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A Method for QRS Delineation Based on STFT using Adaptive Threshold

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Abstract

Electrocardiogram (ECG) is the electrical manifestation of the contractile activity of the heart. In this work, it is proposed to utilize an adaptive threshold technique on spectrogram computed using Short Time Fourier Transform (STFT) for QRS complex detection in electrocardiogram (ECG) signal. The algorithm consists of preprocessing the raw ECG signal to remove the power-line interference, computing the STFT, applying adaptive thresholding technique and followed by identifying QRS peaks. Sensitivity, Specificity and Detection error rate are calculated on MIT-BIH database using the proposed method, which yields a competitive results when compared with the state of art in QRS detection.

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Keywords: Adaptive threshold; Electrocardiogram; QRS detection; Short time fourier transform; Time-frequency analysis.

1. Introduction

ECG is the most commonly known, recognized, and used biomedical signal. Nobel laureate, Willem Einthoven has first recorded the ECG in 1903. The analysis of ECG signal plays a vital role in the diagnosis of heart. The usage of ECG in the state of art of biometric, is increasing rapidly[1,2]. In most of the applications involving ECG signal, QRS detection is a basic milestone. In fact, QRS detection is very difficult because of problems like physiological variability, power-line interference, baseline wander noise, artifacts due to electrode and muscle motion, and resemblance of T wave with QRS complex characteristics[3]. In literature, one can find different QRS detection methods, such as methods from the field of filtering[3,4], time-frequency analysis[5–7], artificial neural networks[8], hilbert Transform[9,10], and heuristic techniques[11,12].

The biomedical signals are non-stationary in nature. They possess highly complex time frequency characteristics[13]. It is not possible to analyse the energy distributions of these signals based on the Fourier transform. This phenomena requires a spectral estimate evolves over time, i.e., how much each frequency component have contributed to the total

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energy of the signal over certain time interval, which can be obtained by *time-frequency analysis* (TFA). The short time fourier transform (STFT) is one of the basic tool used for time-frequency analysis, the STFT is able to produce a time-frequency distribution (TFD) with good time and frequency localization with the limitation of constant window length. In[7], a QRS detection method based on STFT is proposed. In the current work, It is proposed to use an adaptive thresholding technique similar to[3], on the spectrogram computed using STFT.

In Section 2 an overview of STFT is described. The brief idea of each stage in the algorithm is discussed in Section 3. Results and discussions are found in Section 4 and finally the major findings are summarized in Section 5.

2. Short Time Fourier Transform

The problem with the classical fourier analysis is that, it gives the energy/power decomposition of the signal with respect to each frequency component, but it doesn't give the information about *when* this frequency component is contributed (lack of time localization)[14,15]. The reason behind this is, the analysing function exists over the entire time period of the signal. To overcome this one need to consider the analysing function of finite duration, this is the basic idea behind STFT. The STFT is equivalent to windowing the signal ($x(t)$) with a finite width window function ($w(t)$) in to different segments and perform the fourier transform on each segment[15]. The mathematical expression for segmented signal in continuous time domain, is shown in equation (1).

$$x(t_c, t) = x(t)w(t - t_c) \tag{1}$$

where, t_c is the center of the real-valued, symmetric window function. The mathematical expression after applying the fourier transform on the segmented signal is show in equation (2)

$$x(t_c, w_c) = \int_{-\infty}^{\infty} x(t_c, t)e^{-jw_c t}dt \tag{2}$$

Where, w_c is center frequency of the window. From (2), the energy density is defined as $|x(t_c, w_c)|^2$ which is famously known as spectrogram, it gives the energy of $x(t)$ in the vicinity of (t_c, w_c), i.e., in time-frequency plane. The mathematical expressions for segmented signal and STFT in discrete time domain is shown in equations (3) & (4) respectively.

$$x(m, n) = x(n)w(n - m) \tag{3}$$

$$x(m, l) = \sum_{n=-\infty}^{n=\infty} x(n)w(n - m)e^{\frac{-j2\pi ln}{m}} \tag{4}$$

Here, both m and l are discretized versions of t_c and w_c. window function need to satisfy requirements like, compact support i.e. the window should exist over a finite period of time, where the window length is much shorter than the signal length. Another important requirement is normalizing the window function to have unit energy, to preserve the energy in the segmented signal[15].

