ST Segment Analysis Using Wavelet Transform

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Summary
In this work, we present an algorithm for ST segment analysis in electrocardiogram (ECG) using wavelet transform. In preprocessing stage, Discrete Wavelet Transform DWT is used to remove the baseline wander (BW) and power line interference (PLI) in the ECG signal. The decomposition of the ECG signal using Daubechies (Db4) Wavelet up to level 8 allows accurate time-frequency localization of the heartbeat waves (QRS complex, P wave, and T wave). ST segment level was estimated based on the isoelectric level. The algorithm was evaluated against European ST-T Database (EDB) and Long-Term ST Database (LTSTDB).

Key words:
ECG, DWT, QRS detection, ST segment, isoelectric line.

1. Introduction

Ischemic heart disease happens when coronary arteries get narrower and reduce the blood flow to the heart. This is also called coronary heart disease (CHD). This can ultimately lead to heart attack [1]. An Electrocardiogram (ECG) is a series of waves and deflections recording the heart's electrical activity from different views. Each view is called a lead which monitors voltage changes between electrodes placed in different positions on the body. Leads I, II, and III are called bipolar leads. Leads aVR, aVL, aVF, V1 through V6 are called unipolar leads. [2]. An ECG is characterized by a recurrent wave sequence of P, QRS and T waves associated with each beat. The ECG signal is a very important tool in the diagnosis of heart disease. Ischemia and Myocardial Infarction (MI) are among the most serious cardiac abnormalities. These anomalies appear on the ECG signal as ST segment or T wave changes. The ST segment elevation and depression indicate the myocardial ischemia. ST segment elevation is measured from the isoelectric line level (the flat part of the ECG between the P wave and the QRS complex) to the J point. The J point is the "junction" point between the end of QRS complex and the onset of ST segment. Reference points of ST segment are shown in Fig.1. ST segment elevation implies that the J point is situated above the isoelectric and ST segment depression implies that the J point is located below the isoelectric line. There have been

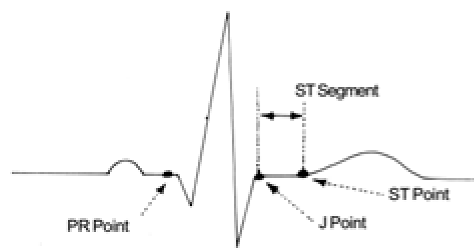

Figure 1. Reference points of ST segment

several methods dealing with ST segment analysis based on digital signal processing. These include Discrete Wavelet Transform (DWT) and Support Vector Machine (SVM) [3], Morphology and Correcting Window Method [4], isoelectric energy function [5], wavelet transform [6], Means of Wavelets [7], Decision Trees Boosting and Random Under Sampling (RUS) techniques [8], Synthesized Algorithm [9], Independent Component Analysis (ICA) and Triangular Method [10], Biosignal Quality Analysis [11], Daubechies Wavelet Transforms and adaptive Neuro Fuzzy Inference System [12], Wavelet Analysis [13], Stress ECG Analysis [14], Morphological Features [15], Bispectral Analysis of ECG [16], Real-time Biosignal Quality Analysis for ECG [17], Machine Learning Techniques [18] etc. We propose an algorithm based on discrete wavelet transform for ST segment analysis to detect ischemia and Myocardial Infarction (MI).

2. Materials and Method

2.1 European ST-T and Long-Term ST Databases

The European ST-T database (EDB) consists of 90 annotated excerpts of ambulatory ECG recordings from 79 subjects. Each record is two hours in duration and contains two signals, each sampled at 250 samples per second with 12-bit resolution over a nominal 20 mV input range [19].

The Long-Term ST Database (LTSTDB) contains 86 lengthy ECG recordings of 80 human subjects. The individual recordings of the Long-Term ST Database are

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between 21 and 24 hours in duration, and contain two or three ECG signals. Each ECG signal has been digitized at 250 samples per second with 12-bit resolution over a range of ±10 mV. Each record includes a set of meticulously verified ST episode and signal quality annotations, together with additional beat-by-beat QRS annotations and ST level measurements [20]. In this work the validation has been carried out on records s20011m, s20021m, s20031m, s20061m, s20081m, s20091m, s20111m, s20121m, s20131m and s20571m from LTSTDB and e0103m, e0104m, e0105m, e0106m, e0107m, e0108m, e0121m, e0166m, e0202m and e0818m from EDB.

