R peak delineation in ECG signal based on Polynomial Chirplet Transform using Adaptive Threshold

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***Abstract*—R peak delineation is fundamental step in any application implicating electrocardiogram (ECG) signal. ECG is non stationary and non linear. Hence, linear transforms like short time fourier transform, wavelet transform and chirplet transform may be inadequate to represent ECG signal and consequently for R peak delineation. Polynomial chirplet transform (PCT) models the frequency into a higher order polynomial to enhance the representation of non stationary signals whose frequency vary non linearly with time. In this paper, PCT based R peak delineation method using adaptive threshold is proposed. The performance of the proposed algorithm is evaluated on ECG ID data base taken from physionet data bank. This work also presents a comparative study of QRS detection methods employing the uni scale family of time frequency analysis methods, short time fourier transform, chirplet transform, stockwell transform , wigner ville distribution, and pseudo wigner ville distribution out of which stockwell transform, pseudo wigner ville distribution along with adaptive threshold are applied to QRS detection for the first time. The results show that the proposed method outperforms the competitors in terms of sensitivity, specificity and detection error rate.**

I. Introduction

Analyzing Electrocardiogram (ECG) via R peak delineation is an important clue for diagnosis to prevent imminent failure of heart [1]–[4], and in other applications [5]–[7]. Many researchers proposed several methods for R peak detection in ECG signal which includes conventional filter theory based methods, transform based methods, and heuristic methods. Few typical algorithms along with the key features of the algorithms are enlisted in Table I. ECG is a non stationary signal with high complex time frequency content. Analyzing ECG signal for QRS detection using fast fourier transform (FFT) is inadequate since FFT doesn't provide time information. In this stand point, time frequency analysis (TFA) methods are very handy. Our previous works, [24], [25] deals with algorithms for QRS delineation based on short time fourier transform, and chirplet transform(CT) using adaptive threshold respectively. The linear transforms congressional to the family of STFT, wavelet, CT may not be commensurate for QRS detection in ECG signal as it contains non linearly varying low frequency content. Quadratic transforms like wigner ville distribution(WVD), PCT are more appropriate. The shortage of WVD in QRS detection is explained in [26]. WVD suffers from cross term interference which makes it incompatible for R peak delineation. WVD is also permeable to noise in case the signal is contaminated by noise, since it derives the basis from the signal itself. To make WVD commodious for R peak detection, the kernel is multiplied with a smoothing function like gaussian to produce pseudo wigner ville distribution (pseudo WVD). However, stockwell transform (ST) provides a frequency dependent resolution. For low frequency signals ST gives a high frequency resolution, poor time resolution,

TABLE I
Literature review on QRS delineation methods

Authors	Key features of Algorithm
M. Okada [8]	Five step digital filter
J. Pan and W. J. Tompkins [9]	Filters, adaptive threshold
V. Afonso et al. [10]	Multi rate signal processing, sub band decomposition
Q. Xue et al. [11]	Neural network modelling and adaptive matching filter
S. Kadambe et al. [12]	Wavelets, Peak matching in different scales
DS Benitez et al. [13]	Hilbert transform, thresholding
Kohler et al. [14]	Count of zero crossings, computationally efficient
J. Martinez et al. [15]	Quadratic spline wavelet, P,QRS, T wave delineation
F. de Oliveira et al. [16]	Hilbert transform of wavelet, peak detector
Mayer C et al. [17]	Combination of wavelet, Pan Tompmpkins methods in a data driven way
Tabakov S [18]	Comb filter to reject powerline interference
N. Uchaipichat and S. Inban [19]	STFT, local maxima finding
Chouakri S.A. et al. [20]	Wavelet packets, and histogram approach
Z. Zidelmal et al. [21]	S Transform, shanon energy
Ramakrishnan A.G. et al. [22]	Integrated linear prediction residual (ILPR), dynamic poison index
P. Phukpattaranon [23]	Quadratic filter and single threshold
Shaik B.S. et al. [24]	STFT and adaptive threshold
Shaik B.S. et al. [25]	Chirplet transform, adaptive threshold

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and for high frequencies, it gives bad frequency resolution, good time resolution. PCT on the other hand, models the frequency with a higher order polynomial which gives it the ability to represent any non stationary signal whose frequency is varying non linearly with time. This ability of PCT makes it suitable for representing the ECG in a more compatible way. In this work, a method for R peak delineation using polynomial chirplet transform using adaptive threshold is proposed. R peak detection is also accomplished with STFT, CT transform, ST, WVD, and pseudo WVD. The performance of PCT is compared with the aforementioned methods.

