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Detection of ECG characteristic points using Multiresolution Wavelet Analysis based Selective Coefficient Method

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ABSTRACT

Automatic extraction of time plane features is important for cardiac disease diagnosis. This paper presents a multiresolution wavelet transform based system for detection and evaluation of QRS complex, P and T waves. Selective coefficient method is based on identification of proper and optimum set of wavelet coefficients to reconstruct a wave or complex of interest from the ECG signal. The performance of the system is validated using original 12 lead ECG recording collected from the physionet PTB diagnostic database. The measured values are compared with the manually determined values and measurement accuracy is calculated. The test result shows over 99% true detection rate for R peak and base accuracy over 97%, 96%, 95%, 98% for heart rate, P wave, QRS complex and T wave respectively.

1. Introduction

The new generation of medical treatment has been supported by computerized processes. Signals recorded from the human body provide valuable information about the activities of its organs. Their characteristic shape, or temporal and spectral properties, can be correlated with a normal or pathological function. In response to dynamic changes in the behaviour of those organs, the signals may exhibit time-varying as well as non-stationary responses. The QRS complex is the most prominent waveform within the electrocardiographic (ECG) signal, with normal duration from 0.06 s to 0.1 s [1]. It reflects the electrical activity within the heart for total ventricular muscle depolarization. Its shape, duration and time of occurrence provide valuable information about the current state of the heart. Because of its specific shape, the QRS complex serves as an entry point for almost all automated ECG analysis algorithms and detection of the QRS complex is the most important task in automatic ECG signal analysis [2]. The QRS detection is not a simple task, due to the varying morphologies of normal and abnormal complexes and because the ECG signal experiences different types of disturbances with complex origin. Once the QRS complex has been identified, a more detailed examination of ECG signal can be performed. The T wave is another important wave in the ECG waveform. It generates due to ventricular repolarization. In some pathological conditions the morphology of the T wave may change from beat to beat, the simplest and most easily recognizable change being an amplitude change and the time duration change of the wave. Since the QRS complex represents ventricular depolarization and the T wave represents ventricular repolarization, the Q-T interval denotes the total duration of ventricular systole. Hence the above-mentioned features are the most vital in cardiological analysis. Different techniques are introduced in last few decades for identification of characteristic points of ECG. Moreover, the detection should be very fast for several cardiac diseases. Various approaches (for example, In many nonsyntactic methods [3,4] for QRS detection, P and T waves and noises are suppressed

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by bandpass filtering and some nonlinear transformation is performed for QRS complex enhancement. Then some rule based technique is used to identify QRS region. Main drawbacks of this method is that the method may not be unique, as signal frequency band for QRS complex varies from subject to subject and even for different beats of same subject. Some other approaches like neural network [5], fuzzy hybrid neural networks [6] have been employed to improve the quality of the QRS detectors. In [5], an adaptive matched filtering technique is used based on artificial neural network (ANN). The low frequencies are modelled by an ANN based adaptive filter and the residual signal is passed through a matched linear filter for detection of QRS location. A fuzzy hybrid neural network based approach as presented in [6] is utilised to recognize different types of beats resulting from same or different source. However, in most of the cases the efficiency of the algorithms is accompanied by higher computational time and cost. Instead of ECG, dECG (i.e. the derivative of ECG) may be a useful tool for analysis as it highlights the QRS complex and suppresses P and T waves [7] because it deals with the wave gradient instead of the wave itself, which is higher in case of QRS region than P and T waves. This technique is difficult to implement for the waves subjected to high frequency noise. Moreover, separate algorithms are required for detection of P and T waves after extracting QRS complex by this method. Keeping all these points in mind a discrete wavelet based simple algorithm is proposed in the present work.

