Evaluation of Energy Power Spectral Distribution of QRS Complex for Detection of Cardiac Arrhythmia

Akash Kumar Bhoi, Karma Sonam Sherpa and Bidita Khandelwal

Abstract The proposed approach involves detection of QRS complex and energy power spectral distribution analysis of the segmented QRS complex to establish the presence of arrhythmic beats in Electrocardiogram (ECG). The methods consist of three steps: (i) the baseline drift and high-frequency artifacts could seriously affect the detection performance, so Moving Average Filtering (MAF) and Stationary Wavelet Transform (SWT) are implemented at preprocessing stage. (ii) Localization of R-peaks by implementing FFT-based windowing and thresholding techniques. Then Q and S points are detected using search interval method based on the medical definition. (iii) The segmented QRS complex is analyzed with period-gram and Continuous Wavelet Transform using FFT (CWTFT) to obtain time–frequency domain power and energy of the complex. (iv) Statistical analysis has been proposed using one-way ANOVA to differentiate the healthy and arrhythmic QRS complex. The proposed QRS detection and analysis methodologies are evaluated with MIT-BIH Arrhythmia Database (MITDB) and FANTASIA database. The detection performance, i.e., Sensitivity $S_e(\%)$ and the Specificity $S_p(\%)$ for FANTASIA 100% each respectively, where as $S_e = 100\%$ and $S_p = 98.18\%$ for MITD. The failed detection percentage, $F_d(\%) = 0$ for FANTASIA and $F_d(\%) = 1.85\%$ for MITDB. The energy power distributed parameters obtained from PSD and CWTFT are statistically analyzed with one-way ANOVA and the p-value are found to be <0.05 (i.e., CI = 95%) for healthy and arrhythmia QRS complex which certainly signifies that the energy

A. K. Bhoi (✉)
Department of Electrical & Electronics Engineering, Sikkim Manipal Institute of Technology (SMIT), Sikkim Manipal University, Majitar, India
e-mail: akash.b@smit.smu.edu.in; akash730@gmail.com

K. S. Sherpa
Sikkim Manipal University, Gangtok, India
e-mail: karmasherpa23@gmail.com

B. Khandelwal
Department General Medicine, Central Referral Hospital and SMIMS, Sikkim Manipal University, Gangtok, India
e-mail: drbidita@gmail.com

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power features of the arrhythmic QRS complex are different than the normal QRS complex.

Keywords QRS complex · CWTFT · One-way ANOVA · Energy power distribution · MITDB · FANTASIA

1 Introduction

Time domain features and morphological fiducial points can add crucial inputs towards decision-making and accurate diagnosis in electrocardiogram (ECG) [1]. Arrhythmia analysis can also be done by shape and time change observation of QRS complex [2]. Difference Operation Method (DOM) was proposed by Yun-Chi Yeh, et al. with a simple and computational-free algorithm for accurate detection of QRS complex [3]. The wavelet transform is widely used in many of the earlier proposed methods for QRS detection and analysis with the limitation of selection of proper mother wavelet and decomposition level [4–9]. Few well-known QRS detection approaches which are more complex *such as* Neural Network (NN) [5], Support Vector Machines (SVM) [10], Genetical algorithms [11], Hidden Markov Models (HMM) [12], K-Nearest Neighbor (K-NN) [13], parallel functioning of different algorithms [14, 15], Pan and Tompkins (PT) [16], Fractal Dimension Transformation (FDT) [17]. Unpredictable QRS Potentials (UIQP) were analyzed using Finite-Impulse-Response (FIR) based prediction model to identify ventricular tachycardia with patients undergoing high-risk ventricular arrhythmias [18]. Soroor and Jafarnia [19] proposed Multiresolution Wavelet with Thresholding Method and achieved 98.2% accuracy for QRS complex detection. QRS complexes could also be detected performing fixed structure Mathematical Morphology (MM) operators [20]. Atiyeh and Reza [21] have discussed a P-QRS-T waves-based detection approach, which is simple and accurate having very less response time during its real-time operation.

As from the literature survey, it is also clear that arrhythmia can be identified by analyzing QRS complex changes. Here the authors propose an algorithm by taking such problem into account. Classification between normal QRS and arrhythmic QRS of ECG is presented with efficient detection techniques and energy power spectral distribution of this complex. The performance evaluation is done with FANTASIA database and the MIT-BIH Arrhythmia Database (MITDB).

2 Materials and Methods

2.1 Datasets

The proposed methodologies have been tested over 30 selected healthy (Fantasia records) data having 1 row (signal) and 900,000 columns (samples/signal) with the duration of 1 h having sampling frequency: 250 Hz and sampling interval: 0.004 s [22]. 30 out of 48 lengthy arrhythmic records from MITDB, with sampling frequency 360 Hz and 11-bit resolution ranging over 10 mV are considered for this analysis. The proposed methodologies have been tested over these 30 selected arrhythmic signals (total beats considered: 4,000) having first row (signal) and 650,000 columns (samples/signal) with the duration of 1 h [23].

2.2 Preprocessing of Noisy ECG Signal

Moving average filter [24] and Stationary Wavelet Transform [25] were implemented to remove baseline drift and signal noise (Fig. 1).

