Fig. 1). Based on the above data, doctors can correctly diagnose human heart diseases. Therefore, analyzing the ECG signals of cardiac arrhythmia is very important for doctors to make correct clinical diagnoses. In order to perform ECG signals classification of the cardiac arrhythmia, the first important task is to determine an appropriate set of features. The feature selection method which chooses the best features from original features to have the maximum recognition rate, simplify classified computation and comprehend the causal relation of classified question.

Signal Processing is undoubtedly the best real time implementation of a specific problem. Wavelet Transform is a very powerful technique for feature extraction and can be used along with neural network structures to build computationally efficient models for diagnosis of Biosignals (ECG in this case). This work utilizes the above techniques for diagnosis of an ECG signal by determining its nature as well as exploring the possibility for real-time implementation of the above model. Daubechies wavelet transform and multi-layered perceptron are the computational techniques used for the realization of the above model. The ECG signals were obtained from the MIT-BIH arrhythmia database and are used for the identification of four different types of arrhythmias. The identification was implemented real-time in SIMULINK, to simulate the detection model under test condition and verify its workability.

KEYWORDS: *ECG, feature extraction, Denoising, Classification.*

I. INTRODUCTION

Recently biomedical signal processing has been a hot topic among researchers. Their most effort is focused on improving the data analysis of automatic systems. Cardiologists by using various values which occurred during the ECG recording can decide whether the heart beat is normal or not. Since observation of these values are not always clear, existence of automatic ECG detection system is required.

It is reported that annually each person has 0.3 ECG recording in European countries. Electrocardiogram provides health information for patients. Cardiologists can detect various heart abnormalities by checking the ECG waveform. Electrocardiogram was created by W. Einthoven in 20th century. Since nowadays heart diseases are a common death reason of people in developed countries, many researchers are working on ECG analysis.

By using some electrode on body surface, they can record the electrical signal which is caused by cumulative heart cells action. The cells do not work simultaneously since they have different potential in a particular moment and electrical currents go through the body organs and distribute around the heart. Since human body consists of many electrical ions it is conductive of electricity so potential

difference generates among two locations of the body and electrocardiography device records its changes in time.
Electrical and mechanical heart actions are joining together. So electrocardiography is essential device to estimate the heart's work and it gives us good information of normal and abnormalities of heart actions. ECG record consists of repeatedly heart beats. Each single heart beat includes many waves and interweaves. The length and appearance will show different heart diseases. The time and potential axis are estimated by milliseconds and millivolts respectively.
Bioelectrical signals express the electrical functionality of different organs in the human body. The Electrocardiogram, also called ECG signal, is one important signal among all bioelectrical signals. The ECG reflects the performance and the properties of the human heart and conveys very important hidden information in its structure. This information has to be extracted and analyzed before any useful and meaningful interpretations can be started. Extracting or decoding this information or feature from ECG signal has been found very helpful in explaining and identifying various pathological conditions. The feature extraction procedure can be accomplished straightforward by analysing the ECG visually on paper or screen. In addition, manual feature extraction is always prone to error. Therefore, ECG signal processing has become an indispensable and effective tool for extracting clinically significant information from ECG signals, for reducing the subjectivity of manual ECG analysis and for developing advanced aid to the physician in making well-founded decisions. ECG analysis systems are usually designed to process ECG signals measured under particular conditions, like resting ECG interpretation, stress test analysis, ambulatory ECG monitoring and intensive care monitoring.
Electrocardiogram (ECG) reflects activity of the central of the blood circulatory system, i.e. the heart. An ECG signal can provide us with a great deal of information on the normal and pathological physiology of heart activity [1]. Thus, ECG is an important non-invasive clinical tool for the diagnosis of heart diseases.
According to the medical definition the most important information in the ECG signal is concentrated in the P wave, QRS complex and T wave. These data include positions and/or magnitudes of the QRS interval, PR interval, QT interval, ST interval, PR segment, and ST segment (see Fig. 1). Based on the above data, doctors can correctly diagnose human heart diseases.[2] Therefore, analyzing the ECG signals of cardiac arrhythmia is very important for doctors to make correct clinical diagnoses. In order to perform ECG signals classification of the cardiac arrhythmia, the first important task is to determine an appropriate set of features. The feature selection method which chooses the best features from original features to have the maximum recognition rate, simplify classified computation and comprehend the causal relation of classified question.