In the proposed method multiresolution wavelet decomposition [8] of the ECG wave under test generates elementary well-localized forms in time frequency domain. The signal is characterized by these elementary blocks in time frequency domain. This feature is used to isolate the ECG signal from different noises and to make other interfering waves inactive while identifying one wave or complex. The wavelet reconstruction coefficient variations are assessed in terms of their shape and size to combine a selected set and eliminate the interfering components for better detection of a particular wave boundary. The main idea of present work is that, proper accumulation of selective reconstruction coefficients reproduces different part of ECG wave in time-scale domain suppressing the others. This eliminates the scope of probable interaction between adjacent regions and thus accurate detection of wave boundaries is ensured.

2. Discrete wavelet transform

A wavelet is a waveform of effectively limited duration that has an average value of zero. Similar to Fourier series analysis, where sinusoids are chosen as the basis function, wavelet analysis is also based on a decomposition of a signal using an orthonormal (typically, although not necessarily) family of basis functions. Unlike a sine wave, a wavelet has its energy concentrated in time. Sinusoids are useful in analyzing periodic and time-invariant phenomena, while wavelets are well suited for the analysis of transient, time-varying signals, thus well suited for ECG signals. Basically wavelet transform is the convolution operation of the subject signal $f(t)$ and the wavelet function $\Psi(t)$. The discrete wavelet transform is expressed as,

$$X_{j,k} = \int_{-\infty}^{\infty} f(t)\Psi_{j,k}(t)dt \tag{1}$$

The approximation coefficient of the signal $f(t)$ is represented as,

$$A_{j,k} = \int_{-\infty}^{\infty} f(t)\phi_{j,k}(t)dt \tag{2}$$

where $\phi(t)$ is scaling function, j and k are scale and location respectively. For a range of scale n, the original signal $f(t)$ under discrete wavelet transform can be represented as,

$$f(t) = f_n(t) + \sum_{j=1}^{n} d_j(t) \tag{3}$$

where $f_n(t)$ is mean signal approximation and is given by,

$$f_n(t) = A_{n,k}\phi_{n,k}(t) \tag{4}$$

and $d_j(t)$ is detail signal approximation in scale j.

Thus given an approximation of a signal using translations of a mother wavelet up to some chosen scale, a better approximation can be achieved by using expansion signals with half the width and half as wide translation steps. The wavelet transform as such decomposes a signal into two sub signals – detail signal and approximation signal. Detail signal contains the upper half of the frequency components and approximation signal contains the lower half. The decomposition can be further repeated on the approximation signal in order to get the second detail and approximation signal. Thus in discrete wavelet domain, multiresolution analysis can be performed.

3. System description and implementation

The proposed multiresolution wavelet based approach for ECG feature extraction is performed with Daubechies 6 (Db6) wavelet. There is no predefined rule to select a wavelet for a particular application, rather the selection is application oriented. It is a common practice to select a wavelet function which is having similar physical properties as the subject signal [9]. Daubechies wavelets have structural similarity with QRS complex and their energy spectrums are concentrated around low frequencies. Thus it is expected that some detail coefficients from multiresolution decomposition will show better resemblance with QRS complex of the ECG wave in time scale domain [10,11]. The proposed algorithm is applied on some arbitrarily chosen ECG data from physionet PTB diagnostic database [12]. Decomposition of the signal is done upto level eight. Level of decomposition is taken to be a high value to ensure the presence of some low frequency components of original signal. Fig. 1 shows the details of the algorithm followed. First a proper selection of the wavelet coefficients is made for R peak detection. After R peak detection, five point differentiation is done on the reconstructed wave generated by suitable choice of coefficients for Q and S points. Then the relevant coefficients are identified for T and P wave peak detection. Once the peak is detected, onset and offset of these waves are captured.

