Military Technical College
Kobry Elkobbah,
Cairo, Egypt

ICEENG 99

2nd International Conference
on Electrical Engineering
ICEENG 99

Features Extraction of ECG Signals Using Wavelet Transforms

M. E. Gadallah*, S. M. Alian**, and Kh. M. Reda***

ABSTRACT

This paper introduces a proposed technique for extracting some of the important features of the electrocardiograph (ECG) signals. The proposed technique is based on the principles of the wavelet transforms (WT). In this work, special attention has been given to the arrhythmia diseases. The proposed approach has been tested using real ECG signals collected from some patients using a computer controlled multi channel data acquisition system. The measured features have been compared with the normal cases, which in turn have been compared with the standard features.

KEYWORDS

Electrocardiograph (ECG), Wavelet Transforms (WT)., Beat per Minute (BPM), Arrhythmia Diseases, Band Pass Filter (BPF), High Pass Filter (HPF), Low Pass Filter (LPF), and MIT/BIH Massachusetts Institute of Technology/Beth Israel Hospital arrhythmia database.

I. INTRODUCTION

ECG is a signal of special interest in cardiological treatment investigation for the automatic analysis of ECG waveforms. These waveforms are important to cardiac disease diagnosis. The electrocardiograms interpretation performed by physicians can be divided into two stages. In the first stage, some characteristic features (waveforms and line segment) are recognized and their parameters (amplitudes and durations) are measured. In the second stage, on the basis of the previous one and some shape details the cardiologist interprets the ECG signal [1].

In wavelet analysis [2], there is a prototype basis function called the mother wavelet function ($\Psi(t)$). A continuos signal x(t) is mapped into the time scale domain as:

*Associate professor, Dpt. of Electronic Engineering, Egyptian Armed forces.
**Professor, Dpt. of Electronic Engineering, Egyptian. Armed forces.
*** Eng., Egyptian. Armed forces.

$$WV(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi(\frac{t-b}{a})dt \qquad (1)$$

The parameter *a* is a scaling of the time variable t, and *b* is a time shift. The signal x(t) has then decomposed in Eq.(1) by basis functions obtained by translation and dilation of the mother wavelet ψ (t). Note from Eq.(1) that for small *a* (high frequency), the basis function is compressed and short. Consequently temporal time information can naturally be captured i.e. high time resolution is attained. When *a* is large, a dilated basis function results that represents low frequency components of the signal, i.e. provides high resolution in frequency. It is obvious that one key advantage of wavelet analysis is the ability to trade automatically resolution in frequency for resolution in time as the frequency change from low to high. In literature, many researches used the MIT/BIH arrhythmia database [1],[2], and [3]. In this paper the used data were collected directly from a group of patients using a computer controlled multi-channel data acquisition system. This paper is organized as follows: section II, gives a general introduction to the concept of the multiresolution analysis. Section III, a review of the used measuring system is provided. In section IV, the selected features and their description are outlined. Section V, discusses the algorithm used for detecting the QRS complex, T, and P wave. In this work, a processing bandpass filter is used to remove the noises that corrupt the ECG due to the measuring system connection. Section VI, outlines this filter and its effect on the ECG signals. Section VII, introduces the modification that has been added to the algorithm. In section VIII, the results of some of the studied cases are introduced. Finally the conclusion deduced from this work are given in section IX.

II. MULTIRESOLUTION ANALYSIS

The introduction of the concept of multiresolution signal analysis has provided a significant tool into the practical application of wavelet analysis.

From the multi-resolution theory, square integrable signal x(t) can be represented by orthogonal subspaces that are spanned by orthogonal bases of different scales. Accordingly, the signal x (t) can be viewed on different resolution levels.

