ECG CLASSIFICATION USING SLANTLET TRANSFORM AND ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Automatic detection and classification of cardiac arrhythmias is important for diagnosis of cardiac abnormality. This paper shows a method to accurately classify ECG arrhythmias through a combination of slantlet transform and artificial neural network (ANN). The ability of the slantlet transform to decompose signal at various resolutions allows accurate extraction of features from non-stationary signals like ECG. The low frequency coefficients, which contain the maximum information about the arrhythmia, were selected from the slantlet decomposition. These coefficients are fed to a Multi-Layer Perceptron (MLP) artificial neural network which classifies the arrhythmias. In the present work the ECG data is taken from standard MIT-BIH database. The proposed system is capable of distinguishing the normal sinus rhythm and nine different arrhythmias. The overall accuracy of classification of the proposed approach is 98.40 %. Three other transformation methods are used and the accuracy of the classification of each was compared with the slantlet system accuracy. These transformation methods are: the Fourier transform which gives 67.80% accuracy, the discrete cosine transform which gives 92.72% accuracy, and the wavelet transform (using Haar and Daubechies-4 scaling function coefficients, which give an accuracies of 96.02% and 96.25% respectively).

الخلاصة:- إن كشف و تصنيف حالات القلب المرضية مهم في تشخيص الحالات القلبية الشاذة. هذا البحث يوضح طريقة لتصنيف الحالات المرضية من تخطيط القلب و ذلك من خلال دمج التحويل (Slantlet) مع الشبكة العصبية الاصطناعية (ANN). قدرة التحويل (Slantlet) على تحليل الأشارة إلى عناصرها ذات الدقة المختلفة تسمح بإستخلاص أدق للميزات التي تحملها الأشارات غير المستقرة مثل الاشكال الموجية لتخطيط القلب الكهربائي. المعاملات ذات التردد الواطيء (و التي تحتوي على أعظم نسبة من المعلومات عن الحالة المرضية) تم إختيارها من التحليل الناتج من إستخدام التحويل (Slantlet). هذه المعاملات تم تجهيزها الى شبكة عصبية اصطناعية متعددة الطبقات و التي بدورها تقوم بتصنيف الحالات المرضية. في العمل المقدم تم أخذ بيانات تخطيط القلب الكهربائي من قاعدة البيانات القياسية (MIT-BIH). إن النظام المقترح قادر على التمييز بين الحالة الطبيعية و تسعة حالات مرضية. الدقة الاجمالية للتصنيف في الطريقة المقدمة هي 98.40٪ . كذلك تم أستخدام ثلاث طرق تحويلات أخرى و تم مقارنة دقة التصنيف لكل طريقة مع الدقة الناتجة بإستخدام التحويل (Slantlet). هذه الطرق هي التحويل (Fourier) الذي يعطي دقة 67.80٪, التحويل (discrete cosine) و الذي يعطي دقة 92.72٪ و التحويل (Wavelet) [بإستخدام معاملات دالة الحجم (Haar) و (Daubechies-4) و التي أعطت دقة 96.02٪ و 96.25٪ على التوالي].

KEYWORDS

Slantlet Transform, Neural Networks, ECG Features Extraction and Classification.

INTRODUCTION

Electrocardiogram (ECG) measurements are used to monitor the contraction of the cardiac muscles by measuring the propagation of electrical depolarization and repolarization in the atria and ventricles. The ECG waveform is divided into P, Q, R, S, T and U elements. **Fig. 1** shows the components of a typical ECG signal. The P wave corresponds to atrial depolarization that shows contraction of both left and right atria. The QRS complex represents the depolarization of the ventricles. The T wave represents ventricles repolarization which setting up the cardiac muscle for another contraction. Sometimes it will follow by U wave that represents the Purkinje fibers repolarization. A highly sensitive electrocardiograph tools can help cardiologists to detect various heart irregularities, cardiac diseases and damages. The ECG interpretation is important for cardiologists to decide diagnostic categories of cardiac problems [1].

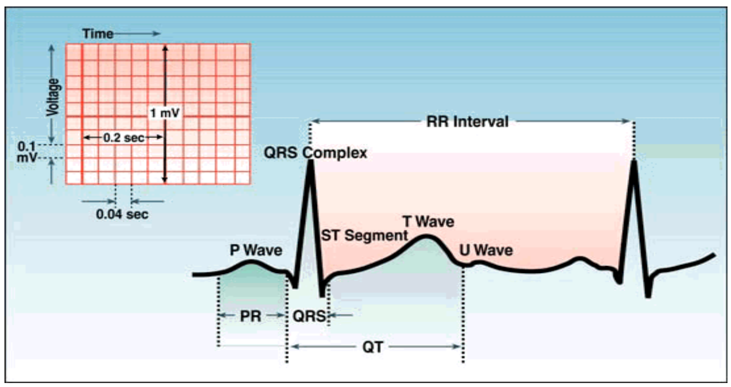


Fig. 1: Components of a typical ECG signal

Classification of ECG is an important area in biomedical signal processing, several algorithms have been developed for classification of ECG beats. These techniques extract features, which are either temporal or transformed representation of the ECG waveforms. The extracted features are used in the pattern recognition system to classify the ECG beats. The subject of pattern recognition can be divided into two main areas of study (1) features extraction and (2) classifier design, as summarized in **Fig. 2**, where x(t) is the input signal.

