Extraction of P wave and T wave in Electrocardiogram using Wavelet Transform

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Abstract ─ **Significant features of the ECG signal include the P wave, the QRS complex, and the T wave. This paper focuses on the detection of the P wave and T wave. Determining the position of the P wave and T wave is complicated due its low amplitude. In this paper we use Wavelet Transform for extracting the features in Electrocardiogram (ECG) data, since wavelet transform is an effective tool for analyzing transient signals. The desired output is the location of the P wave and the T wave. The accuracy of location of features is essential for the performance of other ECG processing such as signal Analysis, Diagnosis, Authentication and Identification. The algorithm was tested using MIT-BIH arrhythmia database**

Keywords: Electrocardiogram, QRS complex detection, P wave, T wave, Wavelet Transform.

I. INTRODUCTION

The **Electrocardiogram** is the electrical manifestation of the contractile activity of the heart. It is a graphical record of the direction and magnitude of the electrical activity that is generated by depolarization and repolarization of the atria and ventricles. It provides information about the heart rate, rhythm, and morphology. The importance of the Electrocardiography is remarkable since heart diseases constitute one of the major causes of mortality in the world. ECG varies from person to person due to the difference in position, size, anatomy of the heart, age, relatively body weight, chest configuration and various other factors. There is strong evidence that heart's electrical activity embeds highly distinctive characteristics, suitable for various applications and diagnosis.

The ECG is characterized by a recurrent wave sequence of P, QRS, T and U wave associated with each beat. The QRS complex is the most striking waveform, caused by ventricular depolarization of the human heart. A typical ECG wave of a normal heartbeat consists of a *P* wave, a *QRS* complex, and a *T* wave. Fig. 1 depicts the basic shape of a healthy ECG heartbeat signal with P, Q, R, S, J, T and U characteristics and the standard ECG intervals QT interval, ST interval and PR interval.
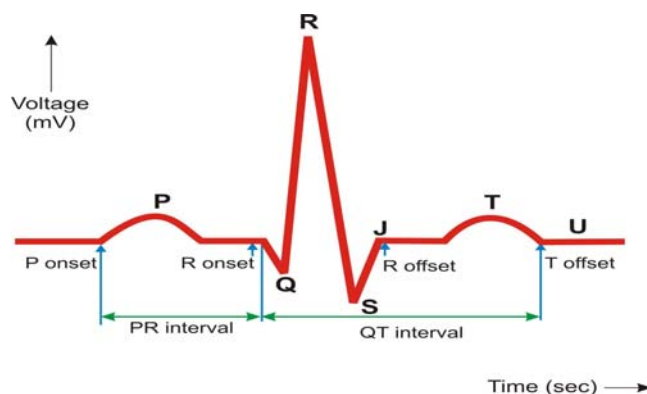

Fig. 1 An ECG waveform

A number of techniques have been devised by the researchers to detect the characteristics in ECG [1]-[6]. Recently wavelet transform has been proven to be useful tool for non-stationary signal analysis. The wavelet transform based technique can be used to identify the characteristic features of the ECG signal to a reasonably good accuracy, even with the presence of high frequency and low frequency noises. Among the existing wavelet approaches, (continuous, dyadic, orthogonal, biorthogonal) we use real dyadic wavelet transform because of its good temporal localization properties and its fast calculations. Discrete Wavelet Transform (DWT) can be used as a good tool for analyzing non-stationary ECG signal.

II. WAVELET TRANSFORM

The Wavelet Transform is a time-scale representation that has been used successfully in a wide range of applications, in particular signal compression. Recently, wavelets have been applied to numerous problems in

Electrocardiology, including data compression, analysis of ventricular late potentials, and the detection of ECG characteristic points. The Wavelet Transformation is a linear operation that decomposes the signal into a number of scales related to frequency components and analyses each scale with a certain resolution [7]-[11]. The WT uses a short time interval for evaluating higher frequencies and a long time interval for lower frequencies.