A square integrable signal x (t) can be expanded in terms of the translates and dilates of the wavelet Ψ(t) [2].

$$x(t) = \sum_{i}\sum_{m} 2^{-i/2}\alpha(i,m)\ \psi(2^{-i}t - m) \qquad (2)$$

Where

$$\alpha(i,m) = 2^{-i/2} \int_{-\infty}^{\infty} x(t)\,\psi(2^{-i}t - m)\,dt \qquad (3)$$

and i, m $\in$ Z, which represents a set of integers. From a signal processing point of view, the wavelet Ψ (t) is band pass filter with central frequency ω_0. Eq.(2) shows that the wavelet coefficients α(i,m) carry information about the signal x(t) at time instant 2m in the proximity of the frequency $2^{-i}\omega_0$.

The wavelet functions $2^{-i/2}\ \Psi(2^{-i}t - m)$, m $\in$ Z, constitute orthnormal bases for the subspaces W_i. The wavelet $2^{-(i+1)/2}\ \Psi(2^{-(i+1)}\ t\ \ m)$ span the sub spaces W_{i+1}. Note that the function $2^{-i/2}\ \Psi(2^{-i}t\ \ m)$ is compressed in time by a factor of 2 relative to the function $2^{-(i+1)}\ \Psi(2^{-(i+1)}\ t\ \ m)$. Thus, the signal in the space W_i, has double resolution in time of the signal in W_{i+1}. Note also that every subspace is orthogonal to the other. That removes the redundancy which is inherently founded in continuos wavelet analysis these subspaces define a multi-resolution analysis of the signal x(t) where the signal space is represented as direct sum of various resolution as follows

$$\text{Signal space} = Wi \oplus Wi+1 \oplus Wi+2$$

$$= \bigoplus_{i\in Z} W_i \qquad (4)$$

It is clear from Eq. (4) that the signal x(t) can be expanded, uniquely, into many subband signals of different time frequency resolutions. This constitutes the essence of discrete wavelet analysis.

Equivalent filter of WT

The discrete Fourier transform of WT is

$$W_{2^j} = f(\omega)\psi(2^j\omega)$$

$$= \begin{cases} G(\omega)f(\omega)\phi(\omega) & j=1 \\ G(2\omega)H(\omega)f(\omega)\phi(\omega) & j=2 \\ G(2^{j-1}\omega)H(2^{j-2}\omega)...H(\omega)f(\omega)\phi(\omega) & j>2 \end{cases} \qquad (5)$$

The symbol $\wedge$ represents the discrete Fourier transform.

$$H(\omega) = e^{i\omega/2}(\cos\frac{\omega}{2})^3 \qquad (6)$$

$$G(\omega) = 4e^{i\omega/2}(\sin\frac{\omega}{2}) \qquad (7)$$

where H(ω) is the lowpass filter, G(ω) is the highpass filter, φ is a smooth function, and $f(\omega)\phi(\omega)$ is the discrete Fourier transform of the ECG signal d_n ($n \in Z$). From (5), the WT of *f(n)* at scale 2^j is equal to filtered signal of d_n that passed through a digital bandpass filter (or highpass filter for 2^1). Fig. (1) 1 shows the frequency characteristics of the equivalent filters at different scales.

Let $Q^j(\omega)$ be the transform function of the equivalent filter.

$$Q^j(\omega) = \begin{cases} G(\omega)f(\omega)\phi(\omega) & j=1 \\ G(2\omega)H(\omega)f(\omega)\phi(\omega) & j=2 \\ G(2^{j-1}\omega)H(2^{j-2}\omega)..H(\omega)f(\omega)\phi(\omega) & j>2 \end{cases} \tag{8}$$