3. Description of the Algorithm

The block diagram of the algorithm is shown in Fig. 1. The algorithm consists of five stages namely Data Acquisition, Pre-processing, STFT, Adaptive Thresholding, Decision Making. The brief description of each stage is presented in the following sections.

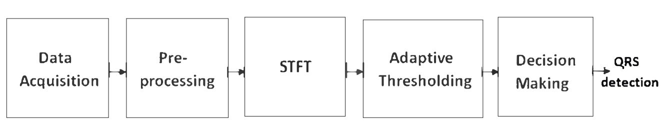

Fig. 1. Block diagram of the QRS peak detection algorithm.

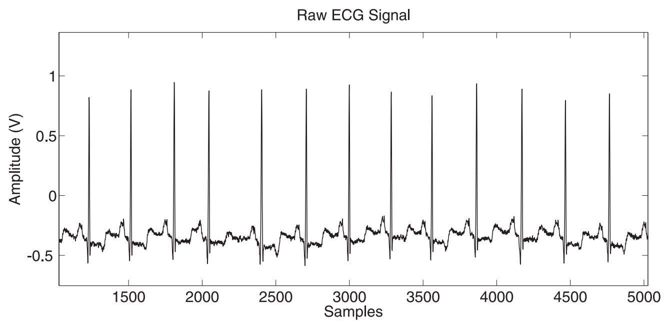

Fig. 2. Raw ECG signal.

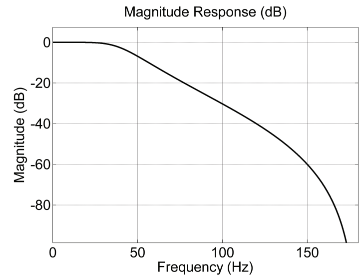

Fig. 3. Magnitude response of the LPF.

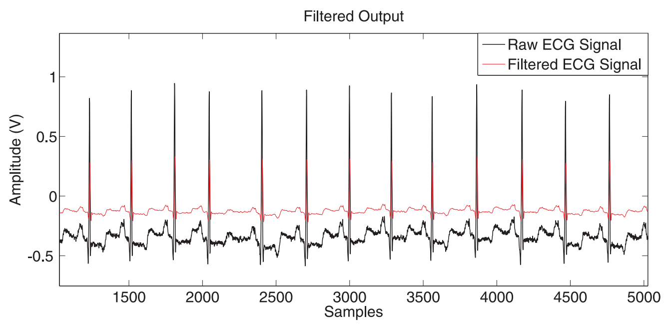

Fig. 4. Filtered ECG signal.

3.1 Data acquisition

The electrical potentials produced due to the electrical activity in one cardiac cycle are faithfully conducted to the body surface, so, ECG is recorded by placing an electrode on the body surface. A standard 12 lead system is used to get the overall view of the heart's activity[16]. In this 12 lead system, Lead I is significant for diagnosing rhythm problems. In this work, the ECG recordings are not measured, an already existed MIT-BIH Arrhythmia database is used for the analysis, which is available in the physionet website[17]. Figure 2 show a typical ECG signal of the record 100 in the MIT-BIH database, up to 5000 samples.

3.2 Pre-processing

Electromagnetic fields from power lines can cause 50–60 Hz sinusoidal interference, this effects low amplitude waveforms, it is known as power-line interference. In this stage a low pass filter (LPF) of cut-off frequency 40 Hz is designed to remove the power-line interference. Figure 3 shows the magnitude response of the LPF. Use of LPF improves the signal to noise ratio and permits the use of lower thresholds. After performing the filtering operation (on record 100 of MIT-BIH database) the ECG signal is shown in Fig. 4.