Wavelet Transform of a signal $f(t)$ is defined as the sum of over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ and is given by,

$$W(a,b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \qquad (2)$$

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi * \left(\frac{t-b}{a}\right) \qquad (3)$$

where $*$ denotes complex conjugation and $\psi_{a,b}(t)$ is a window function called the mother wavelet, $'a'$ is a scale factor and $'b'$ is a translation factor. Here $\psi\left(\dfrac{t-b}{a}\right)$ is a shifted and scaled version of a mother wavelet which is used as bases for wavelet decomposition of the input signal. If the scale parameter is the set of Integral powers of 2, i.e., $a = 2^{j}$ (j ε z, z is Integer set), then the wavelet is called a dyadic wavelet [12]. The Wavelet Transform at scale 2^{j} is given by

$$Wf(2^{j},\tau) = \frac{1}{\sqrt{2^{j}}} \int_{-\infty}^{\infty} f(t)\psi(\frac{t-\tau}{2^{j}})dt$$

We define local maxima of the Wavelet Transform modulus [13] as:-
Let $Wf(x)$ is the Wavelet Transform of a function $f(x)$

➢ We call a local extremum any point x_0 such that

$\dfrac{d\left(Wf(x)\right)}{dx}$ has a zero crossing at $x = x_0$, when x varies.

➢ We call a modulus maximum; any point x_0 such that $\left|Wf(x)\right| < \left|Wf(x_0)\right|$ when x belongs to either a right or left neighborhood of x_0, and $\left|Wf(x)\right| \leq \left|Wf(x_0)\right|$ when x belongs to the other side of the neighbourhood of x_0.

➢ We call maxima line, any connected curve in the scale space x along which all points are modulus maxima

III. METHODOLOGY

In order to extract information from the ECG signal, the raw ECG signal should be processed. ECG signal processing can be roughly divided into two stages by functionality: Preprocessing and Feature Extraction as shown in Fig. 2.
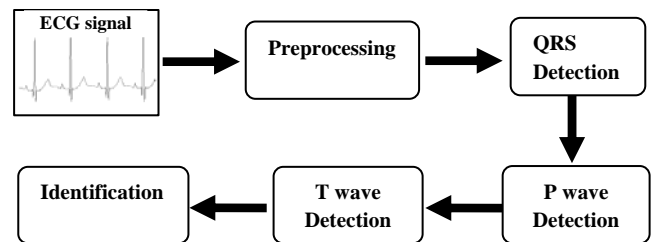

Fig. 2 Structure of ECG Signal Processing.

Feature Extraction is performed to form distinctive personalized signatures for every subject. The purpose of the Feature Extraction process is to select and retain relevant information from original signal. The Feature Extraction stage extracts diagnostic information from the ECG signal. The Preprocessing stage removes or suppresses noise from the raw ECG signal. A Feature Extraction method using Discrete Wavelet Transform (DWT) was proposed by Emran et al [14] - [15].

A. Pre-processing

ECG signal mainly contains noises of different types, namely frequency interference, baseline drift, electrode contact noise, polarization noise, muscle noise, the internal amplifier noise and motor artifacts. Artifacts are the noise induced to ECG signals that result from movements of electrodes. One of the commonest problems in ECG signal processing is baseline wander removal and noise suppression.

1) Baseline Drift Removal

Baseline wandering is one of the noise artifacts that affect ECG signals. We use the median filters (200-ms and 600-ms) [16] to eliminate baseline drift of ECG signal. The process is as follows

➢ The original ECG signal is processed with a median filter of 200-ms width to remove QRS complexes and P waves.

> The resulting signal is then processed with a median filter of 600-ms width to remove T waves. The signal resulting from the second filter operation contains the baseline of the ECG signal.
> By subtracting the filtered signal from the original signal, a signal with baseline drift elimination can be obtained.

2) Noise Removal

After removing baseline wandering, the resulting ECG signal is more stationary and explicit than the original signal. However, some other types of noise might still affect Feature Extraction of the ECG signal. To remove the noise, we use Discrete Wavelet Transform. This first decomposes the ECG signal into several subbands by applying the Wavelet Transform, and then modifies each wavelet coefficient by applying a threshold function, and finally reconstructs the denoised signal. The high frequency components of the ECG signal decreases as lower details are removed from the original signal. As the lower details are removed, the signal becomes smoother and the noises disappears since noises are marked by high frequency components picked up along the ways of transmission.

B. QRS-Detection

QRS detection is one of the fundamental issues in the analysis of electrocardiographic signals. The QRS complex consists of three characteristic points within one cardiac cycle denoted as Q, R and S. The QRS complex is considered as the most striking waveform of the electrocardiogram and hence used as a starting point for further analysis or compression schemes. The detection of the QRS complex is based on modulus maxima of the Wavelet Transform. The QRS complex produces two modulus maxima with opposite signs, with a zero crossing between them shown in Fig. 3. Therefore, detection rules (thresholds) are applied to the Wavelet Transform of the ECG signal.
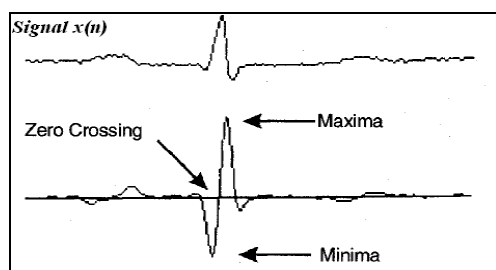