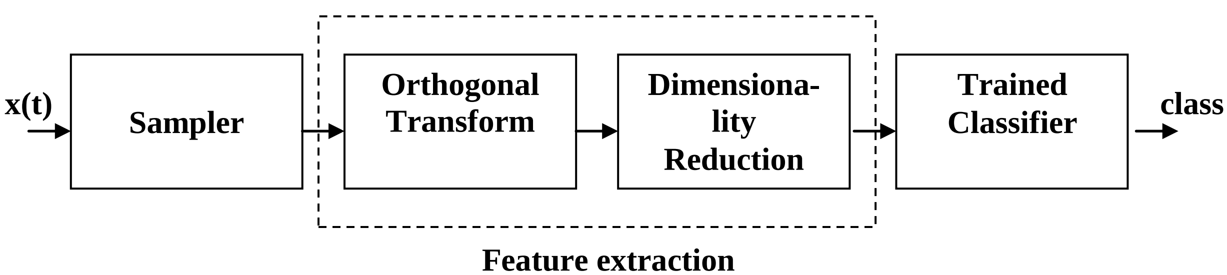


Fig. 2 : Pattern recognition system

The paper presents a slantlet based approach to extract features from the non-stationary ECG signal. The slantlet transform allows improved time-frequency localization of the signal. A supervised artificial neural network (ANN) is developed to recognize and classify the nonlinear morphologies.

ANN trained with back propagation algorithm, classifies the applied input ECG beat to appropriate class.

- WAVELET TRANSFORM

Wavelet transforms (WT) are used to decompose the original signal into a set of coefficients that describe the signal's frequency content at given times. The wavelet transform is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations, which is the case in most biological signals, mainly the Electroencephalogram (EEG), Electromyogram (EMG), and ECG signals [2]. Wavelets are functions defined over a finite interval and having an average value of zero. The basic idea of the wavelet transform is to represent any arbitrary function of time as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts) [3].

The Continuous Wavelet Transform

Wavelet functions generated from one single function ψ, which is called mother wavelet, by the scaling factor a and the translation factor b is given by:

$$\psi_{a,b}(t) = |a|^{-1/2}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

Where a: is the scaling factor, and b: is the translation factor
Where ψ must satisfy:

$$\int_{-\infty}^{\infty}\psi(t)\,dt = 0 \tag{2}$$

The basic idea of wavelet transform is to represent any arbitrary function *f* as a decomposition of the wavelet basis or write *f* as an integral over *a* and *b* of $\psi_{a,b}$.
The continuous wavelet transform of a signal $f(t)$ is defined by [4]:

$$C(a,b) = \int_{-\infty}^{+\infty} f(t)\,\psi_{a,b}(t)\,dt \tag{3}$$

The Discrete Wavelet Transform

The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two, as shown in equation below [5]:

$$y[n] = (x * g) = \sum_{k=-\infty}^{+\infty} x[k]g[n-k] \tag{4}$$

The signal is also decomposed simultaneously using a high-pass filter h.

The outputs give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter. However, since half the frequencies of the signal have now been removed, half the samples can be discarding according to Nyquist's rule.

For many signals, the low-frequency content is the most important part, which gives the signal identity. The high-frequency content, on the other hand, imparts details or noise. In wavelet analysis, all the speaking is about the approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.
The filter outputs are then down-sampled by 2, as shown in the following equations:

$$y_{low}[n] = \sum_{k=-\infty}^{+\infty} x[k].g[2.n-k] \tag{5}$$

$$y_{high}[n] = \sum_{k=-\infty}^{+\infty} x[k].h[2.n-k] \tag{6}$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

Discrete Wavelet Transform Using Filter Bank Structure

The DWT is calculated as described above, the structure uses the high pass filter, low pass filter and subsampling is called Filter Bank. This decomposition is repeated to further increase the frequency resolution and the approximation coefficients decomposed with high and low pass filters and then down-sampled. This is represented as a binary tree with nodes representing a sub-space with different time-frequency localization, the tree is known as a bank and is shown in **Fig. 3**.

At each level in **Fig. 3** the signal is decomposed into low and high frequencies. Due to the decomposition process the input signal must be a multiple of (2^n) where n is the number of levels [5].

