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QRS DETECTION OF ECG - A STATISTICAL ANALYSIS

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Abstract

Electrocardiogram (ECG) is a graphical representation generated by heart muscle. ECG plays an important role in diagnosis and monitoring of heart's condition. The real time analyzer based on filtering, beat recognition, clustering, classification of signal with maximum few seconds delay can be done to recognize the life threatening arrhythmia. ECG signal examines and study of anatomic and physiologic facets of the entire cardiac muscle. The inceptive task for proficient scrutiny is the expulsion of noise. It is attained by the use of wavelet transform analysis.

Wavelets yield temporal and spectral information concurrently and offer stretchability with a possibility of wavelet functions of different properties. This paper is concerned with the extraction of QRS complexes of ECG signals using Discrete Wavelet Transform based algorithms aided with MATLAB. By removing the inconsistent wavelet transform coefficient, denoising is done in ECG signal. In continuation, QRS complexes are identified and in which each peak can be utilized to discover the peak of separate waves like P and T with their derivatives. Here we put forth a new combinatory algorithm builded on using Pan-Tompkins' method and multi-wavelet transform.

Keywords:

Electrocardiogram (ECG), QRS Detection, Wavelet Transform, Denoising, Pan-Tompkins'

1. INTRODUCTION

The most critical part of the electrocardiogram (ECG) is the QRS complex. Its shape and occurrence time accord much statistics and details about the heart function. Since it has a distinguished shape, QRS detection is the principal part of almost all automated ECG analysis algorithms such as heart rate variability and cardiac cycle classification. A typical ECG waveform is shown in Fig.1.

A prototypical QRS detection algorithm generally consists of two phases: preprocessing and decision [1].Comprehensively, the former includes some sort of filtering [2], while the latter attempts to specify the location of QRS complexes in the ECG signal.

Till date, an extensive variety of techniques such as linear filtering, neural networks [5], mathematical morphology and wavelet transforms have been recommended by the researchers of QRS detection.

For instance, a substantial number of QRS detection algorithms principally use linear filtering to remove objectionable parts of the ECG signal. Then, QRS complexes are determined by applying a suitable threshold to the resultant signal. Pan-Tompkins' method [2], [3], is a familiar algorithm of this classification.

Offlate, a number of QRS detection algorithms were suggested based on the wavelet transform. They examine the ECG signal by using the multi-scale sub-band data and statistics provided by the wavelet transform.

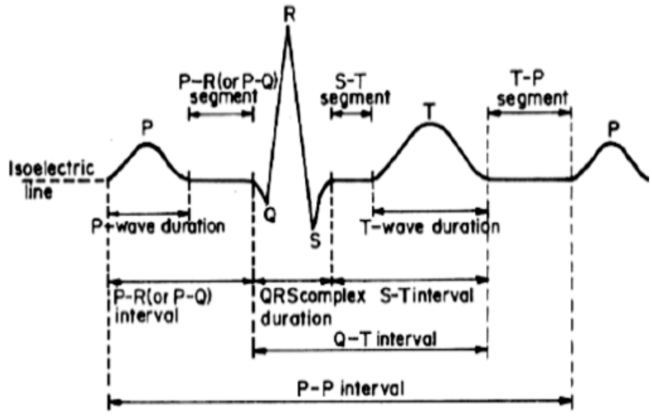

Fig.1. Normal ECG Waveform

In addition, a number of combinatory algorithms were earlier proposed, to be benefitted of the linear filtering and wavelet transform. Predominantly, QRS detection is a not a minor task. It may possibly be malformed by noise caused by the electrode artifact, baseline drift, and power line interference [9]. Almost always, the ECG signal may deform owing to the pathological or obsessive variations, e.g. signals with small QRS complexes or suddenly variable levels. Hence, to provide a dependable and a well-grounded QRS detection algorithm is still an unsolvable open problem.

In this paper, a novel hybrid algorithm is proposed which integrates various wavelet coefficients and Pan-Tompkins' method for extracting features [10] and also improved the computational cost by using different parameters like uniformity, entropy, etc., to analyze ECG signal statistically.

2. HEART DISEASES

The term "Heart Disease" refers to conditions that involve narrowed or blocked blood vessels that can lead to a heart attack, chest pain (angina) or stroke. There are different types of heart diseases, the most common type that affects the electrical system is known as arrhythmias. They can cause the heart to beat very fast (Tachycardia) or very slow (Bradycardia), or unexpectedly (Atrial fibrillation).

These heart diseases include the following types:

- Tachycardia
- Bradycardia
- Atrial Fibrillation
- Premature Atrial Contractions (PAC)
- Atrial flutter, etc.