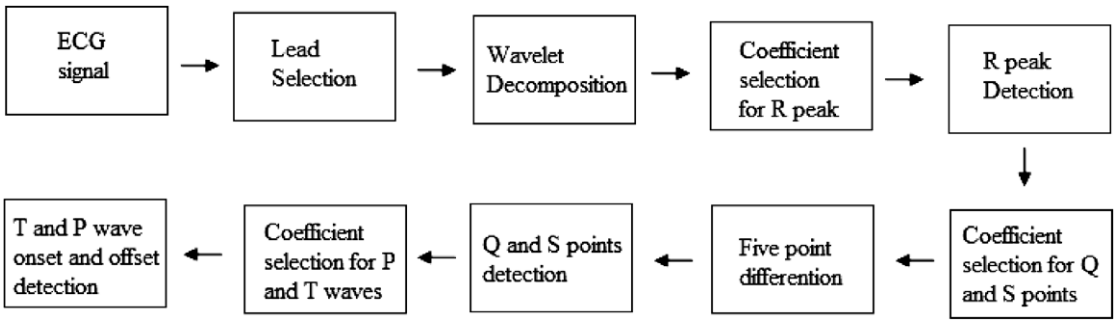

Fig. 1. Description of the algorithm.

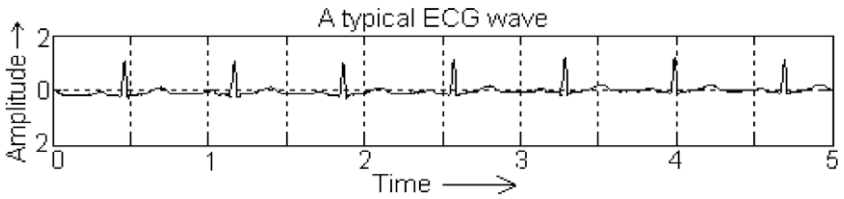

Fig. 2. A typical ECG wave (5 s data is plotted).

3.1. Detection of R peak

The original signal along with the decomposition result is shown in Figs. 2, 3a and 3b. Figs. 3a and 3b represent the wavelet coefficients for scale 1 to 4 and 5 to 8 respectively. From these figures it is seen that small scales represents the high frequency components and large scales represents the low frequency components of the signals. The first and eighth level reconstruction coefficients represent high frequency and low frequency contents of the ECG waveform respectively which in most of the cases appear to be high and low frequency noises. According to the power spectra of the signal [13], it is clear that most energy of the QRS complex is concentrated at decomposition level 3, 4 and 5. Figs. 3a and 3b show that coefficients at level three, four and five show better resemblance with the QRS complex whereas all others appearing to be noisy with respect to the QRS region having most noises at the upper and lower levels. Thus, $d3$, $d4$ and $d5$ coefficients are identified for the detection of QRS complex. The plot of the reconstructed wave comprising of, $d3$, $d4$ and $d5$ is shown in Fig. 4.

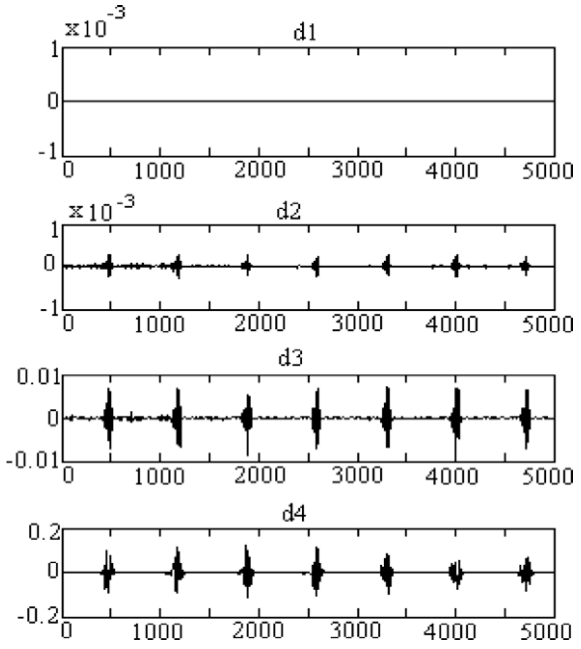

Fig. 3a. Wavelet coefficients for scale levels 1–4.