Fig. 3 Maxima, Minima, and Zero crossing of Wavelet Transform at scale 2^4

Most of the energy of the QRS complex lies between 3 Hz and 40 Hz [17]. The 3-dB frequencies of the Fourier Transform of the wavelets indicate that most of the energy of the QRS complex lies between scales of 2^3 and 2^4, with the largest at 2^4. The energy decreases if the scale is larger then 2^4. The energy of motion artifacts and baseline wander (i.e., noise) increases for scales greater than 2^5. Therefore, we choose to use characteristic scales of 2^1 to 2^4 for the wavelet to detect QRS complex (Fig. 4).

The Q and S waves are high frequency and low amplitude waves and their energies are mainly at small scale. So, the detection of these waves is done with WT at lowscale. The onset and offset of the QRS complex are detected by using scale 2^2. From the modulus maximum pair of the R wave, the beginning and ending of the first modulus maxima before and after the modulus maximum pair are detected within a time window. These correspond to QRS onset and offset points.

C. Detection of P and T waves

1) P wave detection

The P wave generally consists of modulus maxima pair with opposite signs, and its onset and offset correspond to the onset and offset of this pair. This pair of modulus maxima is searched for within a window prior to the onset of the QRS complex. The search window starts at 200 ms before the onset of the QRS complex and ends with the onset of the QRS complex. The modulus maxima is a point where $\left| Wf(2^3,\tau) \right|$

is at maximum (the slope of $\left| Wf(2^3,\tau) \right|$ will equal be zero). The zero crossing between the modulus maxima pair corresponds to the peak of the P wave (Figure - 5).

2) Onset and Off set of P wave

To find the onset, a backward search is made from the point of modulus maxima that is on the left of the zero crossing, to the start of the search window, until a point is reached where $\left| Wf(2^3,\tau) \right|$ becomes equal to or less than 5% of the modulus maximum. This point is marked as the onset of the P wave. Similarly a forward search is made from the point of modulus maxima that is on the right of the zero crossing, to the end of search window, until a point is reached where $\left| Wf(2^3,\tau) \right|$ becomes equal to or less than 5% of the modulus

maximum (modulus minimum). This point is marked as the offset of the P wave

3) *T wave detection*

A normal T wave and its transform clearly display a modulus maxima pair with opposite signs [10]. The T wave is found at the zero-crossing between the two modulus maxima. The T wave's energy is mainly preserved between the scales 2^3 and 2^4. Therefore it was more appropriate to turn away from the dyadic scales and to choose the scale 10 for the WT. The next step consists of the search for modulus maxima. At scale 10 we analyzer a signal and search for modulus maxima larger than a threshold ε. This threshold is determined by using the Root Mean Square (RMS) of the signal between two R-peaks. When there are two or more modulus maxima with the same sign, the largest one is selected. After finding one or more modulus maxima, it is possible to determine the location and character of the T wave. The first situation occurs when there is a modulus maxima pair with opposite signs. This indicates a small hill when the signs are +/- and a small inverted hill when the signs are -/+. When there is only one modulus maxima present, the + sign indicates a T wave that consists only in a ascending. When the sign is -, we see a T wave formed by an descending. The zero crossing between the modulus maxima pair corresponds to the peak of the T wave (Fig. 6).

4) *Onset and Off set of T wave*

The T wave has characteristics similar to the P wave. The modulus maxima correspond to the maximum slopes between the onset of the T peak, and the offset of the T peak. The search for the onset of the T wave is carried out between the first modulus maxima corresponding to the T wave and the QRS offset. The detection procedure is the same as that for the P wave, except that the search window follows the QRS complex. The T wave onset is considered to be same as the offset of proceeding QRS complex.