2.1 PAN-TOMPKINS ALGORITHM

The bottom line for almost all the mechanized ECG analysis algorithms is provided by the QRS detection. A real-time QRS detection algorithm of typical cardiac signal which is proposed by Pan-Tompkins consists of LPF, HPF and operators to perform a method which consists of adaptive threshold operations with differentiation, integration, etc as shown in the Fig.2.

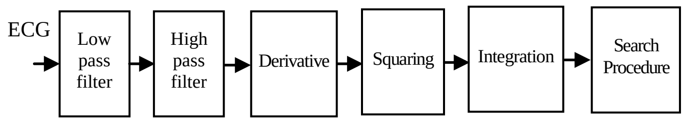

Fig.2. Steps in implementation of Pan-Tompkins Algorithm

3. QRS DETECTION

The strenuous task during the detection of the QRS complex rests in-detecting the peak of the QRS complex or R wave, as in an electrocardiogram (ECG), the signal has a time-varying morphology [6]. This phenomenon occurs owing to the reason that an ECG signal is vulnerable to physiological variations caused by the patient and to corruption due to noise. Considering the fact that the QRS complexes have a time varying morphology, they are not always the strongest and reliable signal component in an ECG signal. To resolve this, P-waves or T-waves with characteristics similar to that of the QRS complex, as well as spikes from high frequency pacemaker's compromise the detection of the QRS complex.

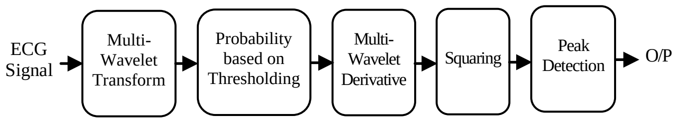

Fig.3. Proposed Algorithm

3.1 WAVELET TRANSFORM

A wavelet can be defined as a small wave with energy concentrated in time. It is a very good tool for the analyzing both time domain and frequency domain. As there are different wavelets which can be used to extract important features from signal, in this paper we have applied ECG signal on different wavelet transforms to obtain sensitive abnormalities in the mild stage.

The multi-wavelet transform used in this work are Haar wavelet, Daubechies wavelet, Bior 3.5 wavelet etc to improve the precision of the feature. The Fig.4 is mapping function of a continuous variable into a sequence of coefficients. Decomposing the wavelet in the multi spectral using multi wavelet is very useful in implementing the sensitivity.

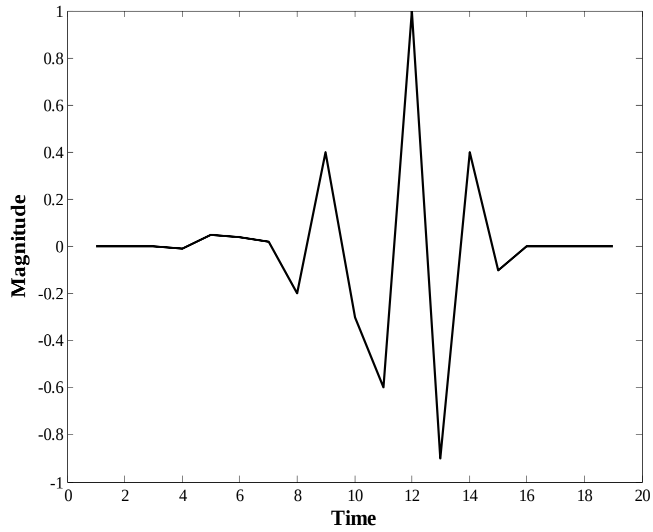

Fig.4. Wavelet function

3.2 THRESHOLDING

At wavelet analysis the signal is disintegrated into approximate coefficients- which represent the smoothed signal, and the detailing coefficients - that describe the noise. Such components can be evicted by implementing the process of thresholding that is by removing the coefficients whose values are less than the value threshold. Thresholding, at present is a perspective tool for the treatment of cardio noise (high frequency components). While here we have used soft thresholding. Threshold is done based on entropy and uniformity.

The four normalized statistical values extracted from each wavelet sub-band can be computed by the following equations:

$$Variance(V) = \sum_{i=1}^{L-1} (z_i - m)^2 \; p(z_i) / (L-1)^2 \tag{1}$$

$$Energy(E_n) = \sum_{i=0}^{L-1} (z_i - m)^3 \; p(z_i) / (L-1)^2 \tag{2}$$

$$Uniformity(U) = \sum_{i=0}^{L-1} p^2(z_i) \tag{3}$$

$$Entropy(E_v) = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i) \tag{4}$$

where, z_i is discrete values and p (zi) is probability of each discrete value and, i=0, 1, 2,…, L-1 is the discrete levels.