$$e1 = d3 + d4 + d5 \tag{5}$$

From Fig. 4, it is clear that although the QRS region is properly captured but it is difficult to identify R peak due to its oscillatory nature. So, a function $e2$ is defined as,

$$e2 = \frac{d4 \times (d3 + d5)}{2^n} \tag{6}$$

where n is the level of decomposition. Then the modulus of $e1 \times e2$ is taken. The corresponding plot is shown in Fig. 5 along with the original wave. It is seen from Fig. 5 that the QRS complex may have less amplitude, but is much closely spaced in time. Hence the R peaks are identified as the maximum amplitude points. The accuracy of the entire feature extraction work mainly depends upon the identification accuracy of R peak. Main advantage of the selective coefficient based approach is that, by selecting an optimum set of coefficients depending on the power spectra of the wave, the probability of error in R peak detection is minimized in spite of the presence of drastic irregularity in the baseline as shown Fig. 6.

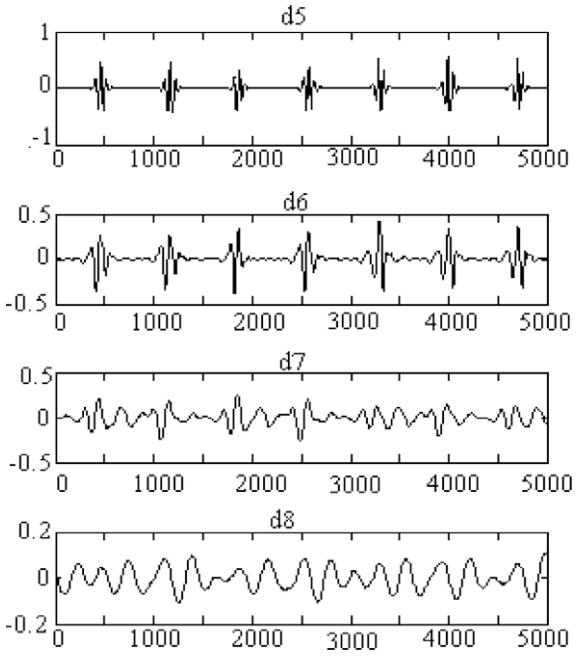

Fig. 3b. Wavelet coefficients for scale levels 5–8.

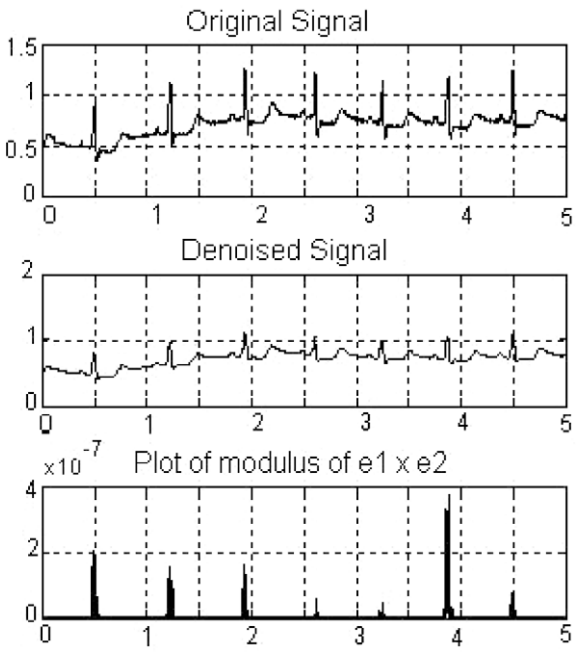

Fig. 5. Original signal and plot of modulus of $e1 \times e2$.

