# A Novel Approach for QRS Delineation in ECG Signal Based on Chirplet Transform

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***Abstract*—ECG analysis is used significantly in diagnosis, and biometrics. QRS complex detection is an important step in any application involving ECG signal. In this work, a novel approach for QRS complex detection based on chirplet transform is proposed. The QRS detection algorithm proposed in this work mainly consists of four steps. A preprocessing step to remove power line interference, computation of chirplet transform, an adaptive threshold technique for detecting possible QRS complex peaks, and followed by a decision making step. The performance of proposed algorithm for QRS complex detection is evaluated on MIT-BIH database and compared with the results of different algorithms in the state of art. The performance of the algorithm is comparable with the state of art of QRS complex detection.**

***Keywords*—ECG, QRS detection, time-frequency analysis, chirplet transform, adaptive thresholding.**

## I. Introduction

The electrical activity produced by depolarization and re-polarization of myocardial cells, which is recorded using electrodes placed on different parts of the body like chest, limbs is called Electrocardiogram (ECG) signal [1]. In literature, ECG signal analysis is used for diagnosis of diseases [2], [3], [4], and biometrics[5], [6], [7]. The QRS complex delineation is the basic step in any application involving ECG signal. QRS delineation is a difficult problem because of physiological variability, power-line interference, baseline wander noise, artefacts due to electrode and muscle motion, and resemblance of T wave with QRS complex characteristics [8]. Different QRS delineation methods in the state of art can be categorized as methods based on the conventional filter theory [8], [9], [10], time-frequency analysis [11], [12], [13], artificial neural networks [14], Hilbert Transform [15], [16], and heuristic techniques [17], [18].

The biomedical signals are non-stationary in nature and they possess highly complex time-frequency characteristics [19]. The conventional Fourier transform will not be able to describe the signal completely in both time and frequency. To represent such a signal, it requires a spectral estimate which evolves over time. This can be obtained by *time-frequency analysis* (TFA). The Short Time Fourier Transform (STFT) is an obvious option for TFA. However, it has limitation of time frequency localization trade off.

In STFT the given signal is represented with a basis function whose frequency is fixed, but in non-stationary signals frequency is varying with time, so to represent such signals one need to represent the given signal with the basis function whose frequency is varying with time. The Chirplet Transform (CT) is an obvious option. In case of Wavelet Transform (WT) the analysis is performed using different window scales due to which the CT results are flat when compared with WT. In this work, a novel method for QRS delineation based on the Chirplet Transform is presented. The performance of the proposed method is compared with different methods in the state of art of QRS delineation.

A glimpse of Chirplet transform is found in Section II. In section III, an overview of the proposed algorithm is presented, and details of different blocks in the algorithm are described. In Section IV, the simulations and the results are summarised, followed by the Conclusion in Section V.

## II. Chirplet Transform

The chirplet transform [20] is a time-frequency analysis method with additional signal dependent parameters. It projects the signal on to a basis functions generated by translating, dilating, and shearing a mother chirplet. It can be viewed as STFT of the analytical signal, obtained by considering the Hilbert transform of the given signal multiplied by a complex window , which is parametrized with translation, dilation and shearing factors [21]. Let us consider a signal $f(t)\epsilon L^2(R)$. Then the CT of the signal f(t) is defined as

$$F(t_0,\omega,\alpha,\sigma) = \int_{-\infty}^{\infty} a(t)\Phi^*_{(t_0,\alpha,\sigma)}(t)e^{-j\omega t}\mathrm{d}t \qquad (1)$$

where $a(t)$ is analytical signal computed using Hilbert transform $H$,

$$a(t) = f(t) + jH[f(t)] \qquad (2)$$

and, $\Phi_{(t_0,\alpha,\sigma)}(t)$ is a complex window, the mathematical expression is shown in equation (3).

$$\Phi_{(t_0,\alpha,\sigma)}(t) = w_\sigma(t-t_0)e^{j\frac{\alpha}{2}(t-t_0)^2} \qquad (3)$$

Here, it can be observed that, frequency is modelled as a linear function of time. Where, $\alpha$, $t_0$ indicates the chirp rate and time respectively, $w_\sigma(t)$ represents a window, if the window is a

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Gaussian function, then the CT is known as Gaussian chirplet transform.

$$w_\sigma(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{t}{\sigma})^2} \quad (4)$$

where $\sigma$ is the standard deviation of Gaussian window.