II. ELECTROCARDIOGRAM

The electrical functionality of different organs in the human body is expressed by bioelectrical signals. The Electrocardiogram, also called ECG signal, is one important signal among all bioelectrical signals. The ECG reflects the performance and the properties of the human heart and conveys very important hidden information in its structure. This information has to be extracted and analyzed before any useful and meaningful interpretations can be started. Extracting or decoding this information or feature from ECG signal has been found very helpful in explaining and identifying various pathological conditions. The feature extraction procedure can be accomplished straightforward by analysing the ECG visually on paper or screen. However, the complexity and the duration of ECG signals are often quite considerable making the manual analysis a very time-consuming and limited solution. In addition, manual feature extraction is always prone to error. Therefore, ECG signal processing has become an indispensable and effective tool for extracting clinically significant information from ECG signals, for reducing the subjectivity of manual ECG analysis and for developing advanced aid to the physician in making well-founded decisions. Over the past few years automatic analysis of electrocardiograms (ECG) has gained more and more significance in the field of clinical ECG diagnosis.
The human heart is located in the chest between the lungs, behind the sternum and above the diaphragm. It weighs between 200 to 425 grams and is a little larger than the size of a fist [2, 3, 4]. The basis end and the apex end of the heart lie on its main axis which is oriented from the back-top-

right to the front-bottom-left of the torso. Every day it beats in average 100000 times pumping about 7600 liters of blood to the body [5]. Like a sack, a double-layered membrane called the pericardium surrounds the heart. Its outer layer covers the roots of the heart's major blood vessels and is attached by ligaments to the spinal column, diaphragm, and other parts of your body. The inner layer of the pericardium is connected to the heart muscle. The layers are separated by a coating of fluid, letting the heart move as it beats and keeping it attached to the body. The normal periodic contractions and relaxations of the heart allow the human cells receiving the necessary amount of oxygen and nutrients and carrying away their end product of the metabolism.

The walls of the heart are composed of cardiac muscle, Myocardium. It is similar to skeletal muscle, because it has striations. The cardiac muscle consists of four chambers: the right and left atria and ventricles. The anterior aspect of the heart is the right ventricle, whereas the posterior aspect is the left atrium giving the heart its orientation. The endocardium is defined as the thin serous membrane that lines the interior of the heart, whereas the epicardium touches the inner layer of the pericardium that is in actual contact with the surface of the heart. The left ventricle pumps blood to the systemic circulation, where pressure is considerably higher than for the pulmonary circulation, which arises from right ventricular outflow. The left ventricular free wall and the septum is much thicker than the right ventricular wall [6]. The tricuspid valve lays between the right atrium and ventricle, and the mitral valve is between the left atrium and ventricle. Between the right ventricle and the pulmonary artery lies the pulmonary valve, while the aortic valve is in the outflow tract of the left ventricle controlling blood flow to the aorta. Carried in the inferior and superior vena cava, the blood returns from the systemic circulation to the right atrium [7, 8, 9]. First, it has to go through the right ventricle, then it is ejected through the pulmonary valve and the pulmonary artery to the lungs. Oxygen-rich blood returns from the lungs to the left atrium and to the left ventricle. Finally blood is pumped through the aortic valve to the aorta and the systemic circulation. The left and right coronary arteries branch off the aorta. They are divided afterward into numerous smaller arteries supplying oxygen and nourishments to all heart muscles.