3.3 Short time fourier transform

In this stage, STFT[18], is computed on the filtered data. A smaller window length yields a high time resolution and low frequency resolution and vice-versa. Based on this, one need to choose a optimum window length. From[3], a pass band frequency range of 5–15 Hz is required to maximize the QRS energy. In[19], a frequency range of 8–20 Hz is suggested for detecting QRS complexes.

Here, a frequency range of 8–15 Hz, a step distance (i.e. number of samples window need to move) of 10, and a Gaussian window of length 75 is used for the analysis. The window length is chosen based on simulations.

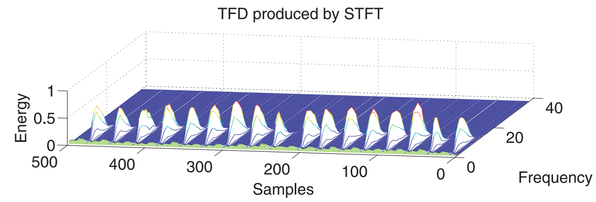

Fig. 5. TFD computed by STFT.

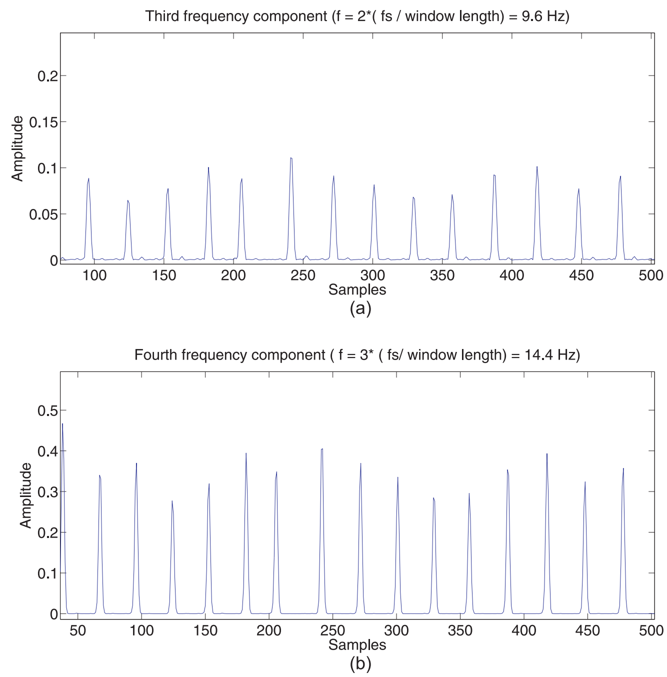

Fig. 6. (a) Third frequency component in spectrogram computed by STFT; (b) Fourth frequency component in spectrogram computed by STFT.

After computing STFT, one can estimate how much each frequency component have contributed to the total energy of the signal over certain interval of time. Figure 5, shows the time-frequency distribution on record 100 of MIT-BIH database, after normalization. Before thresholding, one need to extract the specific frequency components within the frequency range 8–15 Hz. In the analysis, only third and fourth frequency components (9.6 Hz, 14.4 Hz) are within the range of 8–15 Hz, so, we are considering these two frequency components for the analysis. Figure 6, shows the third and fourth frequency components, in the spectrogram of record 100 in MIT-BIH database. Then an adaptive thresholding technique, which is similar to[3] with some modifications, is used to find out the peaks in each frequency component.