2.2 Wavelet Transform

The Continuous Wavelet Transform (CWT) transforms a continuous signal into highly redundant signal of two continuous variables: translation and scale. The resulting transformed signal is easy to interpret and valuable for time-frequency analysis. The continuous wavelet transform of continuous function, x(t) relative to real-valued wavelet, ψ(t) is described by:

$$W_{\Psi}(s,\tau) = \int_{-\infty}^{+\infty} x(t)\psi^{*}_{s,\tau}(t)dt \qquad (1)$$

Where,

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s}) \qquad (2)$$

s and τ are called scale and translation parameters, respectively. Wψ(s,τ), denotes the wavelet transform coefficients and ψ is the fundamental mother wavelet [21].

The Discrete Wavelet Transform (DWT) has become a powerful technique in biomedical signal processing. It can be written on the same form as (1), which emphasizes the close relationship between CWT and DWT. The most obvious difference is that the DWT uses scale and position values based on powers of two. The values of s and τ are: s = 2j, τ = k*2j and (j, k)∈Z 2 as shown in (3).

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{2^{j}}}\psi(\frac{t-k*2^{j}}{2^{j}}) \qquad (3)$$

3. Methodology

The structure of ischemia detection in this work consists of four phases: preprocessing, ECG key points, ST analysis and decision on ischemia. The proposed method is as shown in Fig. 2.

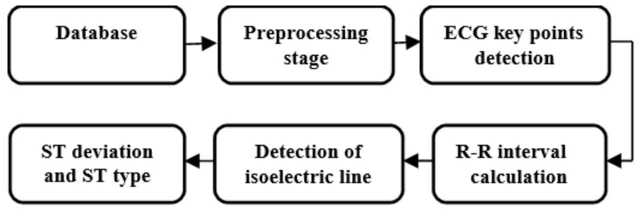

Fig. 2 Schematic diagram for the method

4. Preprocessing

In preprocessing stage, we must remove the Baseline wander (BW) and 60 Hz power line interference. The removal of this disturbance is an important step in ECG signal analysis, to produce a stable signal for subsequent automatic processing [22].

3.1 Removal of Baseline Drift

The Baseline wander having a frequency range of (0-0.5Hz). In accordance with Nyquist's rule, if the original signal has a highest frequency fmax, it requires a sampling frequency fs ≥ 2fmax. Hence, at each decomposition level j, the frequency axis is recursively divided into halves at the ideal cut-off frequencies fj = fmax/2j [23]. Our approach is based on wavelet decomposition up to level 8, which generates a set of approximation coefficients(C8), and nine sets of detail coefficients (d1- d8). By cancellation of approximations, the filtered signal is recovered from the details only [24]. Table 1 gives the correspondence between DWT coefficients and range of frequencies. The results for removal of baseline wanders in the e0108m record of EDB are shown in Fig. 4.

Table 1: Range frequencies of dwt coefficients

DWT Coefficients	***Range frequencies***
d1	125 - 250Hz
d2	62.5 - 125Hz
d3	31.25 - 62.5Hz
d4	15.62 – 31.25 Hz
d5	7.812 - 15.625 Hz
d6	3.906 - 7.81 Hz
d7	1.953 - 3.906 Hz
d8	0.976 - 1.953 Hz
(Baseline wander) C8	0Hz - 0.976 Hz

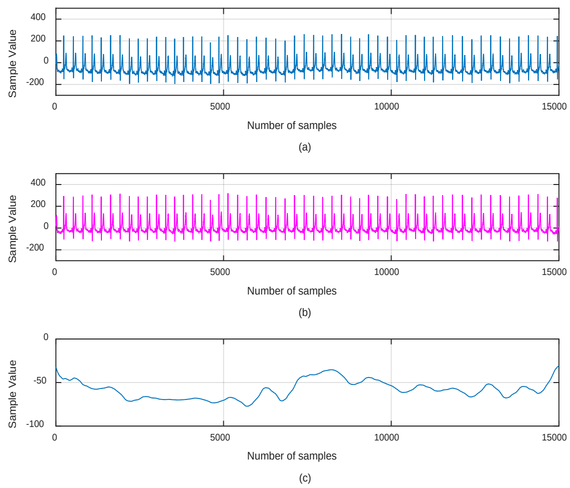

Fig. 3 Results for removal of baseline wanders for e0108m ECG record from EDB (1minute) : (a) noised ECG ; (b) Baseline free ECG ; (c) Removed baseline

