Morphology Analysis and Time Interval Measurements Using Mallat Tree Decomposition for CVD Detection

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Abstract. Electrocardiogram signal is used to identify the heart related abnormalities as cardiovascular disease. Automatic detection and analysis of abnormalities of long duration of ECG signals is tedious and quite subjective as it is difficult to decipher the minute morphological variations. In this paper, Morphology Analysis and Time Interval Measurements using Mallat Tree Decomposition (MTD) are done to obtain the signal in the desired form for calculation of heart rate. ECG signals are analyzed with various mother wavelets using MTD, and analyzed on the basis of performance matrices. It was found for this research work bior 3.9 wavelet is well suited for the processing of ECG signal. Heart rate using Peak Detection Algorithm (PDA) is calculated after pre-processing technique and bior 3.9 wavelet. The experiments were carried out on MATLAB R2016a environment.

Keywords: Cardiovascular disease · Mallat Tree Decomposition
Heart rate · Time interval measurement · Morphology analysis

1 Introduction

Cardiovascular disease (CVD) is a major disorder that results in to hypertension and myocardial infarction. Approximately 30% of worldwide deaths are due to CVD disease [1, 2]. Early detection of CVD disease is an important step to prevent these deaths. Therefore, a regular analysis of ECG signal is required for early detection [3, 4]. An ECG signal consists of five waves namely P, Q, R, S, and T which performs four main events: the R-R interval, the P-Q interval, the QRS complex, and the S-T interval [5]. These events contain their own peaks to analyze the morphology, amplitude and time duration for CVD detection [6–8]. All the important features such as duration and amplitude on this recording must lies within normal range. P wave is the upright positive deflection with respect to baseline in the waveform. The duration and amplitude of this wave should be less than or equal to 0.11 s and 0.25 mV respectively. P-Q is measured from the beginning of P wave to the start of the QRS complex. QRS

complex being the most prominent feature of entire waveform have the duration and amplitude range lies in between 60–100 ms and 2.5–3.0 mV respectively. Resting state of ventricles signified by *T* wave in which repolarization process takes place. The *S-T* segment requires approximately 320 to 350 ms. Repolarization period of ventricles is from 100–250 ms having amplitude in between 0.1–0.5 mV [9]. Machine Learning based ECG analysis is required for an accurate detection of peaks which is a very tedious task as this signal is affected by Baseline Wander noise, Power line interference noise, Burst noise and Electromyography noise [10–12]. False detection of *R*-wave leads to undesired results which further resulted in to poor signal-to-noise ratio (SNR) [13]. Many researchers have done research on heart rate calculation, feature extraction [14–20], ECG compression, *R-R* interval analysis, and *P*, *S*, & *T* wave detection which are mainly categorized in to three categories: Time Detection Technique, Transform Domain Detection Techniques, & Morphologic Filtering Techniques and Template Matching Methods [21].

Wavelet transform has become an important computational tool for performing Signal Processing. It overcomes the shortcomings of time window size which does not vary with frequency. Authors in [22] uses wavelet transform which is applied to extract the coefficients and they uses autoregressive modelling for calculating temporal structure of an ECG signal [22]. A new technique is presented by authors in [23] in which feature sets has been obtained using mathematical morphology. A novel ECG obfuscation method has been formulated which uses cross correlation based template matching approach to distinguish all ECG features [24]. Another method of feature extraction based on Discrete Wavelet Transform (DWT) has been designed to solve the problem of non-stationary ECG signals by providing stable features [25]. A modified technique based on the combined wavelet transform is presented in which two wavelets a Quadratic Spline Wavelet (QSWT) for *QRS* detection and the Daubechies six coefficient (db6) wavelet for *P* and *T* detection have been used [26]. Authors in [27] uses technique based on cepstrum coefficient method for feature extraction and artificial neural network (ANN) models for the classification and has developed a model which gives the accuracy of 97.5% to diagnose cardiac disease [27]. An integrated feature extraction approach has been proposed using Principal Component Analysis and DWT that shows the wavelet features are more significant than time domain feature for better discrimination [28]. An author in [29] proposes an automatic ECG feature extraction system based on DWT for various feature extraction.