3.2. Detection of Q and S point

Once the R peak is detected, the Q and S points are to be identified to detect the complete QRS complex. Generally the *Q* and *S* waves have high frequency and low amplitude and their energies are mainly at small scale. For that, decomposition coefficients from $d2$ to $d5$ are kept and the reconstruction wave is given by

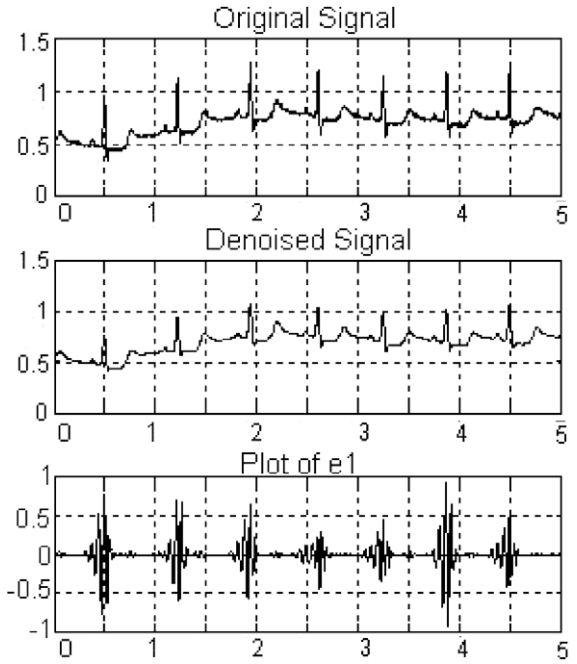

Fig. 4. Original signal and plot of $e1 = d3 + d4 + d5$.

$$e3 = d2 + d3 + d4 + d5 \tag{7}$$

Q and S points are the points of inflexion in either side of the R peak. So the first zero slope points on either side of the R peak will represent the Q and S point. Hence five point differentiation on $e3$ is done using the following formula:

$$f'(x) \approx \frac{-f(x+2h) + 8f(x+h) - 8f(x-h) + f(x-2h)}{12h} \tag{8}$$

where h is time division.

First two zero slope points on either side of R peak (as detected earlier) are identified as Q and S points respectively. At this point of analysis, the differentiation can be done because now the high frequency noise is disregarded as the first level reconstruction coefficient is not taken into account.

3.3. Detection of T and P wave

According to the power spectra of ECG signal [13] the energies of T and P waves are mainly at scale levels 6, 7 and 8. But, baseline drift is serious at scale 8, so reconstruction coefficients $d6$ and $d7$ are selected to detect T and P waves. Hence the reconstructed wave is formed as,

$$e4 = d6 + d7 \tag{9}$$

Then the T peak is identified as the maxima after the detected S point within a predefined stipulated interval. As the T peak is pointed out, T onset and T offset is found out as the minimum potential crossing points on either side of the T peak. The plot of (9) is shown in Fig. 7. Sometimes a serious problem is encountered in automatic ECG feature extraction technique for the signals with myocardial

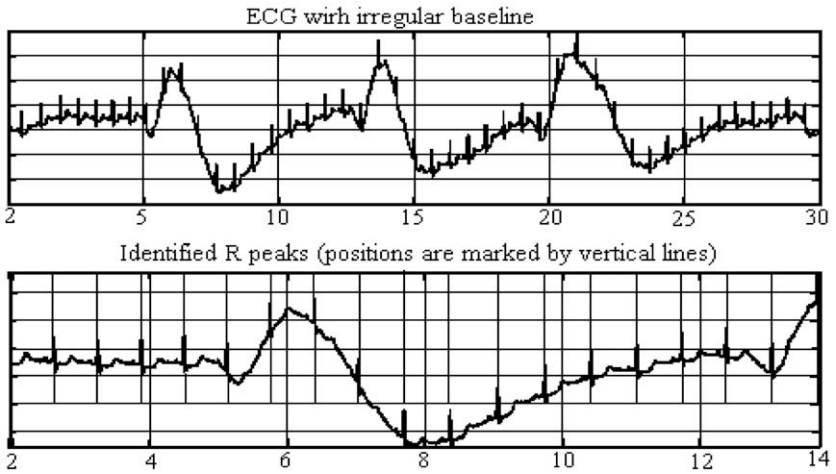

Fig. 6. Detection of R peak for wave having baseline drift (first 18 peaks are shown for better visibility).