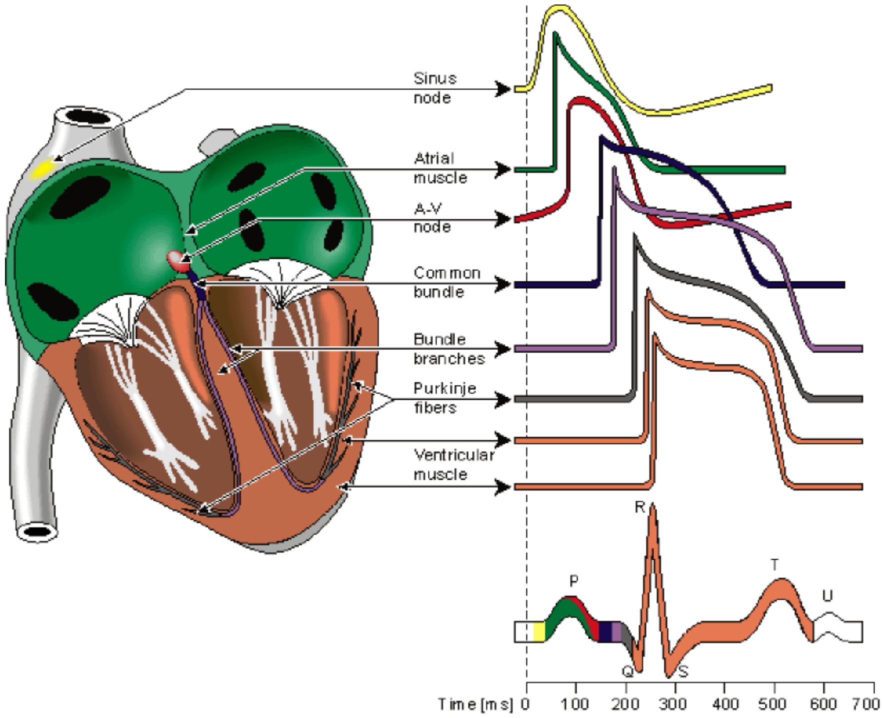

Figure 1. The Genesis of Electrocardiogram: the waveform and timing of different action potentials from

doi: 10.7323/ijaet/v9_iss4_11

III. The Normal ECG Waves, Time Intervals, and Its Normal Variants

The normal ECG signal represents a normal cardiac cycle. Figure 2.8 illustrates the normal ECG of one cardiac cycle along with its components. The normal variances and characteristics of its waves, durations and time intervals are described as follows:

3.1 The P Wave

Depolarization in the atria is registered as the P wave in the ECG. Duration of the P wave should not exceed 0.10 sec in limb leads, or 0.12 sec in chest leads. Its amplitude averages 0.1-0.3 mV. P wave is normally positive in limb leads except in a VR lead, where it is always negative. It is most pronounced in lead II. P wave is always positive in left precordial leads, often biphasic over the right chest wall. The autonomic nervous system activity plays a considerable role in the variation of P wave morphology. The amplitude of P wave may increase remarkably, above all in leads II, III and a VF, when the sympathetic tone is increased. On the other hand, when there is an increased parasympathetic tone, P wave becomes flat in leads II, III, and a VF. The spectral characteristics of a normal P wave is usually considered to be low-frequency, below 10-15 Hz [33].

3.2 The QRS Complex

The ventricular complex represents the initial ventricular depolarization. It usually comprises a Q, R and an S wave. Every positive wave is called R. The first negative wave preceding an R is always called Q and the first negative wave following R is always called S. A possible second or third R wave is called R' or R", figure 2.9 It is also preferable to speak of a split ventricular complex, when several waves are presented. Notation of individual waves of the ventricular complex is different according to amplitude by using small or large letters.

3.3 The PR or PQ Interval

It is measured from the start of the P wave to the start of ventricular complex. It should not be shorter than 0.12 sec, nor longer than 0.20 sec. Prolonged AV conduction time at the rest is which becomes normal on exercise not necessarily a sign of abnormality.

3.4 The T Wave

It expresses repolarization of the ventricles. Its amplitude must always be taken in relation to the R wave. T wave is always positive in lead I and II, and it is always negative in aVR lead.

3.5 The U Wave

After T wave, an ECG can sometimes show a U Wave. It is of the same deflection as T Wave and similar to shape to P Wave. The U Wave is thought to represent late repolarization of the Purkinje fibers in the ventricles [63].