In this research paper, distinct families of discrete wavelets have been applied for multilevel decomposition of MIT-BIH Arrhythmia v5 ECG input signal to extract the *R-R* interval, *P-Q* interval, *QRS* complex, and *S-T* interval along with Heart Rate calculation. This paper is further organized as follows: Sect. 2 introduces signal decomposition using Mallat Tree Decomposition (MTD). Section 3 describes the methodology which is followed by results and discussions and concluded in the last.

2 Signal Decomposition Using Mallat Tree Decomposition Algorithm

DWT derived from sub-band coding result in less computation time and reduced number of required resources. In DWT time scale representation of signal is obtained using digital filtering technique. The signal is passed through filters having different cut-off frequency at different scales. The DWT function is given by

$$W_\psi(j,\,k) \;=\; \frac{1}{\sqrt{m}} \sum x(n)\;\psi_{j,k}(n) \tag{1}$$

where $x(n)$ = input signal, $1/\sqrt{m}$ is a normalizing term, m is the number of samples in the sequence and n is integer = 0, 1, 2 … m–1.

The DWT is defined by MTD algorithm in which output is computed by successive low pass and high pass filtering of discrete signal as shown in Fig. 1.
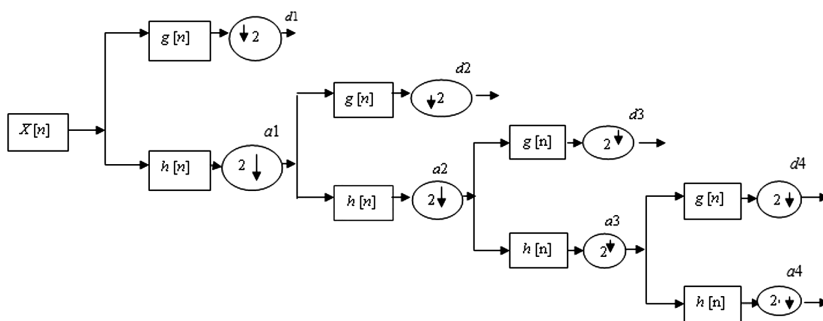

Fig. 1. Multilevel decomposition at level4

In Fig. 1, $x[n]$ is the input signal which is decomposed into two: high pass filter $g[n]$ and low pass filter $h[n]$. Each stage comprises of two digital filters and two down samplers (by 2) to produce further varying frequency digital signals. The down sampled output of first high pass filter $g[n]$ and low pass filter $h[n]$ give detail coefficient $d1$ and approximation coefficient $a1$ respectively. The approximation coefficient $a1$ is further decomposed and this process continues till the set level of decomposition. In this research paper, 4 level of decomposition is used which provide $d1$, $d2$, $d3$, $d4$ as detailed coefficients and $a4$ as an approximation coefficient. Different families of DWT such as Daubechies, Biorthogonal, Reverse Orthogonal, Symlets and Coiflets have been used for signal decomposition.

3 Methodology

Input signal of ECG with 100 record databases from MIT-BIH Arrhythmia v5 is taken from Physio Bank ATM. This input ECG signal has length of 1460 samples which is sampled at rate of 360 Hz. The following steps are followed for Peak Detection (morphology analysis) and computation of different intervals (time interval measurement).

Step 1: MIT-BIH Arrhythmia database ECG signal 100 m.mat is loaded.

Step 2: Pre-processing: Input ECG signal is fed to digital FIR High pass filter using Blackman windowing technique to remove Base Line Wander noise with cut-off frequency 0.5 Hz. The order of filter is taken $N = 10$ by defining the window length i.e. $N + 1 = 11$ [11].

Step 3: Compute Heart Beat rate of pre-processed signal: Output of FIR High pass filter is used to compute the Heart rate of an ECG signal is defined by Eq. 2.

$$Heart\,Rate \ = \ \frac{Sample\,Rate \ \times \ 60}{R_2 \ - \ R_1} \tag{2}$$

where R_2 and R_1 represents the location of two subsequent R peaks on time scale.