L is the number of levels;

$$m = \sum_{i=0}^{L-1} z_i \, p(z_i) \text{ is the mean} \tag{5}$$

3.3 DOUBLE DIFFERENTIATION

An initial filter phase is normally used by all QRS detection algorithms since the typical frequency components of QRS complex ranges from around 5Hz to 25Hz. This process is done before the actual QRS detection to dominate the remaining attributes in the ECG signal which are the P, T waves, noise and baseline drift. Low pass filters are used to restrain the noise and the baseline drifts, while the other components like P and T waves are controlled by high pass filters. Hence the combinations of both the low pass filter and high pass filter yields the application of a band pass filter with cut-off frequencies of 5Hz and 25Hz meant for QRS detection. For many algorithms, the high pass filtering and the low pass filtering are segregated and are distinctly carried out. The QRS complex is detected using the comparison with the threshold using the filtered signals when the algorithms use only the high pass filters. Some other decision rules are employed to mitigate the false positives. Commonly in the older algorithms, the high pass filter was identified as a differentiator, due to which the QRS complex feature of having a large slope was used for its detection. The first order derivative of the ECG signal is shown in Fig.1 [4]. It is observed that double differentiation of wavelets increases positive predictability which solves most of the problems. In this proposed algorithm, multiwavelets have been used to detect exactly the QRS complex with more sensitivity.

The differentiator has the following difference equations

$$QRS = K\frac{d^2}{dt}D_4 Haar + R\frac{d}{dt} * \frac{D_3}{D_b} + M.U.\min\left[D_5 Bior3.5\right] > \Theta \quad (6)$$

where, *K* and *M* are constants, and

$$R = \sum_{L=0}^{p-1}\left(z_i - m_x\right)p\left(z_i\right) \quad (7)$$

m_x is mean

$$Uniformity(U) = \sum_{i=0}^{L-1} p^2\left(z_i\right) \quad (8)$$

Θ is an threshold of the amplitude.

The typical features of such algorithms is given by *z(n)*.The contrast between the feature in the ECG and the threshold value gives the QRS complex. The selection of the threshold levels must be adaptive and flexible in nature and depend on varying signal morphology. When considering feature in equation, the threshold is proposed.

$$\Theta_x = 0.3 \text{ to } 0.4 * max[x] \quad (9)$$

where, the x is the signal segment and its maximum value is determined. This method of getting the threshold value is implemented in almost all QRS detectors [4], following which, various decision rules are applied to avoid false positives by using various peak detection logics represented. Thus, derivative detection method is used for identification of QRS in ECG signal using cumulative differentiation technique.

3.4 SQUARING FUNCTION

After differentiation, the signal is squared point by point, which makes all data points positive [11]. The equation for this is

$$y(nT) = [x(nT)]^2 \quad (10)$$

that is, predominantly the ECG frequencies does nonlinear amplification of the output of the derivative emphasizing higher frequencies is highlighted.

3.5 PEAK DETECTION

For the peak detection, specific points of the signal are opted. Among all waves, the R peak [8] has the largest amplitude. The components of decomposed signals are kept and the others are discarded. So, in precise the QRS complex detection consists of determining the R point of the beat and it is squared. At the end the number of beats is calculated to know the time interval between successive heartbeats [12].

4. RESULTS

The Multiwavelet transform is applied to ECG signal to initiate the undesired frequency. The fourth scale of Daubechies wavelet (db4) is used to attain this. After denoising, QRS Complexes are determined. This is obtained by implementing on MIT-BIH arrhythmia database [7]. It is clearly understood from the Table.1, that there is significant improvement in the error reduction using proposed algorithm.