3.6 The PP Interval and the RR Interval

PP interval is defined as the duration of atrial cycle. It is useful as an indicator of atrial rate. Whereas, RR interval is defined as the distance in msec between two successive R waves. It is an indicator of ventricular rate representing the length of a ventricular cardiac cycle. Moreover it is very important to characterize different arrhythmias and to study the heart rate variability.

3.7 The ST Segment

ST segment represents the period from the end of ventricular depolarization to the be-ginning of ventricular repolarization. The ST segment lies between the end of the QRS complex and the initial deflection of the T-wave and is normally isoelectric. It is clinically important if it is elevated or depressed as it can be a sign of ischemia and hyperkalemia [70]. In order to interpret ST segment correctly, the J point should be localized precisely. The J point, as definition, is the time instant in the ECG when the QRS complex curves into the ST segment.

IV. WAVELET TRANSFORM

The wavelet transform is a remarkable mathematical method with the ability to examine the signal concurrently in time and frequency, in a different way from previous mathematical methods. Wavelet analysis has been used in a wide range of applications: from climate analysis, to signal compression and medical signal analysis. The different application of WT emerged and increased in the early years of the 1990s, directly reflecting the interest of the scientific community [30].

Some of the most frequently used wavelets are depicted in Figure 4.1. We can notice that they have the shape of a small wave, localized on the time axis. Depending both on the signal we need to analyze and what characteristic we are analyzing, one wavelet can be better suited than others.

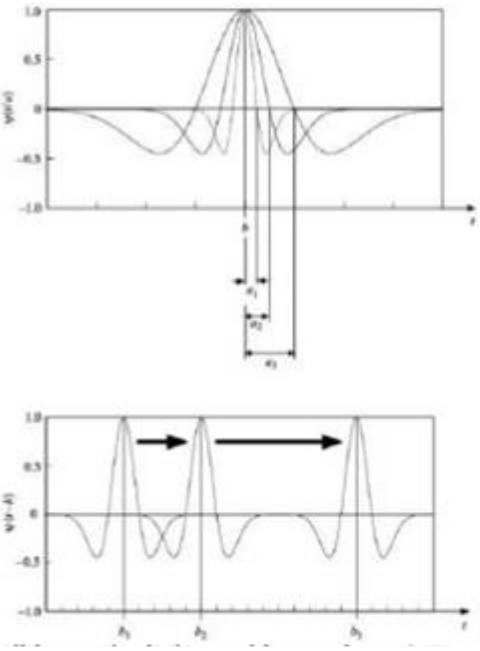

Figure 2: Wavelet Transform

4.1 Implementation and Result Analysis

First the signal is taken and divided into the blocks. Then the mean is taken of the particular beat. Then that mean is subtracted from the original signal. Thus we got the principal components. if the covariance is taken of the resultant we will get the eigenvectors and eigenvalues with the help of which we can reconstruct the original signal.

Wavelet decomposition:

The objective of this analysis was to determine the wavelet that produces result that is the closest to the original signal. Different types of wavelet analysis are shown below.

a. Daubechies decomposition of order 1 (Same as Harr wavelet decomposition):

The stages of wavelet decomposition using Daubechies wavelet of order 1 is as follows the transform was performed on the first 250 samples