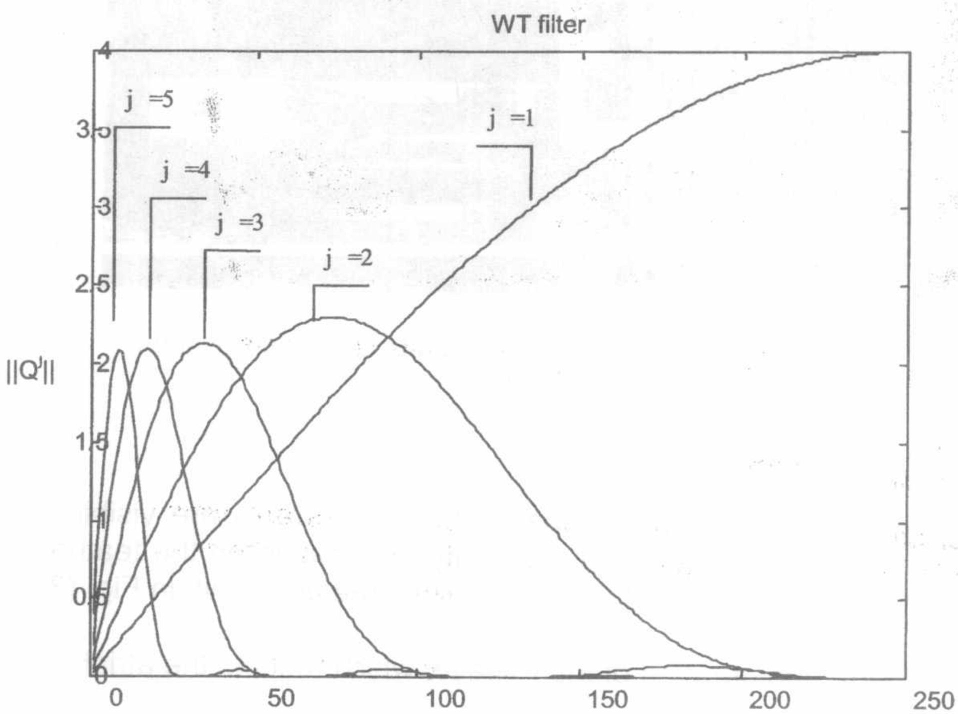

Fig. (1) The amplitude- frequency responses of equivalent filter at different scales

Where $Q^j(\omega)$ is an FIR digital filter with generalized linear phase. The filter is anti-symmetric and the time delay of its central point is $(2^j - 1)/2$ (the delay is considered as 2^{j-1}-1 points in the algorithm).

III. MEASURING SYSTEM SETUP AND DATA COLLECTION

A sixteen channel twelve bits signal data acquisition board is used to digitize the detected ECG signal from ECG device by using one channel with 500Hz sampling rate. A C++ software program has been developed to use a PC equipped with the data acquisition board to collect the ECG signals in files for further processing and analysis. The ECG signal collection system is shown in Fig. (2).

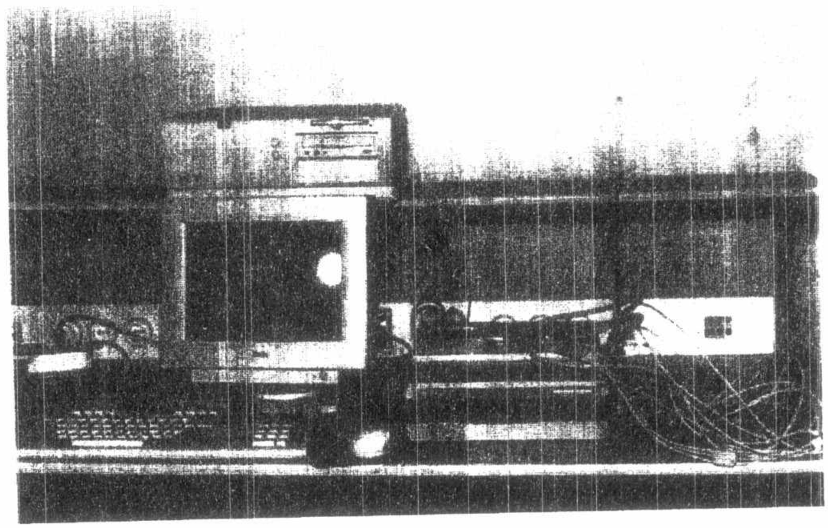

Fig. (2) Photography of ECG Signals Collection System

III. FEATURE SELECTION

Morphological changes in the shape of the ECG waves are visible signs of heart muscle illness. In this paper the analysis is based on the features taken into account by physicians [1],[3], and [4]. They are as shown in Fig. (3):

1-The amplitude and duration of the P wave, which reflects the atrial, depolarization.
2-The amplitude and duration of the QRS complex which reflects the ventricular depolarization
3-The amplitude and duration of the T wave reflects the ventricular repolarization.