## III. Description of the Algorithm

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

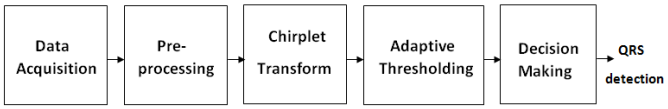


Fig. 1: Block diagram of the QRS peak detection algorithm

### A. Data Acquisition

The electrical activity of myocardial cells during depolarization and re-polarization are measured using 10 electrodes on different parts of body, to obtain a standard 12 lead ECG system. In this 12 lead system, data from Lead II is adequate for diagnosing rhythm problems. The ECG recordings are not measured in this work, an already existing MIT-BIH Arrhythmia database from physionet website [22] is used for the analysis. A typical ECG signal of the record 100 in the MIT-BIH database, up to 5000 samples is shown in Fig. 2.

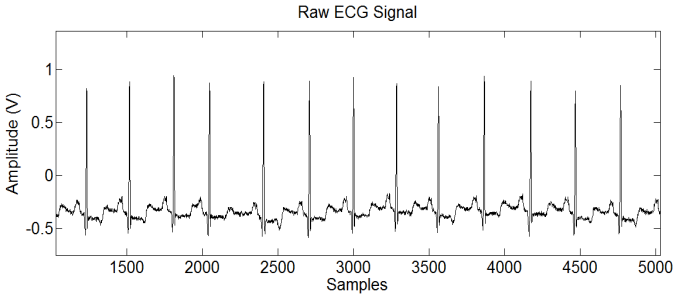


Fig. 2: Raw ECG signal

### B. Pre-processing

The power-line interference in ECG signal is due to the electromagnetic field from the power lines, which causes a 50-60 Hz sinusoidal interference. In this work, a butter-worth low pass filter (LPF) of cut-off frequency 40 Hz, passband ripple of 3 dB and a stop band attenuation of 60 dB is designed to remove the power-line interference, it also increases the signal to noise ratio. The magnitude response of the filter is shown in Fig. 3. The ECG signal after performing the filtering operation (on record 100 of MIT-BIH database) is shown in Fig. 4.