3.4 Adaptive thresholding

The thresholding algorithm[3], consists of two processes: training phase and detection. In training phase, 2 sec of the signal data is used to initialize detection thresholds based upon signal, noise peaks and two RR-interval averages are maintained, one is average of the eight most-recent beats, the other is the average of the eight most-recent beats having RR-intervals that fell with in the range of 92–116 percent of the current RR-interval average, this will be useful in search back procedure to look for a missing QRS complex. In the detection process two threshold levels are used,

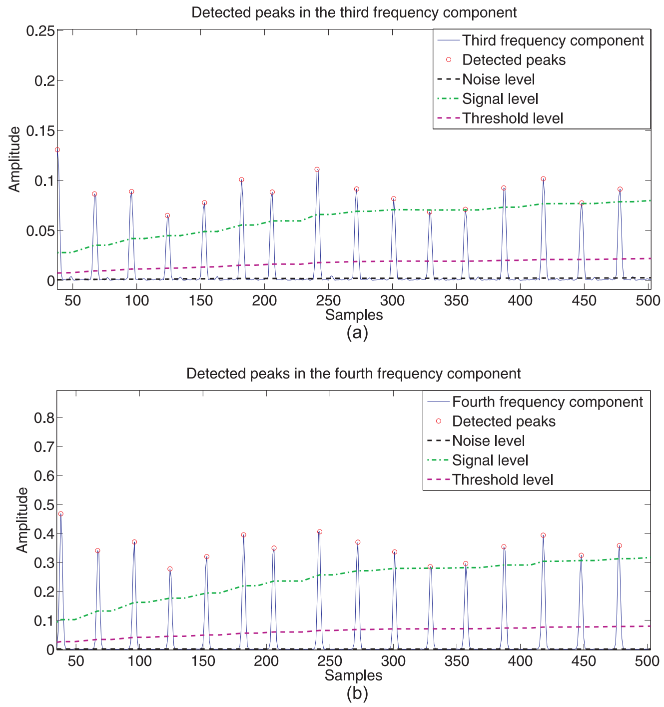

Fig. 7. (a) Detected peaks in third frequency component spectrogram computed by STFT; (b) Detected peaks in fourth frequency component spectrogram computed by STFT.

one level is one fourth of the other. Initially, the higher of the two thresholds is used, lower threshold is used, when no QRS is detected with in a certain time interval corresponding to 166 percent of the current average RR-interval. These two thresholds adjusted continuously to adapt the characteristics of signal.

Each QRS complex has a refractory period of around 200 ms, i.e. if a valid QRS peak is detected, there is a 200 ms time period before the next one can be detected[3]. If the time difference between the two successive peaks is less than 360 ms, we need to determine, weather it is a valid QRS complex or a T wave, here based on the slope information we are deciding, the waveform with the largest slope to be the QRS complex. Figure 7 shows the detected peaks after thresholding on the third and fourth frequency components.

3.5 Decision making

After extracting the specific frequency components, apply adaptive thresholding to each frequency component. If the number of peaks detected in the first frequency component is equal to the number of peaks detected in the second frequency component, then compare the location of each peak, if they are with in the range of ± 10 samples, then choose those locations as QRS peak locations. If the number of peaks detected in the successive frequency components are not equal, then discard the first frequency component and perform the same analysis on second and it's successive frequency components, until the peaks count in both the frequency components are equal. If the peaks are not equal for the frequency components with in the range of 8–15 Hz, in this case the final frequency component peaks locations are considered as the QRS peaks locations.

4. Results and Discussion

The MIT-BIH arrhythmia database[17], is used for the analysis. It consists of total 48 recordings, each recording is digitized at 360 samples per second, it also contains the annotation files for all 48 recordings. For each record,

Table 1. Results of evaluating the STFT based QRS detection algorithm using MIT-BIH database.