3.2 Removal of Power Line Interference

The ECG signals from the Long-Term ST Database are affected by 60Hz PLI. We propose to add to the test signals, a simulated noise of this form:

$$n(t) = A \cdot \sin(2 \cdot \pi \cdot f_0 \cdot t) \tag{4}$$

Where, A is the amplitude, and f0 is the 60Hz frequency of the simulated noise. The noisy signal may then be expressed by:

$$x(t) = ecg(t) + n(t) \tag{5}$$

Where, ecg(t) is the signal from the Long-Term ST database. The maximum frequency is on the order of 130Hz (fmax = 130Hz) [25]. Therefore, the range of real frequency components of the ECG signals is between 0 and 130 Hz. The correspondence between decomposition levels and DWT coefficients is given in Table 2.

Table 2: DWT coefficients of different levels

Level	***DWT coefficients***							
1	C1				d1			
2	C21		d21		d22		d23	
3	C30	d 31	d32	d33	d 34	d35	d36	d37

Table 3 gives the correspondence between DWT coefficients and range frequencies. The ECG signal is recovered from all coefficients except details d33 (48.75 - 65Hz) [26]. The results for removal of PLI interference in the e0108m record of EDB are shown in Fig. 4. (10s for good visualization of the signals).

Table 3: Range frequencies of dwt coefficients

DWT Coefficients	***Range frequencies***
C30	0Hz - 16.25Hz
d31	16.25 - 32.5Hz
d32	32.5 - 48.75Hz
d33	48.75 - 65Hz
d34	65 - 81.25Hz
d35	81.25 - 97.5Hz
d36	97.5 - 113.75Hz
d37	113.75 - 130Hz

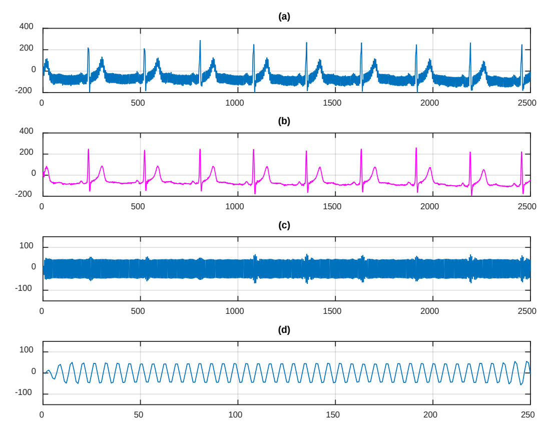

Fig. 4 Results for removal of PLI interference for e0108m ECG record from EDB (10s) : (a) noised ECG ; (b) Filtred ECG ; (c) 60 Hz power line noise ; (d) 60 Hz noise zoomed in 1s.

5. Detection of ECG Key Points

5.1 Detection of QRS, P and T wave

The QRS reflects the electrical activity within the heart during the ventricular contraction, the time of its occurrence as well as its shape provide much information about the current state of the heart. The QRS detection is the most important step for almost all ECG analysis algorithms. Pan and Willis J. Tompkins were the first to develop a real-time QRS detection algorithm that uses an automatically adjustable threshold [21]. In this work, the decomposition of the ECG signal is made using Daubechies (Db4) DWT up to level 8. The decomposition level d3, d4 and d5 contain most energy of the QRS complex. The coefficient d4 has the highest cross correlation compared to other coefficients. Fig. 5 shows

Wavelet coefficients for scale levels 1 to 8. To detect the R Peaks, we use a hard thresholding method [24]. Fig. 6 shows simultaneously the original signal s20121m with R peaks localization. After the R peak detection, the Q and S points must be identified to detect the complete QRS complex. The Q and S waves have low amplitude and high frequency and their energies are mainly at small scale [27], so reconstruction coefficients d2 to d5 are selected to detect Q and S waves. Q point is the point of inflexion before the R peak. S point is the point of inflexion after the R peak.

Depending on the power spectra of ECG signal [27] the energies of P and T waves are mostly at scale levels 6 [3.906 - 7.81 Hz] , 7 [1.953 - 3.906 Hz] and 8 [0.976 - 1.953 Hz] . So, we keep only the coefficients d6 and d7 because the baseline drift is around scale 8 (0.5 - 1Hz). After the detection of the S point, the T peak is identified as the maxima within an interval from S point to T offset.