The paper is organized as follows. In section II, a brief outline of time frequency analysis methods is presented. Section III describes the proposed algorithm while section IV gives a glimpse in to results followed by conclusion and future work in section V.

II. Theory

A. Polynomial chirplet transform

The CT fails to generate time frequency distributions (TFD) with good energy concentration if the frequency of the signal is a nonlinear function of time. PCT has the ability to generate a better TFD than CT for signals with frequency that is an arbitrary function of time. PCT of a signal s(t) is defined in [27] as follows.

$$PCT_s(t,\omega,\alpha_1,..,\alpha_n;\sigma) = \int_{-\infty}^{\infty} z(\tau)\Phi^R_{\alpha_1,..,\alpha_n}(\tau)\times \Phi^M_{\alpha_1,..,\alpha_n}(\tau,t)\omega_{(\sigma)}(\tau-t)e^{-j\omega\tau}d\tau \quad (1)$$

where,

$$\Phi^R_{\alpha_1,...,\alpha_n}(t) = exp(-j\sum_{k=2}^{n+1}\tfrac{1}{k}\alpha_{k-1}t^k)$$
$$\Phi^M_{\alpha_1,...,\alpha_n}(t,t_0) = exp(j\sum_{k=2}^{n+1}\alpha_{k-1}t_0^{k-1}t)$$

are the non linear frequency rotating operator and frequency shifting operator respectively and $z(t)$ is analytical signal of s(t) given by
$z(t) = s(t) + jH(s(t))$, where $H(.)$ represents hilbert transform. $\alpha_1,..,\alpha_n$ are the polynomial kernel characteristic parameters corresponds to slope of instantaneous frequency function. Different uniscale TFA transforms are listed in Table II. (In Table II Assume, $\omega_\sigma(t) = \frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{1}{2}(\frac{t}{\sigma})^2}$).

TABLE II
Definitions of different TFA methods

Method	Formulae
$STFT$ [28]	$\int_{-\infty}^{\infty} z(\tau)\omega_{(\sigma)}(\tau-t)e^{-j\omega\tau}d\tau$
CT [29]	$\int_{-\infty}^{\infty} z(\tau)\omega_\sigma(\tau-t)e^{j\frac{\alpha}{2}(\tau-t)^2}e^{-j\omega\tau}\mathrm{d}\tau$
ST [30]	$\int_{-\infty}^{\infty} z(\tau)\frac{\lvert\omega\rvert}{2\pi\sqrt{2\pi}}e^{-\frac{(t-\tau)^2\omega^2}{8\pi^2}}e^{-j\omega\tau}d\tau$
WVD [31]	$\int_{-\infty}^{\infty} z(\frac{t+\tau}{2})z^*(\frac{t-\tau}{2})e^{-j\omega\tau}d\tau$
$PWVD$ [32], [33]	$\int_{-\infty}^{\infty} z(\frac{t+\tau}{2})z^*(\frac{t-\tau}{2})\omega_{(\sigma)}(\tau-t)e^{-j\omega t}d\tau$
PCT [27]	$\int_{-\infty}^{\infty} z(\tau)e^{(-j\sum_{k=2}^{n+1}\frac{1}{k}\alpha_{k-1}\tau^k)} e^{(j\sum_{k=2}^{n+1}\alpha_{k-1}t^{k-1}\tau)}e^{-j\omega\tau}d\tau$

III. Description of the proposed algorithm

The block diagram of the proposed algorithm is shown in Fig. 1. The proposed algorithm consists of five steps namely data acquisition, pre processing, computation of polynomial chirplet coefficients, employing the adaptive threshold followed by decision making to output the R peak locations. Data acquisition is not performed in this algorithm, instead recorded ECG recordings from ECG ID data base from physionet databank [34] are used. As a part of pre processing, a low pass butterworh filter with cutoff frequency $40Hz$, passband ripple of $3dB$ and a stop band attenuation of $60dB$ is used to remove the high frequency power line interference. A typical raw ECG signal along with the filtered output is shown in Fig. 2. The polynomial coefficients are computed as in [27]. The time frequency distribution (TFD) of the signal is computed using PCT in the next step. The TFD is computed by considering an atom of size 75 samples and moving in steps of 10 time lags. An adaptive threshold used in [24] is employed for obtaining the peaks in the third and fourth frequency components in the TFD followed. The adaptive thresholding algorithm is a dual threshold method in which one of the threshold is 0.9 of the other threshold. These thresholds are decided using a training step as in [9]. The higher threshold is used for QRS complexes initially. If no QRS complex is found in a stipulated time interval corresponds to 166% of the current RR interval, then lower threshold is used for detection of QRS complex. The adaptive thresholding is followed by a decision making step, in which number of peaks, and peak locations in two successive frequency components of TFD are compared. If the count and locations (approximately) matches in the two, these peaks are considered to be true QRS locations. Otherwise, the process of comparison is repeated in between the next two lower successive frequency components. If no match is found between the two successive components, then the peaks locations in the highest frequency component are considered as true QRS locations.