Record	TP	FN	Fp	Sens(%)	Spec(%)	DER(%)
100	2273	0	0	100.00	100.00	0.00
101	1865	0	4	100.00	99.79	0.21
102	2187	0	0	100.00	100.00	0.00
103	2084	0	0	100.00	100.00	0.00
104	2217	12	12	99.46	99.46	1.08
105	2560	12	35	99.53	98.65	1.83
106	2024	3	1	99.85	99.95	0.20
107	2134	3	0	99.86	100.00	0.14
108	1755	8	21	99.55	98.82	1.64
109	2527	5	0	99.80	100.00	0.20
111	2123	1	0	99.95	100.00	0.05
112	2539	0	0	100.00	100.00	0.00
113	1795	0	0	100.00	100.00	0.00
114	1808	71	42	96.22	97.73	6.01
115	1953	0	0	100.00	100.00	0.00
116	2389	23	2	99.05	99.92	1.04
117	1535	0	0	100.00	100.00	0.00
118	2278	0	2	100.00	99.91	0.09
119	1987	0	0	100.00	100.00	0.00
121	1863	0	0	100.00	100.00	0.00
122	2476	0	0	100.00	100.00	0.00
123	1515	3	0	99.80	100.00	0.20
124	1610	9	0	99.44	100.00	0.56
200	2598	3	6	99.88	99.77	0.35
201	1917	46	0	97.66	100.00	2.34
202	2125	11	0	99.49	100.00	0.51
203	2906	74	17	97.52	99.42	3.05
205	2653	3	0	99.89	100.00	0.11
207	1841	19	347	98.98	84.14	19.68
208	2889	66	1	97.77	99.97	2.27
209	3005	0	0	100.00	100.00	0.00
210	2603	47	2	98.23	99.92	1.85
212	2748	0	0	100.00	100.00	0.00
213	3248	3	0	99.91	100.00	0.09
214	2257	5	2	99.78	99.91	0.31
215	3359	4	0	99.88	100.00	0.12
217	2195	13	11	99.41	99.50	1.09
219	2151	3	0	99.86	100.00	0.14
220	2048	0	0	100.00	100.00	0.00
221	2420	7	0	99.71	100.00	0.29
222	2476	7	5	99.72	99.80	0.48
223	2598	7	0	99.73	100.00	0.27
228	2050	3	19	99.85	99.08	1.07
230	2256	0	0	100.00	100.00	0.00
231	1571	0	0	100.00	100.00	0.00
232	1780	0	1	100.00	99.94	0.06
233	3070	9	0	99.71	100.00	0.29
234	2750	3	0	99.89	100.00	0.11
Total	109011	483	530	99.56	99.52	0.93

True Positives (TP), indicates the total number of correctly located QRS peaks by the algorithm, False Negative (FN), occurs when the algorithm failed to detect an actual QRS peaks (quoted in the corresponding annotation file of the MIT-BIH record), and False Positive (FP), represents a false beat detection, i.e, it is not an actual QRS peak, but our algorithm detecting it as a QRS peak are calculated. And also, sensitivity (Sens), specificity (Spec) and detection error rate (DER), similar to[9], are calculated using the mathematical equations 5, 6, and 7.

$$\text{Sensitivity } (\%) = \frac{TP}{TP + FN} \tag{5}$$

Table 2. Comparison of results with other methods.

	Sens(%)	Spec(%)	DER(%)
Proposed Algorithm	99.56	99.52	0.93
Nopadol[7]	99.10	99.60	1.30
Darrington[20]	99.00	99.20	1.70
Chen *et al.*[21]	99.55	99.49	0.96

$$\text{Specificity } (\%) = \frac{TP}{TP + FP} \tag{6}$$

$$\text{DER } (\%) = \frac{FP + FN}{\text{Total number of QRS complex}} \tag{7}$$

The algorithm giving the good results, a sensitivity (Sens) of 99.56%, specificity (Spec) of 99.52% and QRS detection error rate of 0.93% is achieved against the MIT-BIH Arrhythmia database. The results are summarized in Table 1. The comparison of the results, with other methods are summarized in Table 2.

5. Conclusion

In this paper, utilization of an adaptive threshold technique on STFT has been proposed for QRS detection. It has been shown that, with proper adaptive thresholding technique the STFT has the potential to perform well for QRS complex detection. The results of the proposed algorithm has been compared with the other works, it has been observed that the proposed algorithm gives competitive results with the algorithms in the state of art of QRS detection. From above Table 1, the algorithm gives the good results in terms of sensitivity (Sens) of 99.56%, specificity (Spec) of 99.52% and QRS detection error rate of 0.93% achieved against the MIT-BIH Arrhythmia database.

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