doi: 10.7323/ijaet/v9_iss4_11 Vol. 9, Issue 4, pp. 513-523

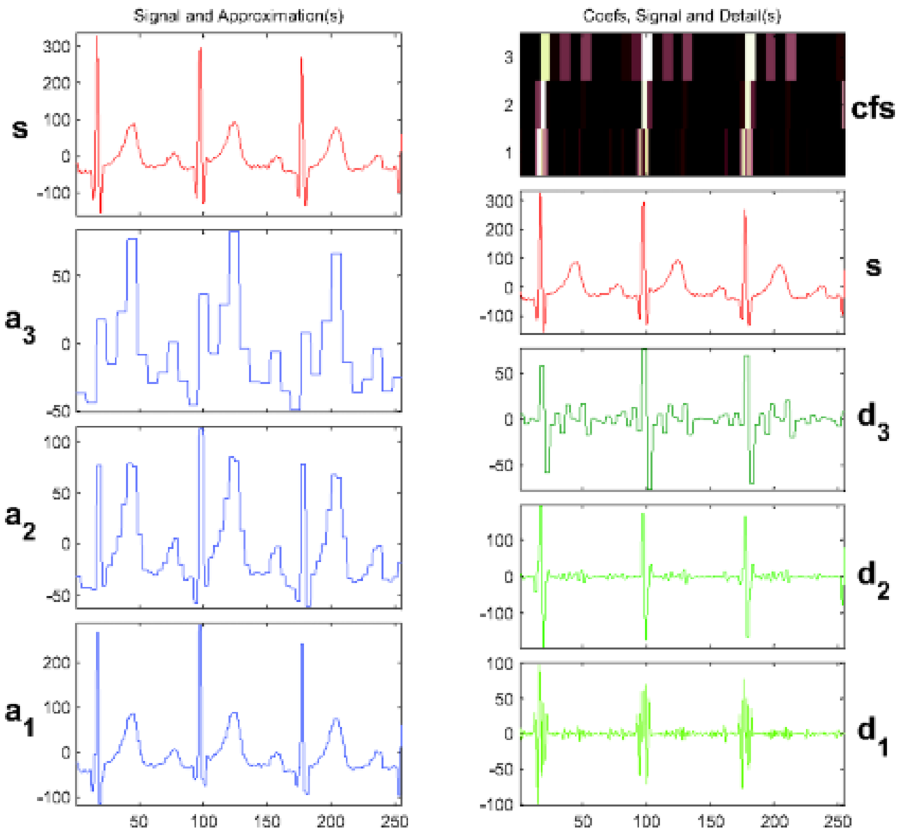

Figure 3 : wavelet decomposition using Daubechies wavelet of order 1

Inference: this wavelet decomposition provides a step output and on higher levels of decomposition, the signal loses its identity, as the peaks are lost. Thus, this signal is unfit for use in neural networks.

b. Daubechies wavelet of order 2: As in the former case, this wavelet decomposition also considers first 250 samples and the results from decomposition are shown below.