Step 4: Different ECG peaks (*P*, *Q*, *R*, *S*, and *T*) and their location (amplitude and time) has been detected using Peak Detection Algorithm (PDA). Out of 5 different waves/peaks, *R* peak has the maximum amplitude of an ECG signal in every cycle.

Peak Detection Algorithm

Input – Pre-processed signal (*Y*)

Output – Peak Detection

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1. Define Sample Rate
2. Detection of *R* peak: The point with maximum amplitude gives the *R* peak location.

If *R* peak is located for each cycle (R_{peak}) , then different other peaks are detected by the following methods :

3. Detection of *P* peak :*P* peak location detection is given as

$$a = \left[R_{peak} - \left(\frac{Sample\,Rate \times 25}{Beat} \right) \right] : \left[R_{peak} - \left(\frac{Sample\,Rate \times 5}{Beat} \right) \right]$$

P peak amplitude= max(*Y*(*a*));

4. Detection of Q peak: Q peak location detection is given as

$$b = \left[R_{peak} - \left(\frac{Sample\ Rate \times 10}{Beat} \right) \right] : \left[R_{peak} - \left(\frac{Sample\ Rate \times 1}{Beat} \right) \right]$$

Q peak amplitude = min($Y(b)$);

5. Detection of Speak : S peak location detection is expressed as

$$c = \left[R_{peak} + \left(\frac{Sample\ Rate \times 1}{Beat} \right) \right] : \left[R_{peak} + \left(\frac{Sample\ Rate \times 5}{Beat} \right) \right]$$

Speak amplitude = min($Y(c)$);

6. Detection of T peak : T peak location detection is represented as

$$d = \left[R_{peak} + \left(\frac{Sample\ Rate \times 10}{Beat} \right) \right] : \left[R_{peak} + \left(\frac{Sample\ Rate \times 30}{Beat} \right) \right]$$

T peak amplitude = max($Y(d)$);

End

Step 5: Detection of Time Interval Measurements: After detecting different ECG peaks, different intervals are calculated. *R-R* interval is calculated by Eq. 3

$$R - R\ \text{interval} = (R_2 - R_1)/\text{sample rate} \tag{3}$$

where R_2 and R_1 are the locations of two subsequent R peaks.
    P-Q interval is given by Eq. 4

$$P - Q\ \text{interval} = \left(Q_{peak} - P_{peak} \right)/\text{sample rate} \tag{4}$$

where Q_{peak} and P_{peak} are the location of Q and P peak in that particular cycle.
    QRS complex is calculated by Eq. 5

$$QRS\ \text{complex} = (S_{peak} - Q_{peak})/\text{sample rate} \tag{5}$$

where S_{peak} and Q_{peak} are the location of S and Q peak in that particular cycle.
    S-T interval is given by Eq. 6

$$S \text{ - } T \text{ interval} = \left(T_{\text{peak}} - S_{\text{peak}}\right)/\text{sample rate} \tag{6}$$

where T_{peak} and S_{peak} are the location of T and S peak in that particular cycle.

Step 6: Decomposition level is set at level 4 to maintain the balance to remove noise without removing important features. Different wavelet families are used: Daubechies, Biorthogonal, Reverse Orthogonal, Coiflets and Symlets.

Step 7: In this step, performance metrics of different wavelet families has been examined using different parameters to find out which wavelet transform is better for ECG signal computation.

1. Signal-to-noise ratio (SNR) is calculated as root mean square amplitude of signal and noise.

$$\text{SNR} = 10 \log_{10} \left(E_{\text{signal}}/E_{\text{noise}}\right)^2 \tag{7}$$

2. Mean Square Error (MSE) signifies the difference between Original signal and cleaned signal without noise.

$$MSE = 1/N \sum_{n=1}^{N} [x(n) - y(n)]^2 \tag{8}$$

3. Percent root mean square difference (PRD) is used to measure the distortion and is defined by Eq. (9)

$$PRD = \sqrt{\frac{\sum_{n=1}^{N} [x(n) - y(n)]^2}{\sum_{n=1}^{N} [x^2(n)]}} \tag{9}$$

In Eqs. 8 and 9, $x(n)$ is noisy input signal and $y(n)$ represents filtered signal.