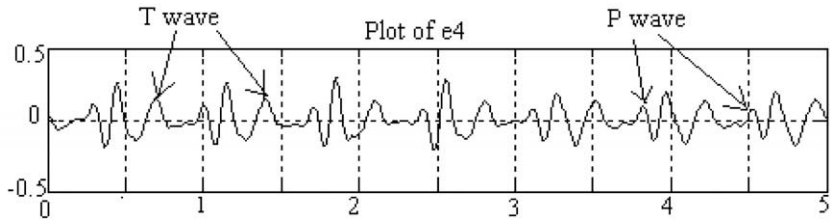

Fig. 7. Plot of *e*4.

diseases. It is the unpredictable shape and slope of T wave, specially, the inverted T waves. This problem is taken into account by identifying the type of the T wave at the beginning of the T peak detection algorithm. The type of the T wave is detected by considering the magnitudes within

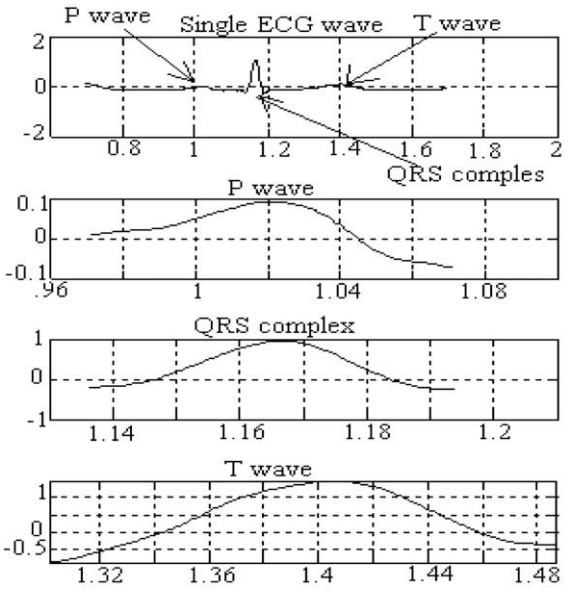

Fig. 8. Original wave, P, QRS and non-inverted T wave.

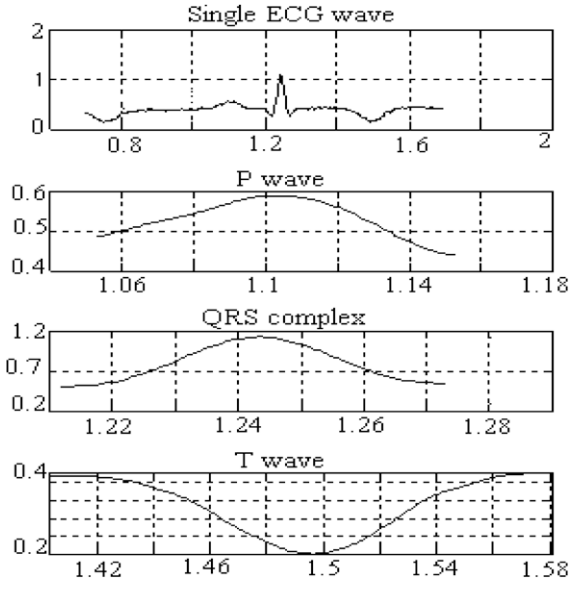

Fig. 9. Original wave, P, QRS and inverted T wave.

Table 1
Result for R peak detection.

Total no. of beats	FP beats	FN beats	Failed detection beats	Failed detection rate (%)
2550	6 (0.24%)	10 (0.39%)	16	0.63

Table 2
Result for P, QRS, T wave duration and heart rate measurement.