4 -R_R rates.
5-The P-R, QT_c, and R_ R intervals.

In the following section an algorithm of fixing the onset and offset the QRS complex, P and T waves is presented.

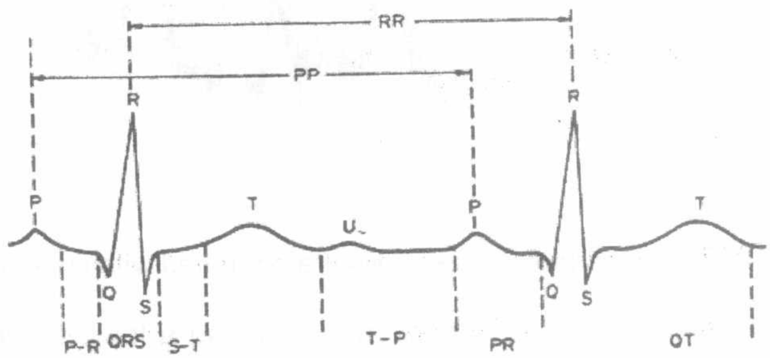

Fig. (3) Parameter of an ECG signals

IV. FEATURE EXTRACTION

Detection Methods

To detect the ECG characteristics (QRS complex, P, and T waves), an algorithm based on the WT [5] is applied. The local maxima of WT modulus at different scales are used to locate the sharp variation points of the ECG signals. The algorithm first detects the QRS complex, then the T wave, and finally the P wave. In this paper, this algorithm is modified to extract the main features like the amplitude and duration of the P, QRS, and T waves. In the following two sections, discuss this modification.

VI. THE PRE-PROCESSING FILTER

During this work, we have noticed that the measured ECG signals are corrupted with some noise as shown in Fig (4). This noise can be referred to the wiring of the system as well as the muscle motion, respiration, and spikes. This noise has shown a bad effect when the WT has been applied, thus we use a bandpass filter (BPF) to reduce the effect of this noise [6].

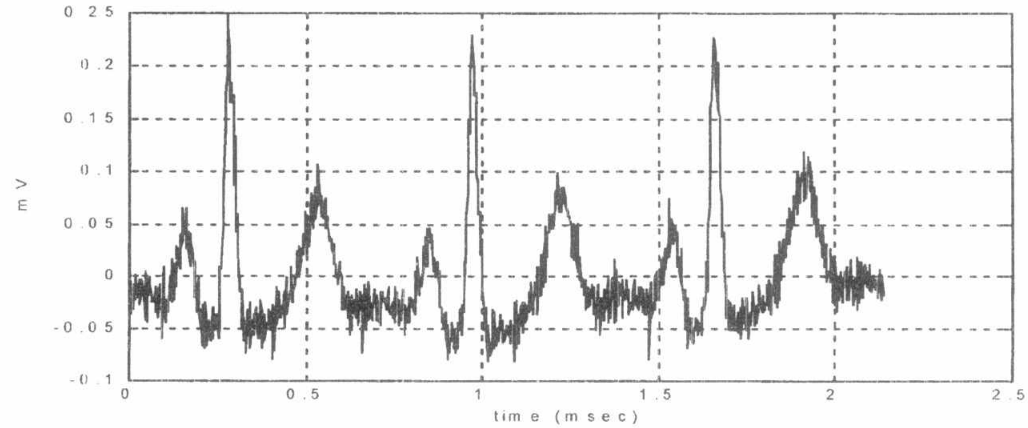

Fig. (4) The measured ECG signals are corrupted with some noise

The integer coefficient BPF is formed by combining a lowpass filter with high pass filter, both based on a sampling rate f_s =500 Hz. The transfer function of LPF is given as

$$L(z) = \frac{1-2z^{-12}+z^{-22}}{1-2z^{-1}+z^{-2}} \tag{11}$$

The LPF is completely eliminated the power line interface at 50 Hz, and high frequency muscle noise is minimized. Once the LPF has removed the high frequency noise. The output of the LPF is presented as input to HPF. The transfer function of the HPF is given as

$$H(z) = z^{-127} - \frac{1}{2^{14}}\left(\frac{1-2z^{-128}+z^{-256}}{1-2z^{-1}+z^{-2}}\right) \tag{12}$$