Step 8: On the basis of performance parameters best wavelet method is analysed which is used for the further experiments. Wavelet coefficients using MTD are extracted and smoothing of coefficients has been done using Global Thresholding followed by denoising.

Step 9: After getting the wavelet coefficients using MTD, different peaks of an output signal has been detected using Peak Detection Algorithm as explained in step 4 which are compared with the peaks obtained after pre-processing techniques.

Step 10: Different time intervals of wavelet coefficients obtained using MTD has been calculated by equations used in Step 5 and compared the results obtained after pre-processed signals.

4   Results and Discussions

In this section, output of an ECG signal has been observed at different stages. In first stage, output has been obtained after removing baseline wander noise. In second stage, output of an ECG signal has been obtained after performing multilevel decomposition using MTD. The best wavelet on the basis of performance parameters such as SNR, MSE and PRD has been selected which is followed by extracting coefficients. Lastly peaks of ECG signal are detected and different time measurement intervals are calculated which are compared with the values obtained after pre-processing.

4.1   Removal of Baseline Wander Noise by Pre-processing Technique and Detection of Various Peaks

To remove low frequency Baseline wander noise, FIR filter has been designed using Blackman window technique explained by Prashar *et al.* [11]. Order of filter is $N = 10$ and window length is $N + 1$. Peaks of the filtered output ECG signal have been detected using Peak Detection Algorithm shown in Fig. 2.
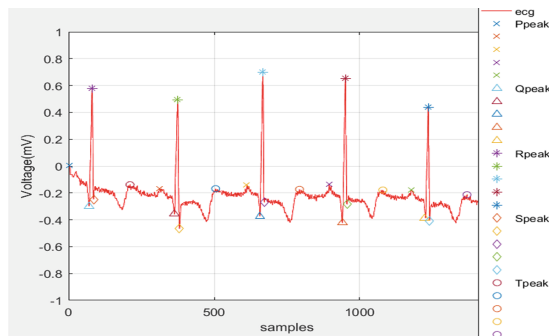

Fig. 2. Time domain analysis of Output ECG signal after filtered by Blackman window with Peak Detection.

4.2   Performing Multilevel Decomposition Using Mallat Tree

The output of High pass FIR filter is fed to the different wavelet families. Different families of wavelet used in this paper are Daubechies- db4, db5, db6, db7, db8, Biorthogonal-bior3.5, bior3.7, bior3.9, Reverse Orthogonal – rbio4.4, rbio5.5, rbio6, Coiflets-coif4, coif5 and Symlets –sym4, sym5, sym6, sym9. Table 1 shows the performance metrics of different wavelets families in terms of SNR, MSE and PRD. Result

shows that bior3.9 wavelet is well suited for ECG signal processing as it has high SNR and low value of MSE and PRD among all the wavelet families.

Table 1. SNR comparison of window based FIR filters

Wavelet families	Type	SNR	MSE	PRD
Daubechies	**db4**	25.0144	2.0134e−04	0.0561
	db5	24.6097	2.2101e−04	0.0588
	db6	24.3737	2.3335e−04	0.0604
	db7	24.5116	2.2606e−04	0.0595
	db8	24.0698	2.5027e−04	0.0626
Biorthogonal	**bior3.5**	26.3158	1.4921e−04	0.0483
	bior3.7	26.4652	1.4416e−04	0.0475
	bior3.9	26.5396	1.4172e−04	0.0471
Reverse orthogonal	**rbio4.4**	24.4049	2.3168e−04	0.0602
	rbio5.5	24.9515	2.0428e−04	0.0565
	rbio6.8	25.1085	1.9703e−04	0.0555
Coiflets	**coif 4**	25.1166	1.9666e−04	0.0555
	coif5	24.8627	2.0850e−04	0.0571
Symlets	**sym4**	24.8996	2.0674e−04	0.0569
	sym5	24.6218	2.2039e−04	0.0587
	sym6	25.2806	1.8937e−04	0.0552
	sym9	24.8941	2.0700e−04	0.0569