P wave		QRS wave		T wave		Heart rate	
Base inaccuracy (%)	Deviation (%)	Base inaccuracy (%)	Deviation (%)	Base inaccuracy (%)	Deviation (%)	Base inaccuracy (%)	Deviation (%)
3.37	−1.68 +1.55	4.08	−2.53 +3.12	1.88	−0.74 +1.72	2.24	−0.57 +1.52

the T wave separated by a predefined interval. Its magnitude and sign change (if any) determine the type of the T wave. Thus the significant points as Q, R, S and T waves are identified by selective coefficient method. P wave is detected by the similar method as T before the Q point.

4. Results and analysis

In the present work, physionet PTB diagnostic database is used to evaluate the algorithm. As discussed in the previous section, simulation and testing has been carried out, the results of which are presented in Figs. 3a, 3b, 4 to 9 and Tables 1 and 2. For validation of the algorithm, more than 80 databases are checked. Present method shows 0.24% false positive (FP) and 0.39% false negative (FN) R peaks with a total detection failure of 0.62% as indicated in Table 1. Fig. 6 shows the ECG wave for 30 seconds and first eighteen annotated R peaks (all the peaks are not considered for better visibility). Fig. 8 shows the detected QRS complex, P and T wave for an ECG waveform with non-inverted T wave. An inverted T wave along with corresponding QRS complex and P wave is shown in Fig. 9.

The result of the proposed method for measurement of durations of P wave, QRS complex, T wave and the heart rate measurement is shown in Table 2. The measured values are compared with the manually measured values and the measurement performance is estimated by a factor called inaccuracy as defined below.

$$\text{Inaccuracy} = \frac{m-n}{m} \times 100\% \tag{10}$$

where m is manually measured duration and n is the respective duration measured by the algorithm.

The heart rate which is the number of beats per second is calculated by the measurement of the time interval of two consecutive R peaks. Heart rate measurement accuracy depends upon the accuracies of two consecutive R peak measurements. So heart rate measurement accuracy is always less than the individual accuracy of R peak detection.

5. Conclusion

In this paper, an algorithm based on Wavelet Transform is presented for the detection of QRS, T, and P waves of ECG. In multiresolution approach, it is easier to characterize the ECG wave so as to identify the different waves and complex. Wavelet Decomposition of ECG wave up to level 8 using orthogonal Daubechis 6 wavelet generates 8 scales of detail coefficients. Smaller scales correspond to high frequency components and higher scales correspond to low frequency components of the signals. Reconstruction scales are selected on the basis of the power spectra of different parts of the signal, which eliminates different noise and artifacts and the interference of other part of the signal while extracting a particular wave or complex. Thus the proposed technique is proved to be accurate especially in presence of different noises. It requires less processing time for parameter calculation. The time scale nature of the proposed algorithm has the advantage of identifying the different waves at the point of occurrence of it without being disturbed by the other waves. Selective coefficient approach eliminates the probability of interaction between the adjacent waves. Due to some pathological reasons, sometimes the T wave may be higher in magnitude than the R wave. In that case there is a probability of wrong identification of R peak in time plane based algorithms. Here this difficulty is eliminated by disregarding the reconstruction coefficients responsible for T peak while detecting the R peak. Thus most of the probable sources of errors in detecting R wave are eliminated here. Once the P wave, QRS complex and T wave is identified and measured, some clinically important regions like PR segment, QT segment, ST segments are easy to measure. Moreover, amplitudes of P, R and T waves can easily be measured by the maximum amplitude in the respective complex or wave. So this feature extraction method can be used as a primary measurement tool for automatic and on line disease classification and biometric recognition. But some of the ECG waveform may show very erratic nature due to electrode contact noise or some complicated cardiac abnormalities. The algorithm is not tested with them because of lack of availability of that special kind of database.

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