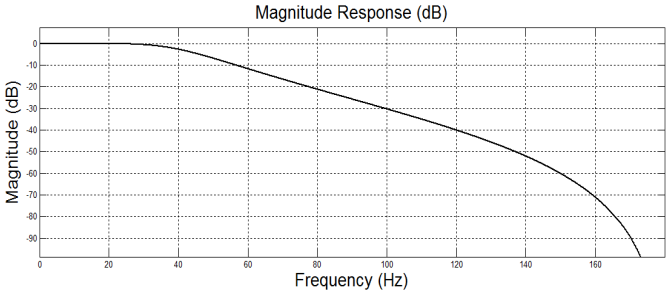


Fig. 3: Magnitude response of the LPF

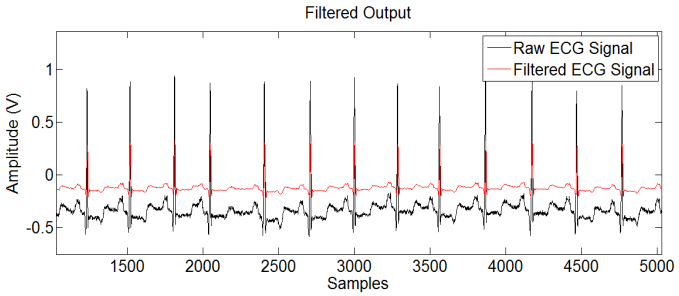


Fig. 4: Filtered ECG signal

### C. Chirplet Transform

CT uses extra signal dependent parameters to obtain highly concentrated time-frequency resolution (TFR). Based on simulations, a chirp rate $(\alpha)$ of 18, the number of samples the signal need to move i.e. step distance of 10 and a Gaussian window is used for analysis. The time and frequency resolutions are directly proportional to the length of the window. If the window length is high, it yields a high frequency, low time resolutions and vice-versa. In [8], Pan et al. mentioned a maximum QRS energy frequency range of 5-15 Hz. In [23], Mohamed et al. suggested a maximum QRS energy frequency range of 8-20 Hz. So, based on the literature work, a frequency range of 8-15 Hz and a window length of 75 is used in this work. With the above considerations, the CT is performed on the filtered data. Once CT is computed, a time-frequency distribution with better energy concentration in frequency domain is obtained from the transformation coefficients. The time-frequency distribution for record 100 of MIT-BIH database is shown in Fig. 5. Now, one need to analyse the specific frequency components with in the range 8-15 Hz, for QRS complex detection in ECG signal. Only, third frequency component, shown in Fig. 6, and fourth frequency component, shown in Fig. 7, are with in the frequency range 8-15 Hz. The values in the extracted frequency components are limited to a value of 0.15 in order to overcome the detection of noisy peaks.

### D. Adaptive Thresholding

The thresholding algorithm [8], consists of two processes: training phase and detection. In training phase, the signal threshold is initialized to 0.05, the noise threshold is initialized to $10^{-3}$, to find out the missed QRS complexes, an average RR-interval of the latest eight beats, and an average RR-interval of the most recent eight beats that fell with in a

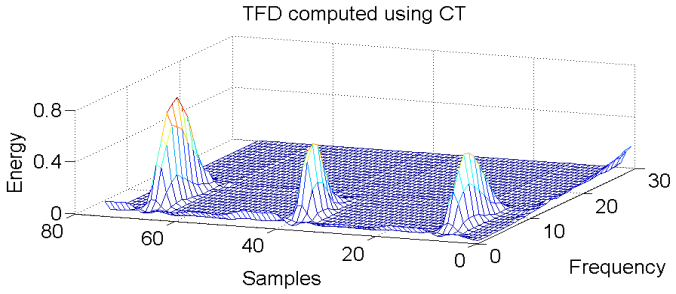


Fig. 5: TFD computed using CT

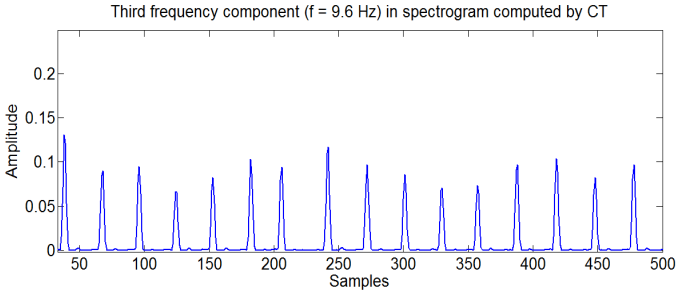


Fig. 6: Third frequency component

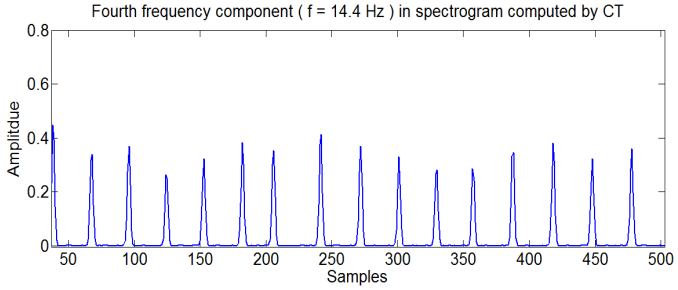


Fig. 7: Fourth frequency component

specific range of 92-116 % of the current RR-interval average are maintained. Two threshold levels are used in the detection process, one level is 90% of the other. To find out the QRS complexes, higher threshold value is used initially, when no QRS peak is detected with in a time interval correspond to 166% of the current RR-interval, then lower threshold value is used to detect the peaks. If a valid QRS peak is detected, there exist a 200ms refractory time period before the next peak is detected [8]. Fig. 8 shows the detected peaks in third frequency component and Fig. **??** shows the detected peaks in fourth frequency components.