IV. RESULT AND CONCLUSION

ECG signals required for analysis are collected from Physionet MIT-BIH arrhythmia database where annotated ECG signals are described by a text header file (.hea), a binary file (.dat) and a binary annotation file (.atr). The database contains 48 records, each containing two-channel ECG signals for 30 min duration selected from 24-hr recordings of 47 different individuals. The methods were developed under Matlab software.
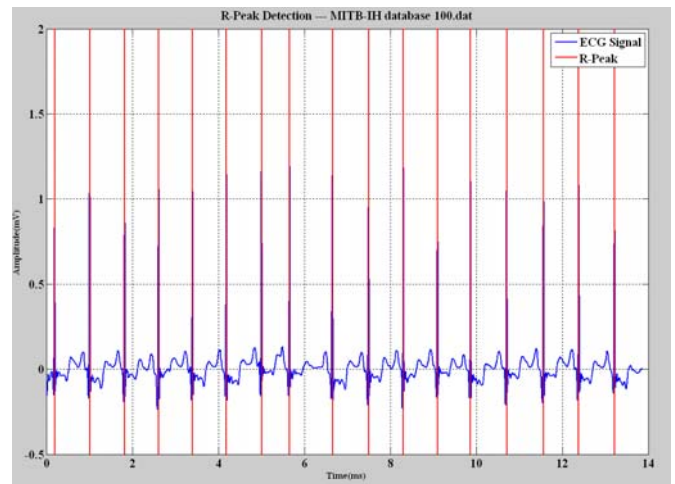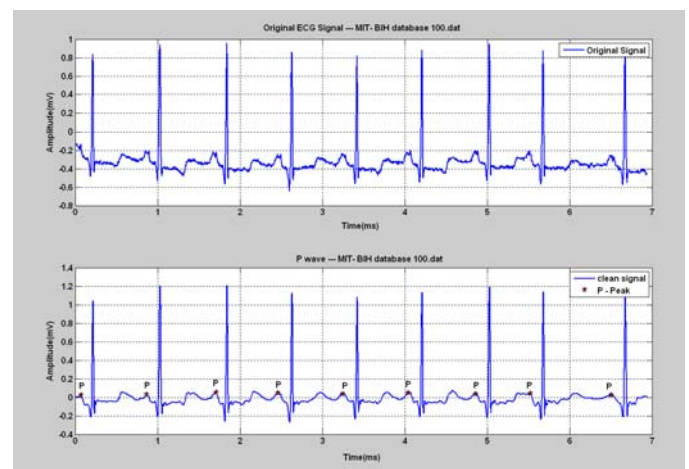

Fig. 4 QRS Complex - R peak
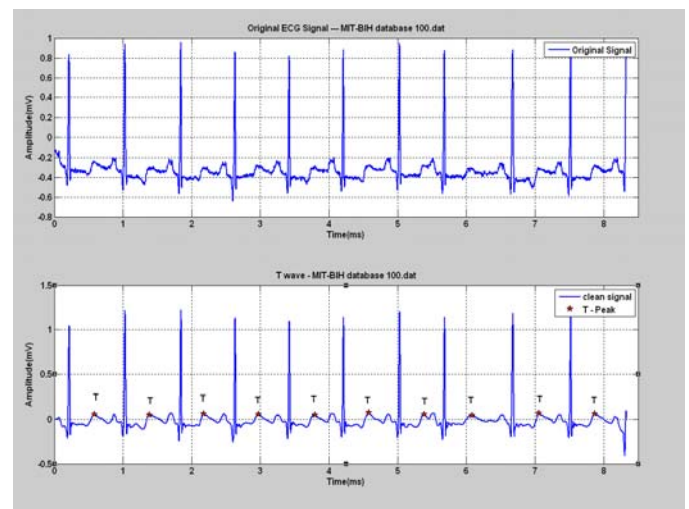

Fig. 5   P - Peak

Fig. 6   T- Peak

In this paper, we present an algorithm based on WT for the detection of QRS, T and P waves of ECG. ECG characteristic points based on WT shows the potential of the

WT, especially for processing time-varying biomedical signals. The power of WT lies in its multiscale information analysis which can characterize a signal very well. It is clear that the WT method will lead to a new way of biomedical signal processing. Table - 1 shows the detection results on the whole database. The information about the features is very useful for ECG Classification, Analysis, Diagnosis, Authentication and Identification.

TABLE - 1: TEST RESULTS SHOW THE DETECTION RESULTS

Record	Total beats	FP	FN	FP + FN	Detection Error Rate	Sensitivity
100	2272	2	0	2	0.09	99.96
105	2543	18	11	29	1.14	100.00
108	1775	27	35	62	3.49	99.83
115	1953	0	0	0	0.00	99.85
118	2278	10	3	13	0.57	99.88
124	1473	1	2	3	0.20	99.75
200	2601	0	1	1	0.04	99.96
202	2136	8	0	8	0.37	100.00
208	2956	0	5	5	0.17	99.83
210	2647	0	4	4	0.15	99.85
215	3256	0	4	4	0.12	99.88
Average	2354	6	6	12	0.58	99.89

Furthermore, ECG signal is a life indicator, and can also be used as a tool for liveness detection. People have similar but different ECG. The physiological and geometrical differences of the heart in different individuals display certain uniqueness in their ECG signals. Hence ECG will be used as a Biometric tool for Identification and Verification of Individuals.