IV. Results and discussions

The proposed algorithm is tested on ECG ID database. ECG ID database contains 299 recordings of $10s$ duration pertaining to 90 different persons which are sampled at $500Hz$. Different variations of this algorithm, i.e the same algorithm with PCT replaced by STFT, CT, ST, WVD, and pseudo WVD transforms are tested on the aforementioned data set. The TFDs of an ECG signal computed using different TFA methods are shown in Fig. 3. From Fig. 3, it can be observed that TFD computed using PCT has better frequency resolution and time resolution compared to TFDs produced by STFT and CT which is the reason for better performance of PCT. It can be deduced that the TFD generated by WVD is not good enough to represent the signal, and TFD generated by pseudo WVD is better than that of TFD computed using WVD in terms of frequency resolution. TFD generated by ST lacks clarity in time resolution when compared to TFDs generated by other TFA methods. The following performance metrics are used for

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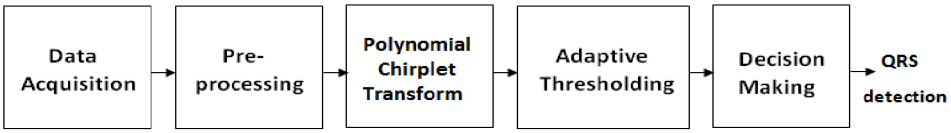

Fig. 1. Block diagram of the proposed algorithm

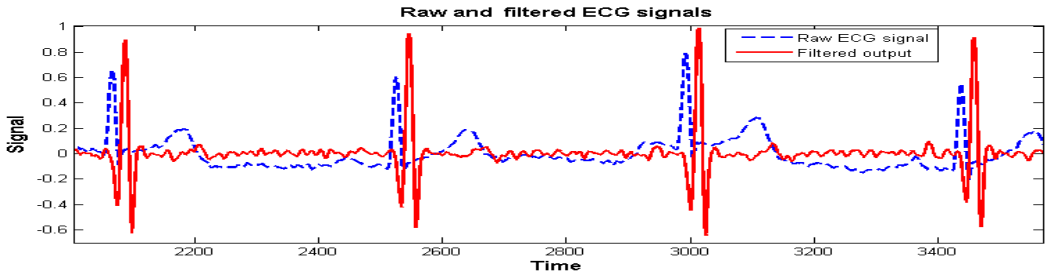

Fig. 2. Raw ECG signal and the filtered signal

TABLE III
COMPARISON OF QRS DETECTION TECHNIQUES USING DIFFERENT TIME FREQUENCY ANALYSIS METHODS

TFA Method	Sens	Spec	DER
STFT	99.19	99.49	1.32
CT	99.46	99.69	0.85
S Transform	99.52	99.56	0.914
WVD	75.10	45.45	115.04
PWVD	98.24	99.28	2.47
PCT	99.49	99.73	0.78

quantifying the results.

$$Sensitivity\ (Sens\ in\ \%) = \frac{TP}{TP+FN} \times 100 \quad (2)$$

$$Specificity\ (Spec\ in\ \%) = \frac{TP}{TP+FP} \times 100 \quad (3)$$

$$Detection\ error\ rate\ (DER) = \frac{FP+FN}{Total\ number\ of\ QRS\ complex} \quad (4)$$

where TP is number of true positive (correctly detected beats), FP is number of false positives (false alarms i.e non R peak detected as R peak), and FN represents false negatives (R peak not detected by the algorithm). The sensitivity, specificity and DER for various methods are computed as per equations 2, 3, 4 and tabulated in Table III. The values given in Table III are shown in pictorial form in Fig. 4. For the sake of convenience results corresponding to WVD are not shown in Fig. 4. From Table III, it is ascertained that the performance of WVD in detection of R peak is poor which supports [26]. The pseudo WVD applied in this work for R peak detection achieved a very good sensitivity, specificity and DER than WVD. It can be also be discovered that PCT is outrunning the other methods in terms of specificity and DER and sensitivity is very much near to that of ST. It is not surprising that ST is handy in R peak detection because of it's ability to produce frequency dependent resolution.