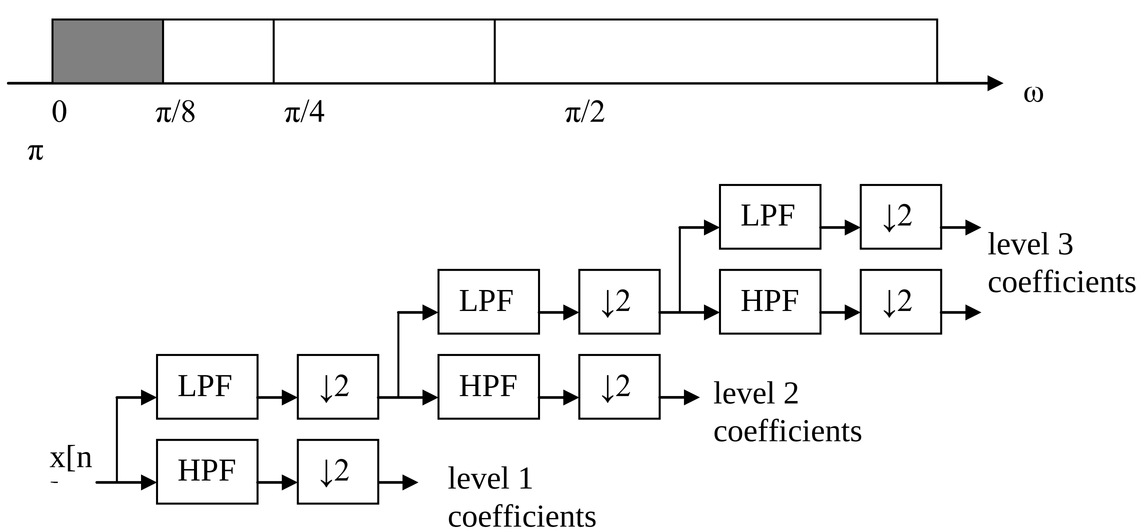


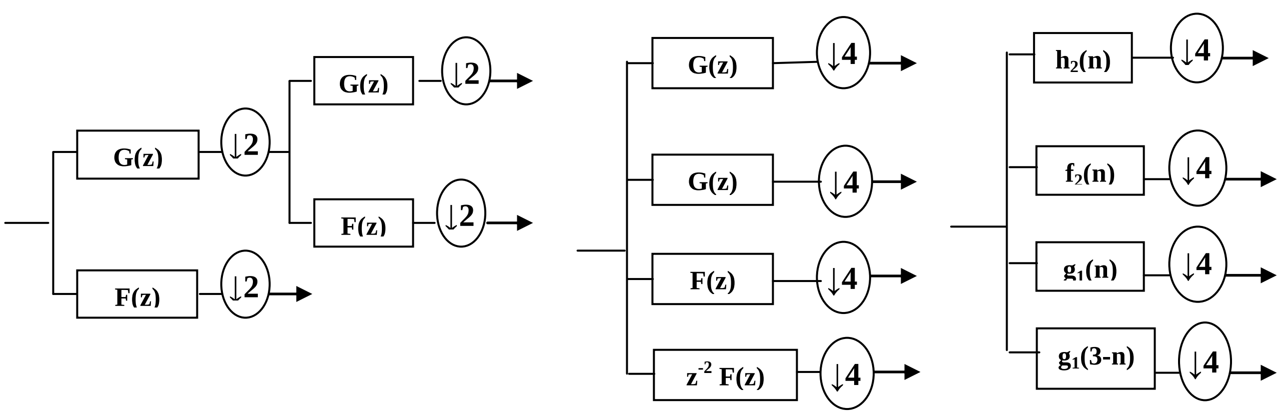
Fig. 3: A 3-level filter bank (A 3-level DWT)

For most physical signals the signal energy is concentrated in the lower frequency bands, thus this representation gives the energy compaction. Many of the resulting wavelet coefficients, especially in the higher frequency bands, are either zero or close to zero. By taking only the larger coefficients, many bits are already discarded without losing significant information [6].

- SLANTLET TRANSFORM

The slantlet transform is an orthogonal discrete wavelet transform with two zero moments and with improved time localization, the construction of the slantlet is based on a filter bank structure where different filters are used for each scale. Let us consider a usual two-scale iterated DWT filter bank shown in **Fig. 4 (a)** and its equivalent form **Fig. 4 (b)**. The slantlet filter bank employs the structure of the equivalent form shown in **Fig. 4 (b)** but it is occupied by different filters that are not products. With this extra degree of freedom obtained by giving up the product form, filters of shorter length are designed satisfying orthogonality and zero moment conditions [7].

For two-channel case the Daubechies filter is the shortest filter which makes the filter bank orthogonal and has K zero moments. For K=2 zero moments the iterated filters of **Fig. 4 (b)** are of lengths 10 and 4 but the Slantlet filter bank with K=2 zero moments shown in **Fig. 4 (c)** has filter lengths 8 and 4. Thus the two-scale Slantlet filter bank has a filter length which is two samples less than that of a two-scale iterated Daubechies-2 filter bank. This difference grows with the increased number of stages. Some characteristic features of the Slantlet filter bank are orthogonal, having two zero moments and has octave-band characteristic. Each filter bank has a scale dilation factor of two and provides a multiresolution decomposition. The slantlet filters are piecewise linear. Even though there is no tree structure for Slantlet it can be efficiently implemented like an iterated DWT filter bank. Therefore, computational complexities of the Slantlet are of the same order as that of the DWT, but slantlet Transform gives better performance in denoising and compression of the signals [8].



(a) (b) (c)

Fig. 4
(a)Two-scale iterated filter bank DWT
(b) Equivalent form using the DWT
(c) Two-scale filter bank using SLT

<u>Derivations of The Slantlet Filters Coefficients</u> [8]

The filters that construct the slantlet filter bank are $g_i(n)$, $f_i(n)$, and $h_i(n)$. The L-scale filter bank has 2L channels. The low-pass filter is to be called $h_L(n)$. The filter adjacent to the low-pass channel is to be called $f_L(n)$. Both $h_L(n)$ and $f_L(n)$ are to be followed by downsampling by 2^L. The remaining 2L-2 channels are filtered by $g_i(n)$ and its shifted time-reverse for i=1,…,L-1. Each is to be followed by downsampling by 2^{i+1}.

The sought filter $g_i(n)$ is described by four parameters and can be written as:

$$g_i(n) = \begin{cases} a_0 + a_1 n & \text{for } n = 0,\dots,2^i - 1 \\ b_0 + b_1(n - 2^i) & \text{for } n = 2^i,\dots,2^{i+1} - 1 \end{cases} \tag{7}$$

To obtain $g_i(n)$ such that the sought L-scale filter bank is orthogonal with 2 zero moments, requires obtaining parameters a_0, a_1, b_0, b_1 such that

$$m = 2^i$$
$$s_1 = 6\sqrt{m/((m^2-1)(4m^2-1))}$$
$$t_1 = 2\sqrt{3/(m.(m^2-1))}$$
$$s_0 = -s_1.(m-1)/2$$
$$t_0 = ((m+1).s_1/3 - mt_1)(m-1)/(2m)$$
$$a_0 = (s_0 + t_0)/2$$
$$b_0 = (s_0 - t_0)/2$$
$$a_1 = (s_1 + t_1)/2$$
$$b_1 = (s_1 - t_1)/2$$