Detailed coefficients and approximation coefficients are extracted from the ECG signal. Global Thresholding has been applied to smooth the wavelet coefficient. Lastly, different peaks of denoised signal are detected using PDA along with computation of different time interval measurements. Detection of various peaks of denoised ECG signal is shown in Fig. 3.
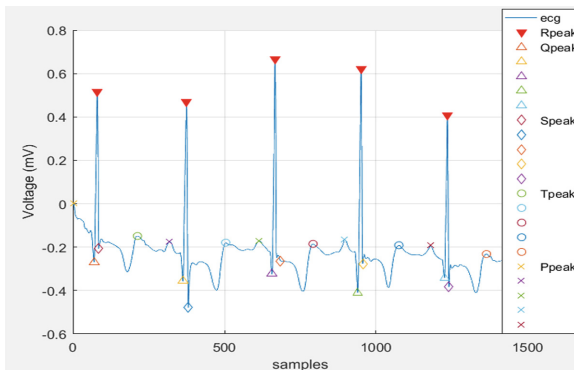

Fig. 3. Detection of peaks of denoised signal using PDA

Table 2 shows the computation of Heart Rate after pre- processing of an ECG signal and after processing by bior3.9 wavelet.

Table 2. Heart Rate computation

Heart Rate per minute	Heart Rate computation after High pass FIR filter	Heart Rate computation after processing by bior3.9 wavelet
	74.8882	74.8256

Table 3 shows the various peak errors such as *P* peak error, *Q* peak error, *R* peak error, *S* peak error and *T* peak error. Peak error is computed by equation

Table 3. Different peak error computation

Peak type	Peak error (%)
R peak error	0.2000
P peak error	2.000
Q peak error	0.4000
S peak error	2.4000
T peak error	2.4000

Table 4. Calculation of different peak intervals

S. No.	Types of intervals	Indications	Normal values of intervals (sec)	Output after high pass FIR filter (sec)	Output after processing by bior3.9 wavelet (sec)
1	*R-R* interval	Useful to calculate Heart Rate	0.6–1.2	0.8014	0.8021
2	*P-Q* interval	*P-Q* interval specifies the certain medical conditions. *P-Q* interval over 0.2 s indicates first degree of Heart blockage. Prolongation also indicates Hypokalemia, acute rheumatic fever	0.12–0.2	0.1378	0.1333
3	*QRS* complex	It indicates the depolarization of the right and left ventricle of human heart. Useful in diagnosing Cardiac arrhythmia, myocardial infraction	0.06–0.1	0.0461	0.0517
4	*S-T* interval	Variations in ST interval indicate the disease like transmural myocardial infarction	0.32–0.35	0.3451	0.3479

$$Peak\,Error \; = \; abs\left(x_p \; - \; x_p'\right) \qquad\qquad (10)$$

where x_p is output from high pass filter and x_p' is identified after MTD.

Table 4 shows the time level measurement of different peak intervals i.e. *R-R* interval, *P-Q* interval, *QRS* complex and *S-T* interval in every cycle of an ECG signal at two levels: (a) Output of ECG signal after High pass FIR filter using Blackman window and (b) Output of ECG signal after processing through bior3.9 wavelet.

5   Conclusion

The manual detection method is not suitable for a long-term monitoring system, and whenever an ECG is acquired from a patient body, a lot of noises accumulate with it, so proper detection is not feasible. Machine Learning based ECG analysis is required for an accurate detection of peaks which is a very tedious task as this signal is affected by various noise. In this paper, Morphology Analysis and Time Interval Measurements using Mallat Tree Decomposition (MTD) are done to obtain the signal in the desired form for calculation of heart rate. ECG signals are analyzed with various mother wavelets using MTD, and analyzed on the basis of performance matrices.

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