REFERENCES

[1] J. Pan and W. J. Tompkins, "*A real-time QRS detection algorithm*", *IEEE Trans. Biomed. Eng.*, vol. 32, pp. 230–236, 1985.

[2] V.X. Afonso, W.J. Tompkins, T.Q. Nguyen, and S. Luo, "*ECG beat detection using filter banks*", *IEEE Trans. Biomed. Eng.*, vol. 46, pp. 192–202, 1999.

[3] M.Bahoura, M. Hassani, and M. Hubin, "*DSP implementation of wavelet transform for real time ECG wave forms detection and heart rate analysis*", *Comput. Methods Programs Biomed,* vol. 52, no. 1, pp. 35–44, 1997.

[4] Y.H. Hu, W.J. Tompkins, J.L. Urrusti, and V.X. Afonso, "*Applications of artificial neural networks for ECG signal detection and classification*", J. *Electrocardiology*, vol. 26 (Suppl.), pp. 66-73, 1993.

[5] R.V.Andreao, B. Dorizzi, and J. Boudy, "*ECG signal analysis through hidden Markov models*", *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 8, pp. 1541–1549, 2006.

[6] B.U.Kohler, C. Hennig, and R. Orglmeister, "*The principles of software QRS detection*", *Engineering in Medicine and Biology Magazine, IEEE*, vol. 21, pp. 42 – 57, Jan.-Feb. 2002

[7] Mallat S: "*Multiresolution frequency channel decomposition of images and wavelet models*", *IEEE Transactions on Acoust, Speech Signal Processing,* 37, No. 12: 2091-2110, 1989.

[8] Chui K.: "*An Introduction to Wavelets*", Academic Press, Inc.1992

[9] S. Kadambe, R. Murray, and G.F. Boudreaux -Bartels, "*Wavelet transform - based QRS complex detector*", *IEEE Trans. Biomed.Eng.*, vol. 46, pp. 838–848, 1999.

[10] Cuiwei Li, Chongxun Zheng, and Changfeng Tai, "*Detection of ECG Characteristic Points using Wavelet Transforms*", IEEE Transactions on Biomedical Engineering, Vol. 42, No. 1, pp. 21-28, 1995.

[11] Saritha, V. Sukanya, and Y. Narasimha Murthy, "*ECG Signal Analysis Using Wavelet Transforms*", Bulgarian Journal of Physics, vol. 35, pp. 68-77, 2008.

[12] Mallat S: "*Zero crossings of wavelet transform*", *IEEE Trans. Infomtion Theory,* 31, No. 4, 1019-1033, July 1991.

[13] S. Mallat and W.L. Hwang. "*Singularity detection and processing with Wavelets*", IEEE Transactions on Information Theory, vol.38, no.2, 1992.

[14] E. M. Tamil, N. H. Kamarudin, R. Salleh, M. Yamani Idna Idris, M. N. Noorzaily, and A. M. Tamil, (2008) "*Heartbeat electrocardiogram (ECG) signal feature extraction using discrete wavelet transforms (DWT)*", in Proceedings of CSPA, 1112–1117.

[15] S. Z. Mahmoodabadi, A. Ahmadian, and M. D. Abolhasani, "*ECG Feature Extraction using Daubechies Wavelets*", Proceedings of the fifth IASTED International conference on Visualization, Imaging and Image Processing, pp. 343-348, 2005.

[16] P. de Chazal, C. Heneghan, E. Sheridan, R.Reilly, P. Nolan, M. O'Malley, "*Automated Processing of the Single-Lead Electrocardiogram for the Detection of Obstructive Sleep Apnoea*", *IEEE Trans. Biomed. Eng.*, 50(6): 686-689, 2003.

[17] N.V.Thakor, J.G.Webster and W.J.Tompkins, "*Estimation of QRS complex power spectra for design of a QRS filter*", IEEE Transactions on Biomedical Engineering, vol. BME-31, no. 11,pp. 702-706, 1986, pp. 702-706, Nov,1986.

[18] R. Almeida, J.P. Martnez, S. Olmos, A.P. Rocha, and P. Laguna. "*A wavelet - based ECG delineator: Evaluation on standard databases*", IEEE Transactions on Biomedical Engineering, vol.51, no.4, 2004.