 doi: 10.7323/ijaet/v9_iss4_11 Vol. 9, Issue 4, pp. 513-523

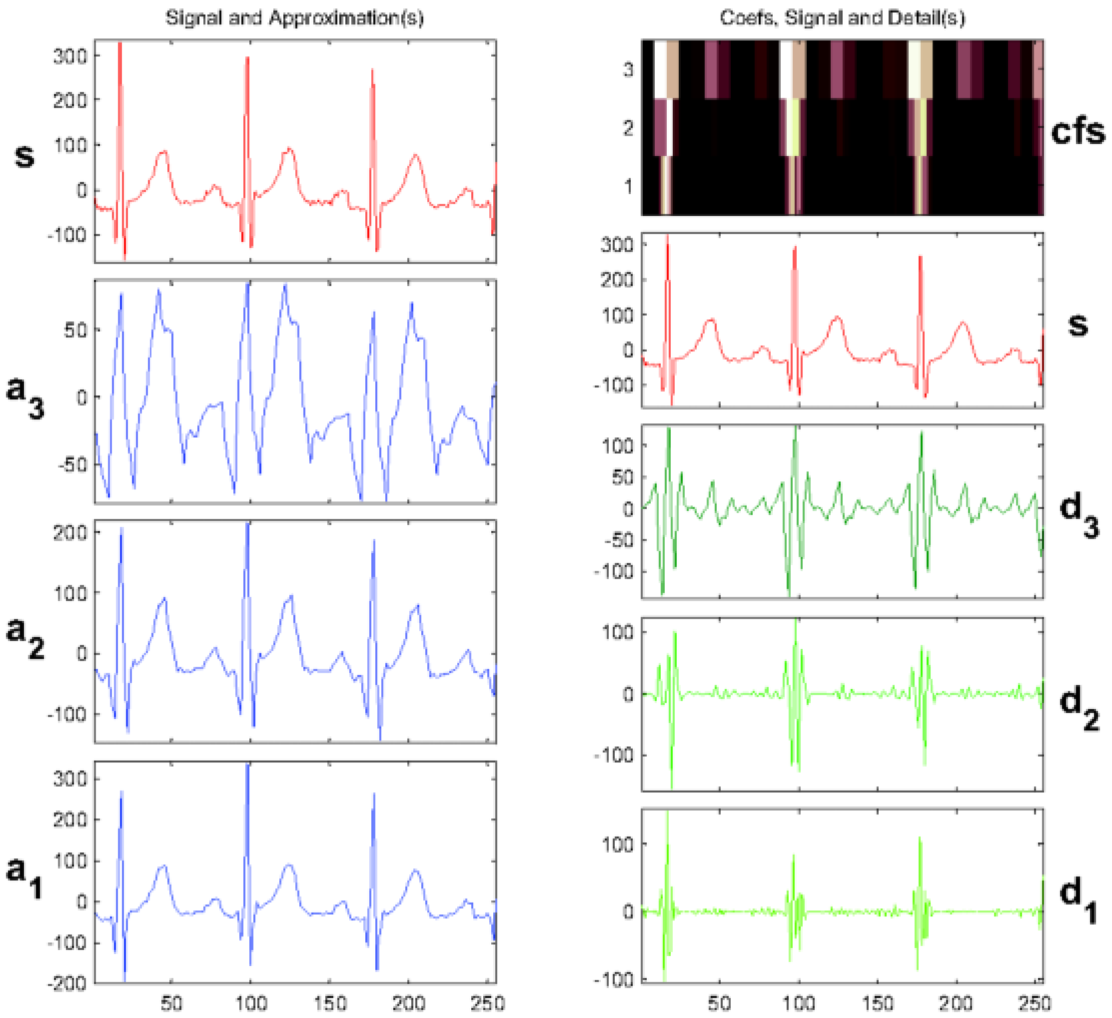

Figure 4: wavelet decomposition using Daubechies wavelet of order 3

Daubechies wavelet decomposition of order 3: As in the former case, this wavelet decomposition also takes first 250 samples into account and the results from decomposition are shown below.

Inference: this decomposition leads to a large deviation from original hence not recommended for further processing.

Note: Higher order wavelet decomposition produces more deviation and was not taken into account for further processing. Thus, the second order Daubechies wavelet transform was used for further processing in the neural network.

4.2 Simulink Model Implementation

The offline analysis was followed by the implementation of the results so obtained in a SIMULINK model for simulation of a real-time implementation of the model. The different parts of the model are described below.

Basically the system structure is same as described in the first chapter. However the final SIMULINK structure looks like the figure given below. The additional blocks are due to the different input and output compatibility of the blocks in SIMULINK. For example, the DWT block takes in a frame based input of frame size of two elements and the input blocks outputs

a frame size of one. Therefore, a buffer block is needed to convert the frame size from one to two.
The individual blocks and their usage are described below.