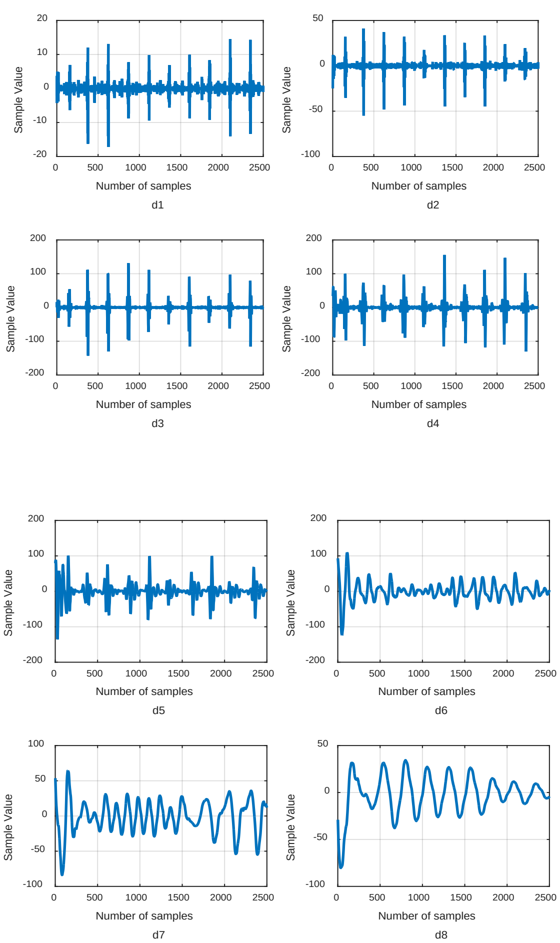

Fig. 5 Wavelet details coefficients for scale levels 1–8 for record s20121 ECG record of LTSTDB

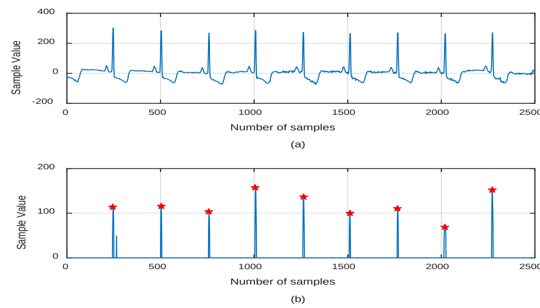

Fig. 6 R peak detection for s20121m ECG record of LTSTDB (10s)

Two performance measures are used to assess the algorithm performance: sensitivity (Se) and Positive predictivity (+P) defined respectively as:

$$S_e = \frac{TP}{TP + FN} * 100 \tag{7}$$

$$+P = \frac{TP}{TP + FP} * 100 \tag{8}$$

Where TP means a true positive, FN means a false negative and FP denotes a false positive detection. Table 4 shows average 99,13% Se and 97.14% average +P for LTSTDB. Table 5 shows average 98,20% Se and 97.17% average +P for EDB.

5.2 Heart Rate Measurement

The Heart Rate is computed from the RR intervals (measurement of samples between two consequent R peaks) using.

$$HR = \frac{60}{RR\,\mathrm{int}\,erval}[bpm] \tag{6}$$

5.3 ST Segment Localization

To locate the ST segment, the isoelectric line, the J point and the heart rate must be accurately detected. The J point is the ending point of QRS complex or the first inflection point after the S point. The ST segment is the portion bounded between the J-point and K-point. Depending on the heart rate, the K point is located in an interval between 40 ms and 80 ms after the J point.

5.4 Detection of Isoelectric line

The isoelectric line is the flat part of the ECG between the offset of P-wave and the onset of Q-wave. The windowing and backward search up to 80 ms before the QRS complex are used to find the zero crossing between the P and T waves. The isoelectric line is the average, after repetition for 30 beats.