The same approach work for $f_i(n)$ and $h_i(n)$.

$$h_i(n) = \begin{cases} a_0 + a_1 n & \text{for } n = 0,\dots,2^i - 1 \\ b_0 + b_1(n - 2^i) & \text{for } n = 2^i,\dots,2^{i+1} - 1 \end{cases} \tag{8}$$

$$f_i(n) = \begin{cases} c_0 + c_1 n & \text{for } n = 0,\dots,2^i - 1 \\ d_0 + d_1(n - 2^i) & \text{for } n = 2^i,\dots,2^{i+1} - 1 \end{cases} \tag{9}$$

Where

$$m = 2^i$$
$$u = 1/\sqrt{m}$$
$$v = \sqrt{(2m^2+1)/3}$$
$$a_0 = u.(v+1)/(2m)$$
$$b_0 = u.(2m-v-1)/(2m)$$
$$a_1 = u/m$$
$$b_1 = -a1$$

$$q = \sqrt{3/(m.(m^2 - 1))}\,/\,m$$
$$c_1 = -q.(v - m)$$
$$d_1 = -q.(v + m)$$
$$d_0 = d_1.(v + 1 - 2m)/2$$
$$c_0 = c_1.(v + 1)/2$$

- NEURAL NETWORK

A generic artificial neural network can be defined as a computational system consisting of a set of highly interconnected processing elements, called neurons, which process information as a response to external stimuli. The inputs received by a single processing element, see **Fig. 5**, can be represented as an input vector X= (x_1, x_2,…x_m), where i=1,…,m and x_i is the signal from the ith input. The weights connected to the neuron can be represented as a weight vector of the form W = (w_1, w_2, …, w_m), which represents the weight associated to the connection between the input vector X, and the processing element. A neuron contains a threshold value that regulates its action potential which is called the bias (x_0) and the weight of the connection is w_0. While action potential of a neuron is determined by the weights associated with the neuron's inputs, a threshold modulates the response of a neuron to a particular stimulus confining such response to a pre-defined range of values [9].

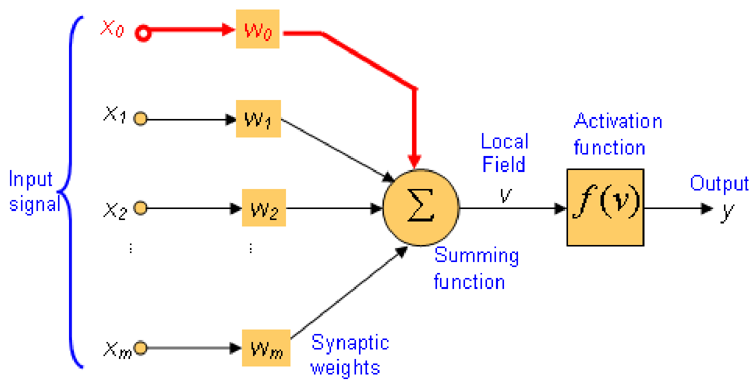


Fig. 5: Basic Model of a Single Neuron

The equation below describes the summation of weighted input process of the active neuron as shown in **Fig. 5**.

$$v = \sum_{i=1}^{m} x_i w_i \tag{10}$$

The equation below shows the y output of a neuron as an activation function *f* of the weighted sum of m inputs.

$$y_k = f(\sum_{i=1}^{m} x_i w_i)$$

(11)

The activation function, denoted by f (v), defines the output of a neuron in terms of the induced local field v.

Structure of ANN [9]

Neural networks are typically arranged in layers. Each layer in a layered network is an array of processing elements or neurons. Information flows through each element in an input-output manner. In other words, each element receives an input signal, manipulates it and forwards an output signal to the other connected elements in the adjacent layer.

Back Propagation Algorithm [10]

Different network topologies with powerful learning strategies to solve nonlinear problems have been reported. For the present application, back propagation with momentum is used to train the feed forward neural network. The output units (y_k units) have weights w_{jk} and the hidden units have weights w_{ij}. During the training phase, each output neuron compares its computed activation y_k with its target value d_k to determine the associated error E for the pattern with that neuron, i.e.,

$$E = \sum_{k=1}^{m} (d_k - y_k)^2$$

(12)

Where m is the number of the output neurons

The ANN weights and biases are adjusted to minimize the least-square error. The minimization problem is solved by the gradient technique. This is achieved by back propagation of the error. When using momentum, the net is proceeding not in the direction of the gradient, but in the direction of a combination of the current gradient and the previous direction of weight correction. Convergence is sometimes faster if a momentum term is added to the weight update formula.

The BPA is a supervised learning algorithm, in which a mean square error function is defined, and the learning process aims to reduce the overall system error to a minimum. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall system error. The weight updating starts with the output layer and progresses backward. The weight update is in the direction of 'negative descent', to maximize the speed of error reduction.

For effective training, it is desirable that the training data set be uniformly spread throughout the class domains. The available data can be used iteratively, until the error function is reduced to a minimum.

The accuracy of the neural network classifier depends on several factors, such as the size and quality of the training set, the method of the training imparted and also the parameters chosen to represent the input.

- SYSTEM DESIGN STAGE

The problem under study is to classify the ECG signals into normal cases and nine abnormal cases depending on the features of the ECG signals. In this work the physionet database of biological signals is used as the source of ECG records, namely the MIT-BIH ECG Database. This database is accessible on the internet and is widely used in experimental works on classification of ECG signals and biological signals in general [11].