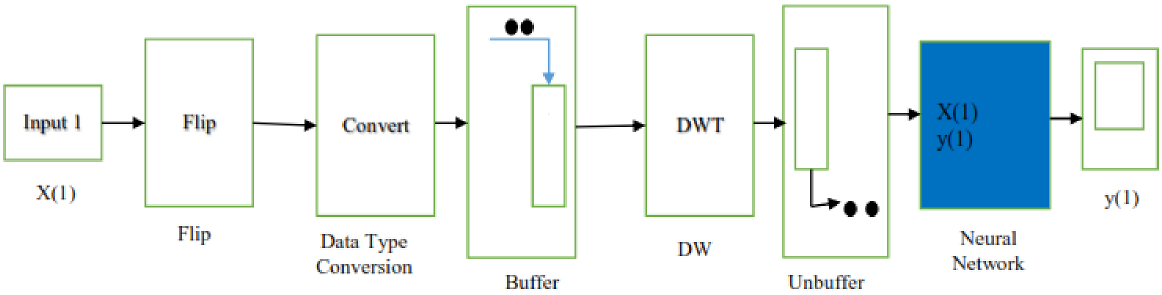

Figure 5. SIMULINK diagram for the whole structure

(i) Input block: This block holds the input values of the signal, which is passed on to the preprocessing blocks for wavelet decomposition. The frame size of the signal is one, which is incompatible with the DWT block, which takes in an input of frame rate 2. Thus, some other blocks are added to the network in between those blocks.
(ii) Matrix flip block: the function of this block is to flip the matrix input from input block to form a column matrix. This makes the input format of the buffer compatible with the input block.
(iii) Data type conversion: converts the data format for compatibility.
(iv) Buffer: buffer adjusts the frame rate so that the frame rate is same as that required by the DWT block.
(v) DWT block: This part does the actual processing in the preprocessing part of the model. As in the offline analysis, the DWT block decomposes the signal into approximation and detail parts using the Daubechies wavelet of order 2, and in the process reduces the number of samples to one fourth of the original. This makes processing at the neural network part lot simpler.
(vi) Unbuffer: This block has the same functionality as the buffer block; the only difference being the frame size is converted from two to one, which makes it compatible with the neural network block.
(vii) Neural network block: the neural network block recognizes the type of arrhythmia, thus diagnosing the disease.
(viii) Scope: used for visualization of the output.

Simulink Results

The results of simulation are shown below. The simulation is done with the help of a synthesized input signal. The topmost figure is the source signal and the subsequent are normal sinus atrial fibrillation and supraventricular arrhythmia respectively.