The cutoff frequency of this filter is at 1 Hz, where the gain is unity. Thus, it successfully removes the drift caused by respiration at about 0.2 Hz. The magnitude characteristic is shown in fig. (5) with a passband from 1 to 40 Hz.

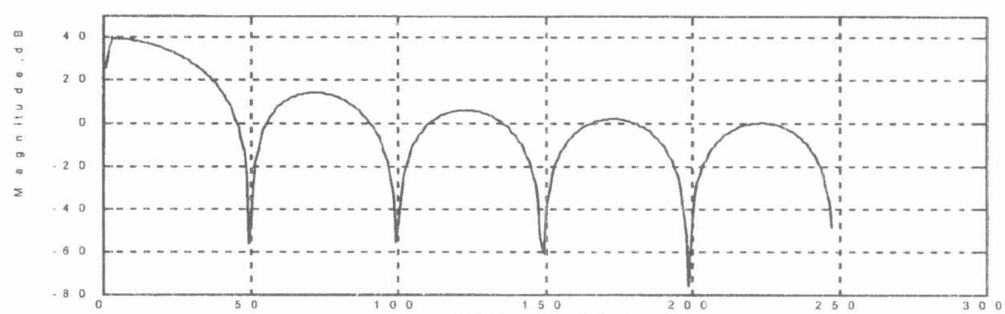

Fig. (5) Magnitude characteristic of the band bandpass filter

This filter has resulted in ECG signals enhancement. This can be noticed from Fig. (6) that illustrates a signal after the application of that filter

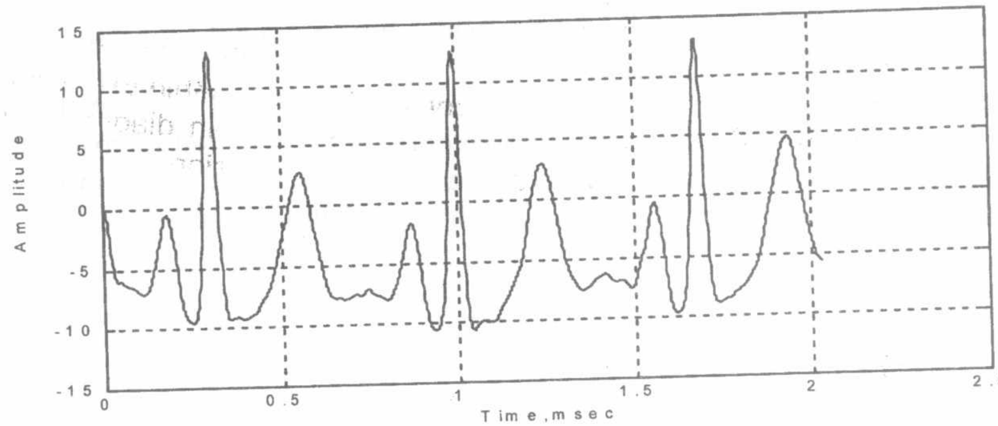

Fig. (6) The measured ECG signal after filtering

VII.THE MODIFIED ALGORITHM

From the algorithm described in the previous section, it is clear that to detect the onset and the offset of the T and P waves, there are empirical values that should be used. In this work, the algorithm has been modified in order to dispense with these empirical values. This modification is in brief as follows.