### *E. Decision Making*

After detecting the peaks in each frequency component, compare the number of peaks and their locations with in the two successive frequency components. If the peaks counts are equal and their locations are almost same then consider the locations of these peaks as the QRS peaks locations, else perform the comparison between previous and latest frequency components, and do the same analysis. If the two successive frequency components are not satisfying the above condition

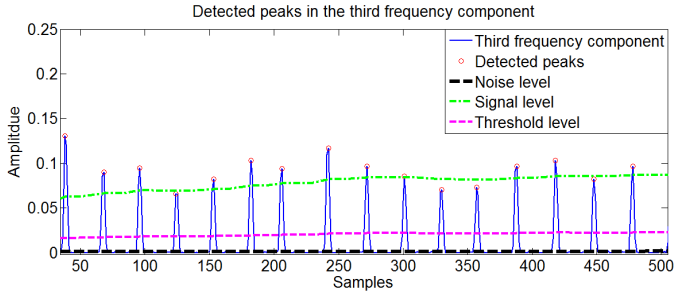


Fig. 8: Detected peaks in third frequency component

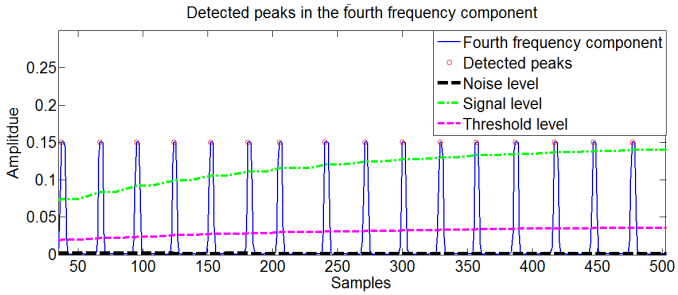


Fig. 9: Detected peaks in fourth frequency component

with in the frequency range then the peaks locations in the highest frequency component are considered as QRS peaks locations.

## IV. Results and Discussion

The proposed algorithm is applied on MIT-BIH arrhythmia database [22]. There are total 48 recordings in the database, along with annotation files for all 48 recordings. Each recording is digitized at 360 samples per second. For each record, True Positives (TP), indicates the total number of correctly located QRS peaks by the algorithm, False Negatives (FN), indicates the number of beats the algorithm is failed to detect, and False Positives (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. By using these values, parameters like sensitivity (Sens), specificity (Spec) and detection error rate (DER) [15], are calculated using the mathematical equations (5), (6), and (7). The proposed algorithm giving a sensitivity of 99.78%, specificity of 99.60%, DER of 0.61%.

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

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

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

The evaluated results using MIT-BIH Arrhythmia database are shown in TABLE I. The comparison of the results with other methods are summarized in TABLE II. The proposed algorithm is giving the better results when compared with the techniques based on filtering [8], STFT [13]. It is giving flat results when compared with multi-scale approach (Wavelet Transform) [12]. So, one can expect better results in multi-scale chirplet transform when compared with chirplet transform.