Table 4: Results for R peaks detection for (1 minute) 10 records from LTSTDB

Record	*Actual Peaks*	*Detectedp eaks*	*FP*	*FN*	*Se (%)*	*+P (%)*
s20011m	70	69	1	1	98.57	98.57
s20021m	72	71	1	1	98.61	98.61
s20031m	76	75	2	1	98.68	97.40
s20061m	92	92	2	0	100	97.87
s20081m	79	78	4	1	98.73	95.12
s20091m	106	105	0	1	99.06	100
s20111m	84	84	5	0	100	94.38
s20121m	60	60	3	0	100	95.24
s20131m	78	77	2	1	98.72	97.47
s20571m	91	90	3	1	98.90	96.77
Total	808	801	23	7	**99.13**	**97.14**

Table 5: Results for R peaks detection for (1 minute) 10 records from EDB

Record	*Actual Peaks*	*Detected peaks*	*FP*	*FN*	*Se (%)*	*+P (%)*
e0103m	60	60	2	0	100	96.77
e0104m	72	70	1	2	97.22	98.59
e0105m	54	54	2	0	100.00	96.43
e0106m	57	55	1	2	96.49	98.21
e0107m	52	49	2	3	94.23	96.08
e0108m	54	54	3	0	100	94.74
e0121m	75	74	3	1	98.67	96.10
e0166m	51	50	0	1	98.04	100
e0202m	85	84	2	1	98.82	97.67
e0818m	69	68	2	1	98.55	97.14
Total	629	618	18	11	**98.20**	**97.17**

6. Calculation of ST segment level

The Region of interest for the ST segment is located between J point and K point. The mean value for the J point and the T point was computed. The ST level is the mean of ST segment measured with respect to the isoelectric line [28]. If the deviation is between "- 0.1mV" and "0.1mV" then the ST segment is normal. Otherwise, the ST segment is said to be elevated if the deviation is greater than "0.1mV" or depressed if this deviation is less than "- 0.1mV" [29].

7. Results

The ST segment level (elevation or depression) is an important parameter for detecting ischemia. It is measured with respect to the isoelectric line. The algorithm is validated for 10 representative records of the annotated LTSTDB and 10 records of the annotated EDB. These records are preprocessed using DWT to remove baseline wanders and power line interference. After the preprocessing stage, QRS complexes, P and T waves must be detected. The heart rate is measured for each beat using the RR interval to locate the K point. The heart rate and corresponding ST classification type are shown in Table 6 for the Record e0108m from EDB and s20121m from LTSTDB.

Table 6: The heart rate and corresponding ST classification for 30 beats of records e0108m from EDB and s20121 from LTSTDB

Beat N°	*Record e108m*			*Record s20121m*		
	[RR] (s)	*HR*	*ST segment level*	*[RR] (s)*	*HR*	*ST segment level*
1	1.07	56	Elevated	1.07	56	Depressed
2	1.03	58	Elevated	1.03	58	Depressed
3	1.09	55	Elevated	1.02	59	Depressed
4	1.11	54	Elevated	1.05	57	Depressed
5	1.13	53	Elevated	1.09	55	Depressed
6	1.09	55	Elevated	1.11	54	Depressed
7	1.05	57	Elevated	1.13	53	Depressed
8	1.02	59	Elevated	1.09	55	Depressed
9	1.00	60	Elevated	1.11	54	Depressed
10	1.09	55	Elevated	1.00	60	Normal
11	1.11	54	Elevated	0.98	61	Normal
12	1.13	53	Elevated	0.97	62	Depressed
13	1.09	55	Elevated	1.03	58	Depressed
14	1.07	56	Elevated	1.05	57	Depressed
15	1.13	53	Elevated	1.09	55	Depressed
16	1.18	51	Elevated	1.15	52	Depressed
17	1.09	55	Elevated	1.18	51	Depressed
18	1.03	58	Normal	1.11	54	Depressed
19	1.00	60	Normal	1.09	55	Depressed
20	1.11	54	Elevated	1.03	58	Depressed
21	1.07	56	Elevated	0.98	61	Normal
22	1.03	58	Elevated	1.02	59	Depressed
23	1.11	54	Elevated	1.09	55	Depressed
24	1.09	55	Normal	1.13	53	Depressed
25	1.03	58	Elevated	1.11	54	Depressed
26	1.00	60	Elevated	1.11	54	Depressed
27	1.11	54	Elevated	1.03	58	Depressed
28	1.15	52	Elevated	1.02	59	Depressed
29	1.13	53	Elevated	1.02	59	Depressed
30	1.11	54	Elevated	1.09	55	Depressed

8. Conclusion

This algorithm, based on wavelet analysis of ECG, was successful in detecting early stage of myocardial ischemia through ST segment elevation or depression with respect to isoelectric line and heart rate. We have used a single lead ECG records from European ST-T Database and Long-Term ST Database. In the future, a lot of scope for improving accuracy of ischemic beat classification by combining some promising techniques. This work can be integrated with STEMI detection algorithm using 12 leads standard databases.

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