The data files were recorded with different sampling frequencies, so it is needed to resample the records to a unified frequency. The unified frequency used in the proposed work is 360 Hz.

The proposed work is done on ten classes where the data used are collected from the following databases in the MIT-BIH ECG database: Arrhythmia, Atrial fibrillation, Malignant Ventricular Ectopy, Supraventricular Arrhythmia, Normal Sinus rhythm, and the PTB (Physikalisch-Technische Bundesanstalt, i.e. The National Metrology Institute of Germany) Diagnostic ECG Database.

- PROPOSED FLOW DIAGRAM

The general block diagram for the proposed system of the classification is shown in **Fig. 6**. In the present work, MATLAB software package version7.4.0.287 (R2007a) is used to implement the software design and algorithms. The main components of the system are the sampling block in which the sampling rate of the signal is made 360 Hz so if the sampling rate of input signal is not equal to 360 Hz then re-sampling is done. The data files used consists of time stamps and values recorded from two electrodes, some of these files contain more than two electrodes records. The PTB Diagnostic ECG Database consists of time stamps and values recorded from 15 leads, each record includes 15 simultaneously measured signals: the conventional 12 leads (I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6) together with the 3 Frank lead ECGs (VX, VY, VZ). Each signal is digitized at 1000 samples per second. For each record the sampling rate is mentioned in its associated header file. The records used are taken from lead II to find the ECG beats that are used in the pattern recognition system. After the sampling block, the beat detection block is introduced in which one beat of the signal is extracted. The extracted beat is introduced to the feature extraction block for dimensionality reduction and for the creation of the feature vector. The feature vector creation process is done by using SLT, DWT, DCT and FFT. The new feature vector is used as an input to the BP-NN to classify them into normal and abnormal ECG beats. Some of the extracted beats are used for the training of the neural network and others are used for the testing. The classifier performance was evaluated by calculating accuracy of the network in classification process.

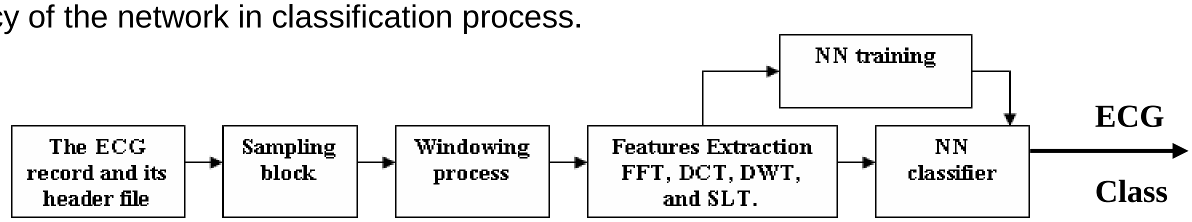


Fig. 6: Flow Diagram for classification and analysis of ECG signals

<u>The Input ECG Signal</u>

The ECG record that needs to be classified must be taken with its header, where the ECG record contains the ECG signals from a number of leads and the header file contains the sampling rate used to sample that signal. For the used records in this work the sampling rate for the Arrhythmia data base is 360 Hz, for the Atrial fibrillation recodes, Malignant Ventricular Ectopy, Supraventricular Arrhythmia, and Normal Sinus rhythm, is 250 Hz and for the PTB Diagnostic ECG Database the sampling rate is 1000 Hz [11].

<u>Sampling Block</u>

The sampling rate must be 360 Hz for whole records in order to make the ECG record suitable for the processing stages following this stage. The sampling rate change depends on the information contained in the header file of the record.

<u>Windowing Process</u>

First of all, one lead must be chosen to extract the ECG beat, the lead chosen in the proposed work is lead II since most of the rhythms are seen in this lead record. As the shape of each beat in ECG waves is asymmetric, P-QRS-T complexes are selected by using windows with a range of 100 samples before the R-wave maximum point and 155 samples after the R-wave maximum thus the number of samples in each extracted beat is 256 samples. This is to extract a single beat ECG signal from the multi-beat data. The flow chart for the windowing process is shown in **Fig. 7**. The extracted beat is now ready for the feature extraction step. **Fig. 8 (a)** shows the record (103) from the MIT-BIH arrhythmia database which contains the normal beats this record is from the modified lead II (MLII) and lead V2. The record from lead II is used to extract only one beat from it. **Fig. 8 (b)** shows the extracted beat (normal beat).