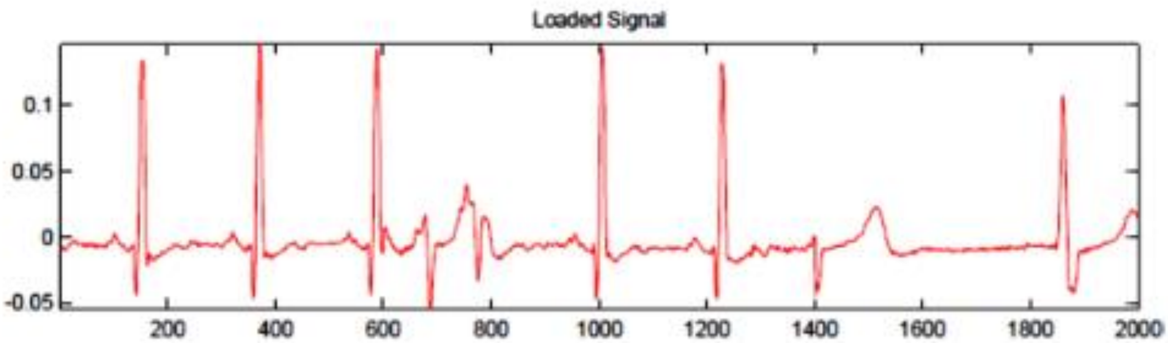

Figure 6 : Loaded ECG signal

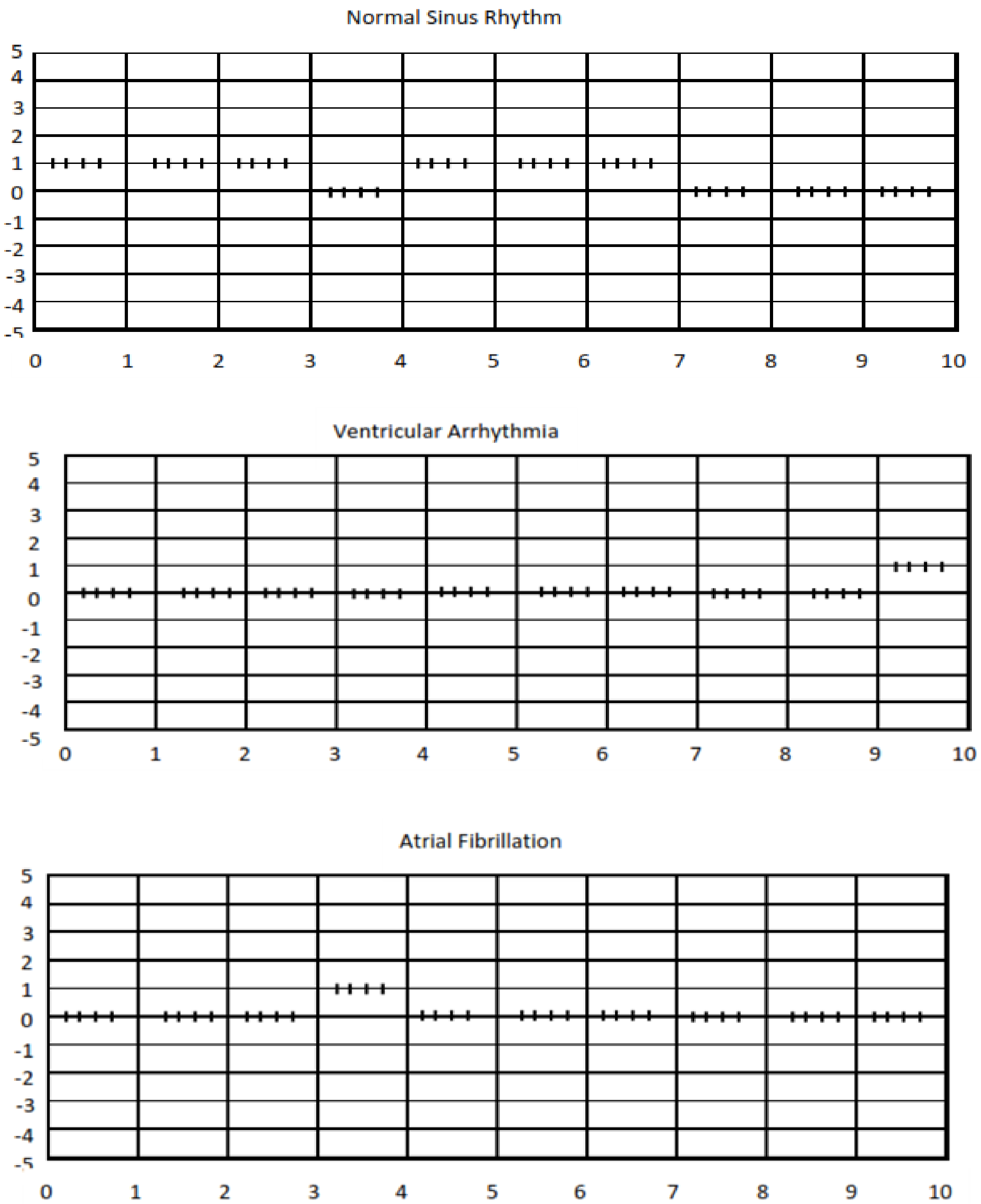

Figure 6: Ventricular Arrhythmia of ECG Signal

Table 1: Accuracy of the proposed method and other methods for ECG classification

Method	Number of beat type	Accuracy (%)
KNN-DWT	4	96.65
Neuro Fuzzy	4	98
MLP-VQ	2	96.8
SOM-SVD	3	92.2
Wavelet-SVM	7	97.59

V. CONCLUSION

A multiple ECG classifier is implemented based on temporal and wavelet features that are submitted individual SVM classifiers for different types of cardiac arrhythmia.
The use of ECG signals enabled the use of reliable and long duration recordings for the extraction of characteristic ECG features.
Combining temporal and wavelet features resulted in the description of ECG signals in time, frequency and morphological dimensions.
Effectiveness of using this set of features can easily be seen on the achieved recognition rates.
Using simple SVM classifiers for each of the six cardiac arrhythmia, the recognition rates achieved change from 92.33% to 99.97%. Compared to well-known methods such as DWT and neuro-fuzzy classifier.

VI. FUTURE WORK

The aim of Discrete Wavelet Transform is to reduce the number of samples and eventually reducing the complexity of the neural network and the computation time of the neural network. However, modern technology has made intensive processing highly feasible and economical. Computing platforms such as FPGA, DSP and microprocessors can be used for interfacing the model with the actual Holter Device. Of all devices mentioned above FPGA is the most promising because of its speed and flexibility. FPGA platforms provide great support for many types of interfacing standards and are hence recommended for implementation in a real time scenario.

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