TABLE I: Results of evaluating the CT 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 | 1864 | 1 | 4 | 99.95 | 99.79 | 0.27 |
| 102 | 2187 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 103 | 2084 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 104 | 2226 | 3 | 11 | 99.87 | 99.51 | 0.63 |
| 105 | 2566 | 6 | 21 | 99.77 | 99.19 | 1.05 |
| 106 | 2023 | 4 | 1 | 99.80 | 99.95 | 0.25 |
| 107 | 2135 | 2 | 0 | 99.91 | 100.00 | 0.09 |
| 108 | 1759 | 4 | 5 | 99.77 | 99.72 | 0.51 |
| 109 | 2527 | 5 | 0 | 99.80 | 100.00 | 0.20 |
| 111 | 2123 | 1 | 0 | 99.95 | 100.00 | 0.05 |
| 112 | 2539 | 0 | 2 | 100.00 | 99.92 | 0.08 |
| 113 | 1795 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 114 | 1832 | 47 | 1 | 97.50 | 99.95 | 2.55 |
| 115 | 1953 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 116 | 2392 | 20 | 3 | 99.17 | 99.87 | 0.95 |
| 117 | 1535 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 118 | 2278 | 0 | 1 | 100.00 | 99.96 | 0.04 |
| 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 | 1518 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 124 | 1619 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 200 | 2600 | 1 | 5 | 99.96 | 99.81 | 0.23 |
| 201 | 1934 | 29 | 0 | 98.52 | 100.00 | 1.48 |
| 202 | 2132 | 4 | 0 | 99.81 | 100.00 | 0.19 |
| 203 | 2926 | 54 | 8 | 98.19 | 99.73 | 2.08 |
| 205 | 2653 | 3 | 0 | 99.89 | 100.00 | 0.11 |
| 207 | 1857 | 3 | 344 | 99.84 | 84.37 | 18.66 |
| 208 | 2940 | 15 | 3 | 99.49 | 99.90 | 0.61 |
| 209 | 3005 | 0 | 1 | 100.00 | 99.97 | 0.03 |
| 210 | 2628 | 22 | 6 | 99.17 | 99.77 | 1.06 |
| 212 | 2748 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 213 | 3250 | 1 | 0 | 99.97 | 100.00 | 0.03 |
| 214 | 2258 | 4 | 0 | 99.82 | 100.00 | 0.18 |
| 215 | 3363 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 217 | 2207 | 1 | 1 | 99.95 | 99.95 | 0.09 |
| 219 | 2154 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 220 | 2047 | 1 | 0 | 99.95 | 100.00 | 0.05 |
| 221 | 2426 | 1 | 0 | 99.96 | 100.00 | 0.04 |
| 222 | 2481 | 2 | 2 | 99.92 | 99.92 | 0.16 |
| 223 | 2604 | 1 | 0 | 99.96 | 100.00 | 0.04 |
| 228 | 2050 | 3 | 12 | 99.85 | 99.42 | 0.73 |
| 230 | 2256 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 231 | 1571 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| 232 | 1780 | 0 | 3 | 100.00 | 99.83 | 0.17 |
| 233 | 3078 | 1 | 0 | 99.97 | 100.00 | 0.03 |
| 234 | 2753 | 0 | 0 | 100.00 | 100.00 | 0.00 |
| **Total** | **109255** | **239** | **434** | **99.78** | **99.60** | **0.61** |

TABLE II: Comparison of CT results with other methods

| | Sens(%) | Spec(%) | DER(%) |
|---|---|---|---|
| Proposed Algorithm | 99.78 | 99.60 | 0.61 |
| Pan et al.[8] | 99.75 | 99.54 | 0.71 |
| Nopadol et al.[13] | 99.10 | 99.60 | 1.30 |
| Poli et al.[24] | 99.60 | 99.50 | 0.90 |
| Darrington et al. [25] | 99.00 | 99.20 | 1.70 |
| Chen et al. [26] | 99.55 | 99.49 | 0.96 |
| Martinez et al.[12] | 99.80 | 99.86 | 0.34 |

## V. Conclusion

In this work, a novel approach for QRS complex detection using chirplet transform has been proposed. By the results, it has been shown that for non-stationary signals chirplet transform is giving better energy concentration in frequency domain. The proposed algorithm gives a sensitivity of $99.78\%$, specificity of $99.60\%$, DER of $0.61\%$. It has been observed that the proposed algorithm gives competitive results in the state of art of QRS detection. A multi-scale approach of chirplet transform for QRS detection is considered as future work.


## Acknowledgement

The authors would like to thank Mr. B. Sreenivasulu, Department of Electronics and Communication Engineering, NITK for his support in this work.


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