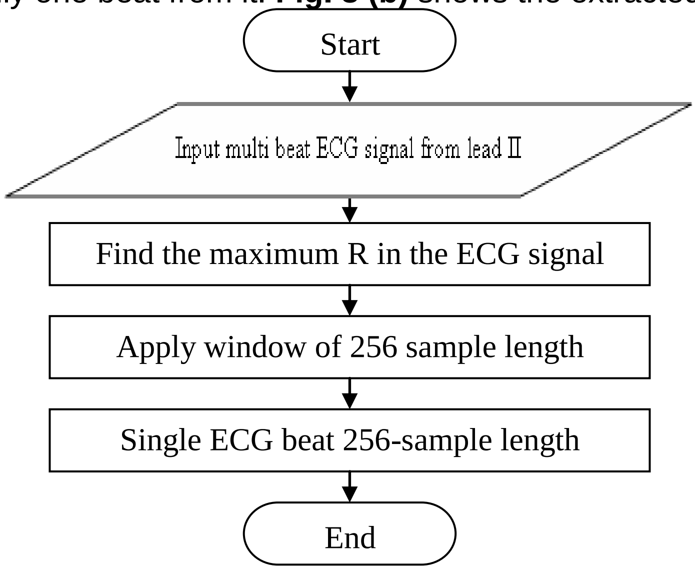


Fig. 7 : Flow chart describing windowing process

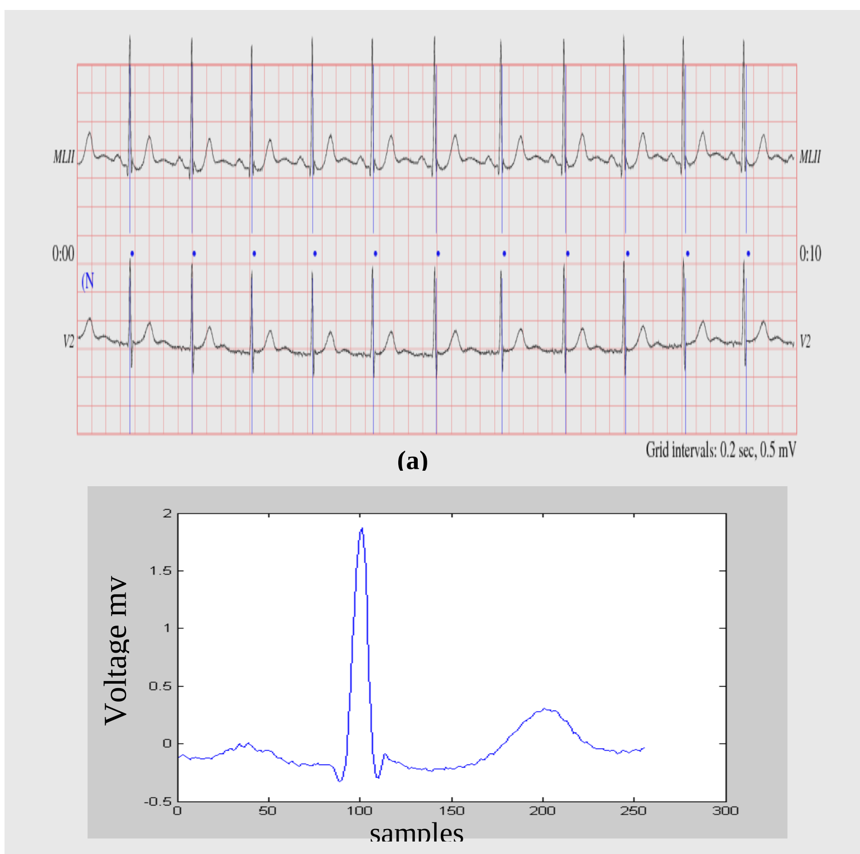


Fig. 8 (a) The ECG record (Normal Sinus Rhythm)(b) The Extracted single beat

Features Extraction

A- Feature Selection

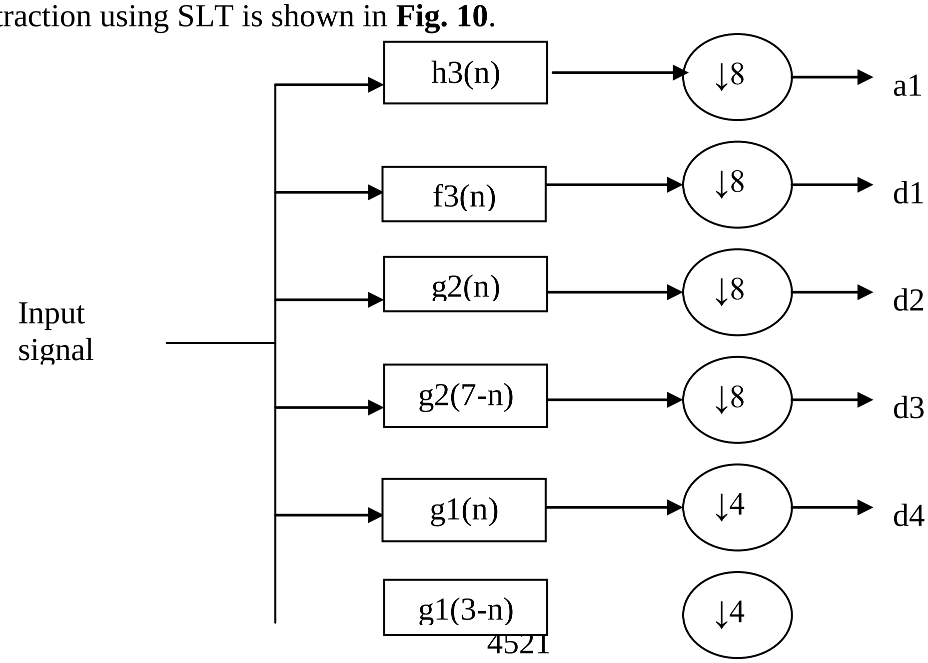
It is basically impossible to apply any classification method directly to the ECG samples, because of the large amount and the high dimension of the samples necessary to describe such a big variety of clinical situations. A set of algorithms from signal conditioning to measurements of average wave amplitudes, durations, and areas, is usually adopted to perform a quantitative description of the signal and a parameter extraction. On this set of extracted ECG parameters, several techniques for medical diagnostic classification are then applied, such as probabilistic approaches, heuristic models, and knowledge-based systems. The aim of this work was to determine suitable input feature vectors which would discriminate between normal and different types of heart diseases.

B. DWT Coefficients Extraction

In the present work Db4 and Haar wavelets have been used as the mother wavelets. For achieving good time-frequency localization, the preprocessed ECG signal is decomposed by using the DWT up to the third level. The 3-level wavelet decomposition structure is shown in **Fig. 3**, where the result is 4 different subsets, three subsets for the details (the wavelet function coefficients) and the forth is the approximation subset (the scaling function coefficients). Since most of the information is concentrated in the low frequency components only the 32 samples result from the level-3 low pass filter will be considered as the features of the input signal.