After the detection of T wave or P wave, the minimum-maximum pair which represents the wave at any scale, starts with the minimum point and goes backward seeking for the beginning of the wave and looks for the first point at which the signal changes from increasing to decreasing or constant. This point represents the onset of the wave. Also, starts with the maximum point and goes forward seeking for the end of the wave and looks for the first point at which the signal changes from decreasing to increasing or constant. This point represents the offset of the wave, and obtain the zero crossing which represents the onset or the offset. Then, the intervals can be calculated as the difference between the onset and the offset of the wave.

VIII. RESULTS

The modified algorithm has been applied to measure some features of ECG signals collected from patients. The ECG signals have been captured using lead II of the ECG device. Selection of lead II is the best to detect the arrhythmia diseases. To evaluate the performance of the developed algorithm, it is applied to some normal cases, tachycardia cases, and bradycardia cases. To show the results, an example for each of these three cases is illustrated below.

Case study 1:

In this case, an ECG signal is captured from a patient and shown in Fig. (7). A cardiologist no change diagnose this case as a normal case. The ECG signal from this normal patient is processed using the modified algorithm. The features extracted are given in table 1.
It is clear from the values of the extracted parameters that they lie within the normal range. Also the heart rate has shown constant values within the normal range. So, from the analysis of the extracted features we can diagnose the patient as a normal one, which agrees with the physician decision.

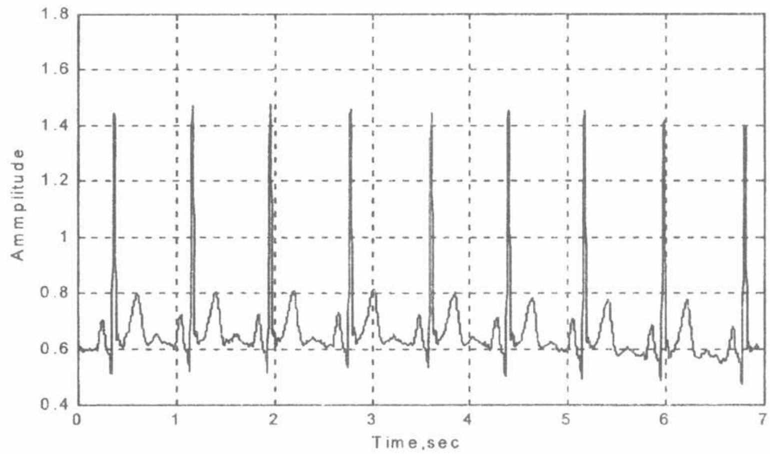

Fig. (7) ECG signal with normal heart rate 75 BPM

Case study 2:

In this case, an ECG signal from a patient, which is show in Fig. (8), is analyzed using the modified algorithm. The features extracted from this signal are given in table 1. It is clear from these results that all values lie within the normal range except the heart rate. This heart rate is 182 BPM, which means that this patient is suffering from tacky cardiac

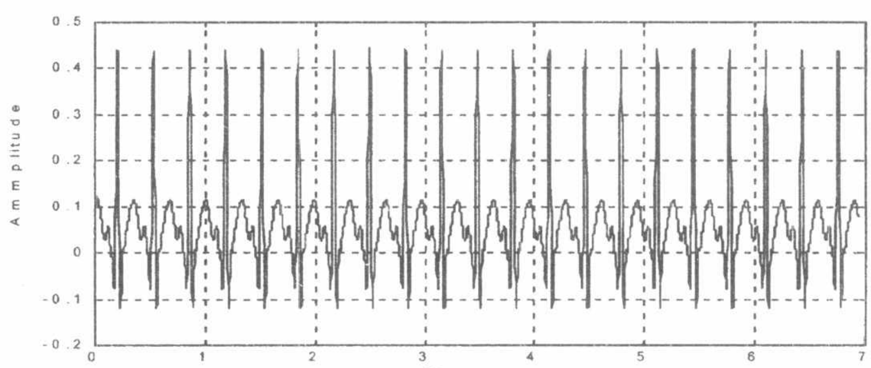

Fig. (8) ECG signal with heart rate 182 BPM (Tachycardia)

Case study 3:

In this case, the ECG signal from a patient has been analyzed using the modified algorithm. The features captured from the signal shown in Fig. (9) and results are given in table 1. It is clear from these results that all values lie within the normal range except the heart rate. This heart rate is 30 BPM, which means that this patient is suffering from bradycardia. So, from the analysis of the above case studies we may summarize the results as shown in table 1

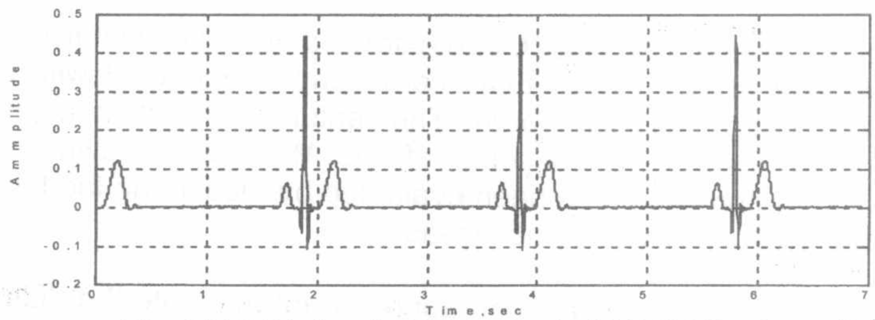

Fig. (9) ECG signal with heart rate 30 BPM (bradycardia)

TABLE 1 The Extracted Features From The Three Cases

Extracted Parameter	Normal Case	Case 1	Case 2	Case 3
P Amplitude (mV)	≤ 0.25	0.048	0.058	0.065
Q Amplitude (mV)	-0.2	-0.034	-0.071	-0.060
R Amplitude (mV)	1	0.416	0.437	0.446
S Amplitude (mV)	-0.4	-0.010	-0.115	-0.104
T Amplitude (mV)	0.35	0.096	0.116	0.122
QT_C Interval (sec)	0.34:0.42	0.4	0.5	0.3
R Interval (sec)	0.4:0.11	0.1	0.1	0.1
PR Interval (sec)	0.12:0.2	0.2	0.2	0.3
R-R Interval (sec)	1:0.6	0.79	0.328	1.95
Heart Rate(HR) (BPM)	60-100	75	182	30

This table helps the cardiologists to give the diagnostic decision directly and fastly. In conventional standard methods, the cardiologists compare the differences between the position of onsets and offsets of particular waveform. They do a lot of effort to calculate the discrepancy in pointing the onset & offset of QRS, T, and P waves. On the other hand, our proposed algorithm

and simply.

IX. CONCLUSION AND DISCUSSION

In this paper, the main features of ECG are extracted using wavelet transform. The measuring system consists of ECG cardiograph connected with a PC equipped with a data acquisition board. The features extraction algorithm, which depends on using the concepts of the WT, has shown a high performance. The performance has been evaluated by measuring the features of some normal cases as well as some diseases.

As a future work, we want to develop an approach to automate the diagnosis process. This can be achieved by applying pattern recognition features.

X. REFERENCES

[1] E. Pietka, "*Feature Extraction In Computerized Approach To The ECG Analysis,*" *Pattern Recog.* vol.24, pp.139-146, 1991.

[2] K. Mayyas and B. El-Asir, "*Discrete Wavelet Analysis of Heart sounds using Filter Banks,*" -1048, 1997.

[3] A. L. Goldberger, and E. Goldbeger, "*Clinical Electrodiography A Simlified Approach,* " Mosby, (1994).

[4] D. Davis, "*Differential Diagnosis of Arrhythmias,* "W.B. Saunders Company, (1997).

[5] C. Li, C. Zheng, and C. Tai, "*Detection of ECG Characteristic Points Using Wavelet Transforms,*" *IEEE Trans. Biomed. Eng.* vol.42, NO.1, pp.21-28, 1995.

[6] F. M. Ham, and S. Han,. "*Classification of Cardiac Arrhythmias Using Fuzzy ARTMAP,*" *IEEE Trans. Biomed. Eng.* vol.43, NO.4, pp.425-430, 1997.