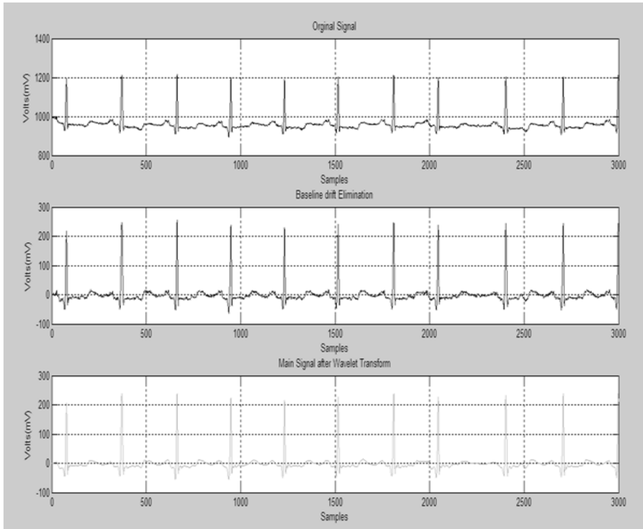

Fig.5. Results of the proposed algorithm for record 100 after Wavelet Transform

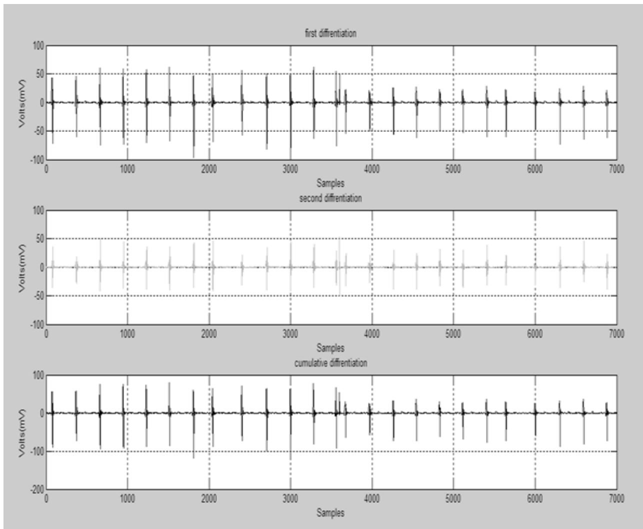

Fig.6. Cumulative of 1st and 2nd differentiation

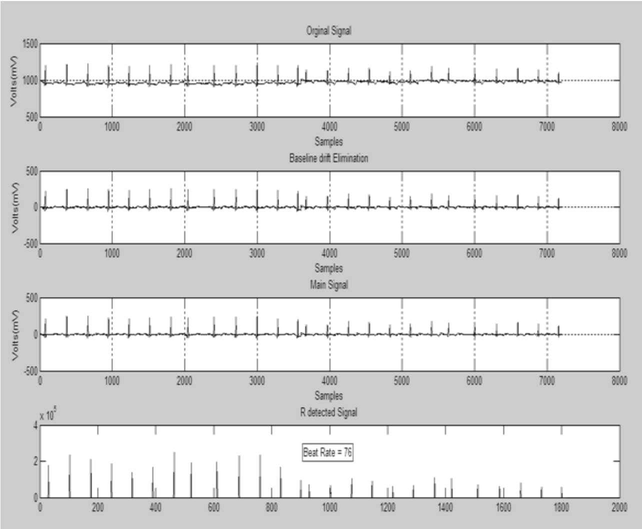

Fig.7. Results of the proposed algorithm for record 100

Table.1. Results of Pan Tompkins and Proposed Algorithm

Data	Heart rate			Error %	
	Practical	Pan Tompkins	Proposed Algorithm	Pan Tompkins	Proposed Algorithm
100	78	76	76	2.56	2.56
101	66	74	96	10.81	28.8
102	72	68	68	5.55	5.55
103	66	68	68	3.03	3.03
104	72	68	68	5.55	5.55
105	84	53	61	36.9	27.38
106	60	60	60	0	0
107	120	71	107	40.83	10.83
108	60	61	57	1.63	4.9
109	96	84	102	12.5	6.25
111	72	71	75	1.38	4.16
112	90	85	79	5.55	12.2
113	108	56	116	50	6.89
114	54	54	65	0	16.66
115	60	60	53	0	11.66
116	78	80	80	2.56	2.56
117	108	53	97	50.9	10.18
118	144	72	148	50	2.77
119	60	62	69	3.33	15
121	60	60	60	0	0
122	90	91	91	1.11	1.11
123	48	48	76	0	36.84
124	48	49	49	2.08	2.08
Total	1614	1524	1821	286.27	216.96
Mean				12.43	9.39

5. CONCLUSION

In this work, we have assessed the performance of the proposed algorithm with existing algorithms and identified that double differentiation and multi-wavelet transforms improves the quality of feature extraction and the early detection is possible by the proposed algorithm more precisely. The result is analyzed statistically by taking different data records. The error percentage for the proposed algorithm when compared to the existing algorithm is low and same for few data records, but for some data records it is little bit high. Since the analysis is taken from different records of heart rate data, the comparison is done for all the points. By taking mean, it is directly showing that the proposed algorithm is having less error compared to the existing algorithm. Due to this, the proposed algorithm is more efficient.

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