C. SLT Coefficients Extraction

The slantlet filter bank used to extract the features of the ECG signal is 3-scale (L=3) filter bank. The structure of this filter bank is shown in **Fig. 9**, where 6 different filters are used. These filters are constructed using the derivations explained previously. The low pass filter h3(n) output is the approximation of the signal and the other outputs are the details so it can be efficient to take only the coefficients of the low pass filter as features of the signal and discard the remaining coefficients without losing many information about the signal. Since the slantlet transform gives better time localization the results of the classification will be better using this transformation method. The features extraction using SLT is shown in **Fig. 10**.



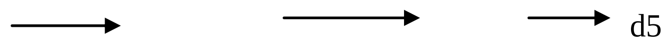


Fig. 9 : 3-scale slantlet filter bank

Where:

- a1: is 32 samples which are the outputs of the low pass filter h3 after down sampling by 8. Only this vector will be used as the features of the ECG beat.
- d1: is 32 samples which are the outputs of the band pass filter f3 after down sampling by 8.
- d2: is 32 samples which are the outputs of the band pass filter g2 after down sampling by 8.
- d3: is 32 samples which are the outputs of the band pass filter (shifted time reverse of g2) after down sampling by 8.
- d4: is 64 samples which are the outputs of the band pass filter g1 after down sampling by 4.
- d5: is 64 samples which are the outputs of the band pass filter (shifted time reverse of g1) after down sampling by 4.

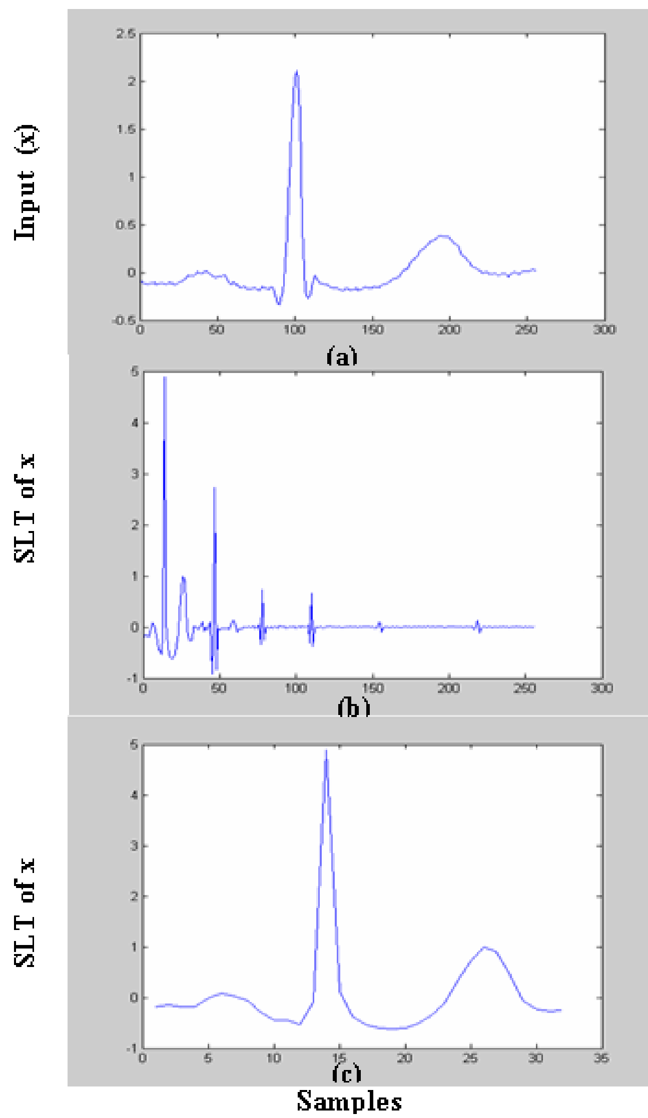


Fig. 10 (a) ECG beat (Normal) (b) SLT of the ECG beat (c) 32 samples of the SLT

D. DCT Coefficients Extraction

The discrete cosine transform has an important property that its basis vectors closely approximate the original signal with a little number of coefficients. The DCT is an orthogonal transform and most of the energy of the signal transformed is concentrated in the low frequency components. To extract the features of the ECG signal only the 32 samples in the lower part of the coefficients will be used.

E. FFT Coefficients Extraction

The amplitude of the signal using FFT is symmetrical so it is enough to consider only one side of the coefficients resulted to extract the features of the signal. The phase coefficient with dimensionality reduction will not give efficient result when the number of classes is large, so that the phase will not be used. It is important to notice that the features extracted using the FFT contains only the amplitude information. For dimensionality reduction first 32 samples are used as the features of the input signal.

Neural Network Classifier

The ECG record contains number of beats, this number of beats in each record is different according to the recording time, also the sampling rate in some records different from that of the other record. To extract one beat from the multi beat record the re-sampling is done if the sampling rate is not 360 Hz, then the windowing process is done. After the extraction of one beat, the features of each beat are found using transformation methods and dimensionality reduction to obtain an acceptable number of features that can be used in the neural network.

The neural network used as the classifier uses the features obtained from the feature extraction process for training and testing. The neural network structure used in the proposed work consists of 32 neuron input layer, 20 neuron hidden layer and 1 neuron output layer is shown in **Fig. 11**, and it's specifications are illustrated in **Table 1**.

The activation function for the input layer and the hidden layer neurons is the Tan-sigmoid function, the activation function for the output layer neuron is the Linear function.