V. CONCLUSION AND FUTURE WORK

A method for R peak delineation based on PCT using adaptive threshold has been proposed in this work. It has been shown that because of the ability of PCT to represent a non stationary signal with frequency varying non linearly with respect to time, PCT is a better choice for R peak delineation in ECG signal. The performance of different variants of the proposed algorithm with PCT replaced by STFT, CT, ST, WVD, and pseudo WVD has been evaluated on ECG ID database along with the proposed algorithm. In terms of sensitivity ST performed well with 99.52 % which is closely followed by the proposed algorithm with sensitivity of 99.49. However in terms of specificity and DER the proposed algorithm outperformed the other competitors with specificity of 99.73 and DER of 0.78. It has been also shown that by multiplying the WVD kernel with smoothing function like gaussian WVD can be made suitable for R peak detection. The results obtained using pseudo WVD are superior to that of WVD and comparable with the other TFA methods with sensitivity of 98.24, specificity of 99.28 and DER of 2.47. Application of different multi resolution techniques for QRS delineation and comparative study of multi resolution techniques for QRS detection is author's current objective.

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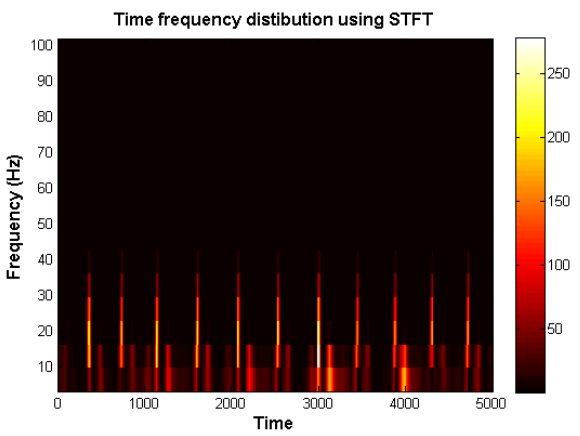
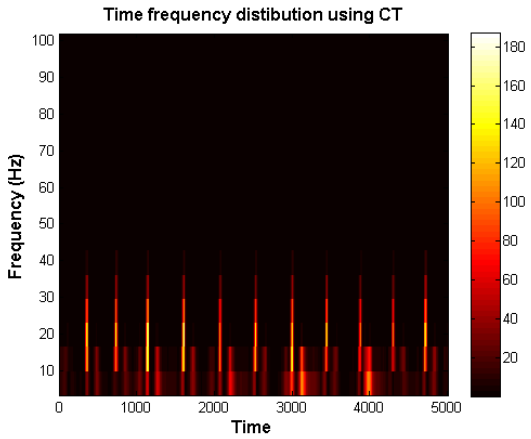
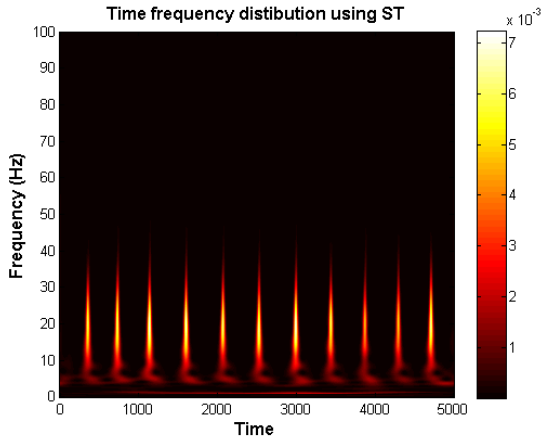