The neural network after identifying its parameters [identifying the number of layers and the activation functions] was trained using the BPA. After the training process of the neural network, the testing process was done to test the performance of the neural network in classifying the input patterns. The maximum number of iterations for the neural network used in this work is 1000.

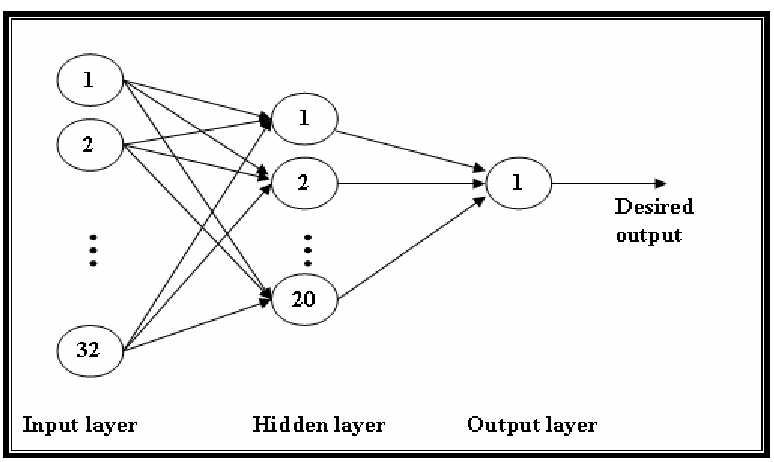


Fig. 11 : Structure of ANN

Table 1 : Neural Network specifications

No.	Item	Value
1	Training pattern vectors number	670
2	Layers number	3
3	No. of neurons in the input layer	32
4	No. of neurons in the hidden layer	20
5	No. of neurons in the output layer	1
6	Goal MSE	0
7	Maximum no. of iterations	1000

- RESULTS AND DISCUSSION

Data Manipulation

The system has been applied on ten classes of ECG beats, one of them is the normal beats class and the others were some of the heart arrhythmias. These ten classes and their corresponding number of beats are shown in **Table 2**.

Table 2: The ECG classes and their corresponding number of beats

Class number	Class name	Symbol of the class	The total number of beats used
1	Normal	N	708
2	Paced beat	P	247
3	Right Bundle Branch Block	R	128
4	Left Bundle Branch Block	L	103
5	junctional escape beat	j	19
6	Premature Ventricular contraction	V	28
7	Ventricular tachycardia	VT	50
8	Supraventricular	S	40
9	Atrial Fibrillation	A	92
10	Inferior Myocardial	IMI	134

	Infarction		

The number of beats of each class has been divided into two parts:

a- One part of these beats is used for the training of the neural network called (training beats), the training of ANN starts by computing the local errors from the output of the network towards the input. At first, the data sample is sent through the network to find an output and then calculate the error introduced at the output layer and reflect it to find the overall error, all weights are updated until the required performance is obtained.

b- The other part is used for the testing of the network called (testing beats), at the completion of training, the testing beats are tested on the feed forward network and their resultant error is used to give the measure of the generalization ability of the network.

Whole results obtained after classification are shown in **Table 3**, where the number of errors result from the classification process is different according to the type of the transformation method used to extract the features of the signal.

Table 3 : Results of classification for all systems

No	Beat type	training beats	testing beats	FFT errors	DCT errors	DWT(H) errors	DWT(db4) errors	SLT errors
1	N	300	408	100	2	0	1	6
2	P	100	147	106	47	0	0	0
3	R	50	78	26	0	2	6	1
4	L	50	53	15	6	5	4	0
5	j	9	10	0	0	0	0	0
6	V	10	18	8	5	1	3	1
7	VT	25	25	0	3	11	5	1
8	S	20	20	12	0	0	14	0
9	A	40	52	15	1	16	0	5
10	IMI	66	68	1	0	0	0	0
	Tot.	670	879	283	64	35	33	14

Performance Evaluation of Neural Network

The Neural Network used for the classification purpose in this work has the same structure overall the types of transformation methods applied to find the features of the signal, so that the complexity in all types is the same. When the comparison is done between the results obtained after testing each network the differences are affected by the transform used to find the features.

To compare the performance of the network combined with each type of transformation methods the accuracy of each one has been computed.

$$Accuracy = \frac{Total\ number\ of\ correct\ classifications}{Total\ number\ of\ testing\ beats} * 100\% \tag{13}$$

Therefore, **Table 4** is constructed to compare between the accuracy of different classification systems used in this work.

Table 4 : Accuracy of each classification system

Classification system	Total number of testing beats	Total number of correct classifications	Accuracy
FT-NN	879	596	67.80 %
DCT-NN	879	815	92.72 %
DWT-NN (Haar)	879	844	96.02 %
DWT-NN (db4)	879	846	96.25 %
SLT-NN	879	865	98.40 %

CONCLUSSIONS

In this work different transformation methods are used to extract the features of the ECG beat. The pattern recognition system used to classify the ECG signals used these features as the input to the neural network classifier. The slantlet transform is one of the transformation methods used to extract the features of the ECG beat which make the recognition of the ECG beats more accurate.

It can be concluded from this work, the transformation of the ECG signal from time domain to time-frequency domain gives better results than the transformation to frequency domain. This was clear in the results of the WT and SLT. The SLT is an orthogonal transform and provides improved time localization than WT, therefore it will improve the classification results. To improve the accuracy for the heart beat recognition system, five different transformation methods are applied to find the features of the signal and a suitable neural network used for the classification. The comparison of the accuracy of the SLT system with the four other systems used in this work gives a conclusion that the SLT system gives improved accuracy for the heart beat recognition.

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