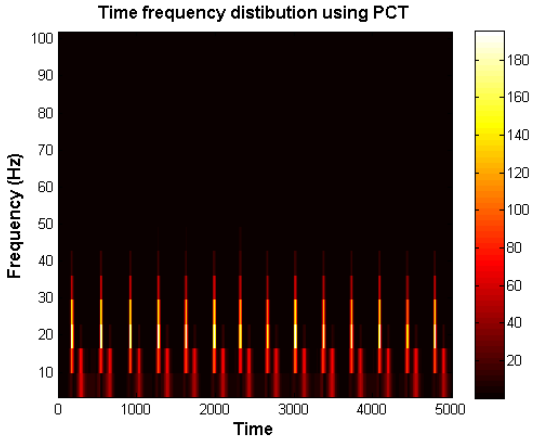
(a) TFD computed using $STFT$



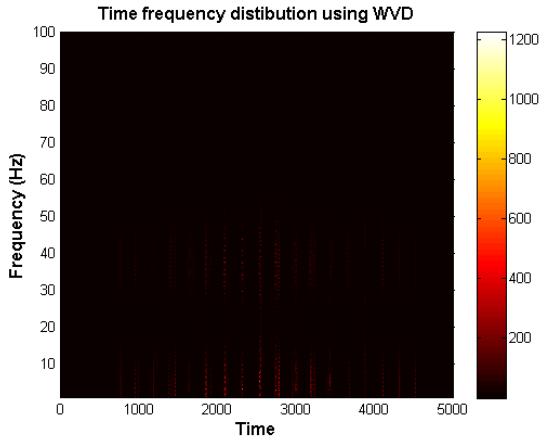
(b) TFD computed using CT



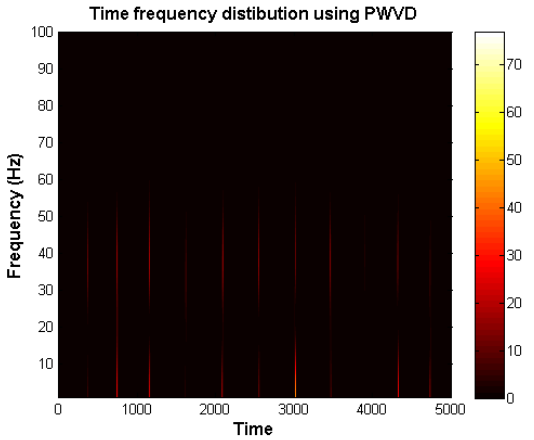
(c) TFD computed using ST



(d) TFD computed using PCT



(e) TFD computed using WVD



(f) TFD computed using $PWVD$

Fig. 3. TFD computed using different TFA methods

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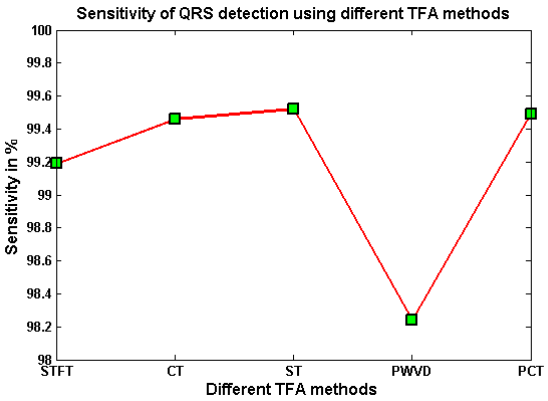
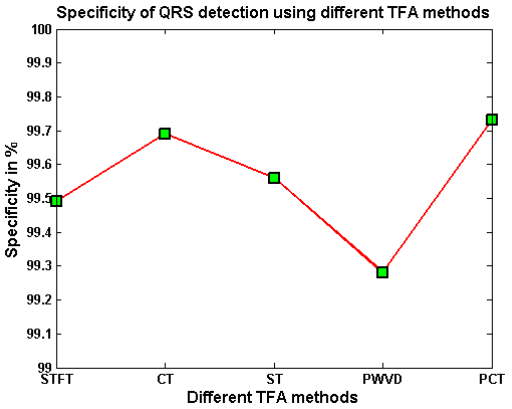
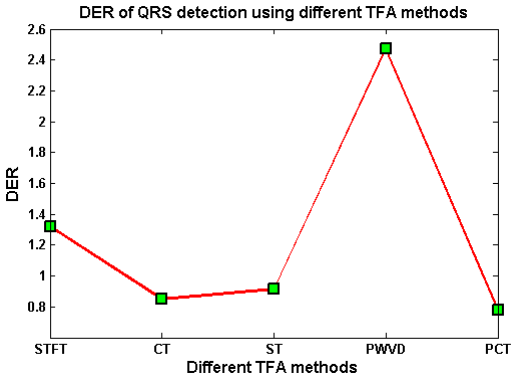


(a) Sensitivity of QRS detection using different TFA methods



(b) Specificity of QRS detection using different TFA methods



(c) DER of QRS detection using different TFA methods

Fig. 4. Performance of QRS detection algorithms using different TFA methods

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