2.3 R-Peaks Localization

Step 1: Discrete Fourier Transform (DFT) is computed from Fast Fourier Transform (FFT) and the Fourier transform is an integral (4) of the form

$$F(u) = \int_{-\infty}^{\infty} f(x)e^{-i2\pi ux}dx \tag{4}$$

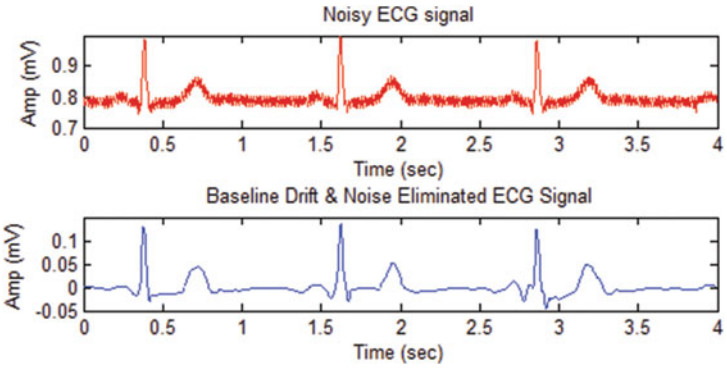

Fig. 1 Noise cancelation for FANTASIA data #f1o04 (4 s data for better visualization)

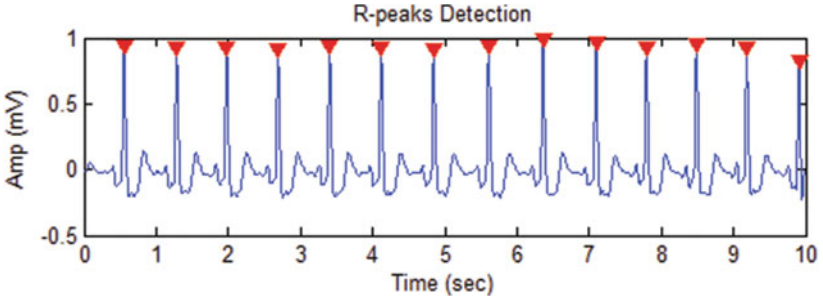

Fig. 2 R-peaks localization for MITDB data #105 (10 s data for better visual representation)

Low-frequencies component from the ECG signal is removed using FFT.

Step 2: Restoration of ECG signal is done with Inverse Fourier transform (5) and the expression for inverse Fourier transform is

$$f(x) = \int_{-\infty}^{\infty} F(u)e^{i2\pi ux}du \tag{5}$$

Step 3: Windowed filter with default size for localization of maxima (only maximum values are being considered and other values are ignored).

Step 4: Implementation of threshold filters to remove small values and preserve significant ones.

Step 5: Repeat Step 3 with adjusting the size of the windowed filter to improve filtering performance. Then R-peaks are detected (Fig. 2).

Step 6: In case of negative QRS complexes, localization of minima is performed for detection of R-peaks and the other above steps remains same.

2.4 Q and S Inflection Points Localization

Step 7: Taking R point as standard, the search interval-1 locates 20 sampling points from prior and succeeding of R point. The least value found ahead of R point marked as Q1 and the same found after, marked as S1 [3].

Step 8: Search interval-2 is defined such that, it covered 40 sampling points prior and succeeding of R point. The least sampling point forth to R is Q2 and succeeding to R is S2 [3].

Step 9: Localization of Q by checking the location and amplitude values of Q1 and Q2. If Q1 and Q2 located at different points and Q1 amplitude > Q2 amplitude, then Q1 is the location of Q or vice versa.

Step 10: Localization of S by checking the position of S1 and S2. (i) If the position of S1 = position of S2, then S1 = S2 = S. (ii) If VS2 > VS1, then S = S1; else S = S2, where VSi = amplitude of Si and i = 1, 2 (Fig. 3).

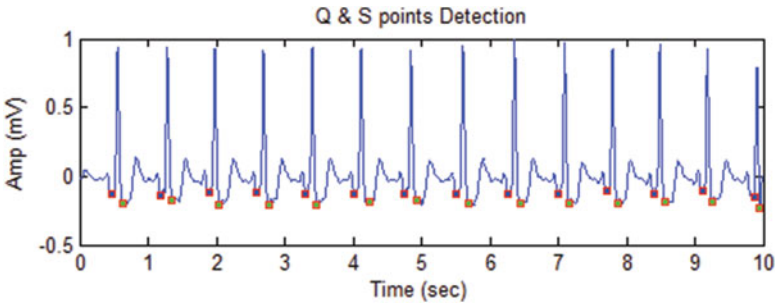

Fig. 3 Q & S point's localization for MITDB data #105 (10 s data for better visual representation)

The failed detection rates are calculated for both FANTASIA and MITDB databases. Failed detection is calculated by [3]:

$$F_d(\%) = \frac{FP + FN}{\text{Total Beats}} \times 100 \tag{6}$$

The failed detection percentage, $F_d(\%) = 0$ for FANTASIA and $F_d(\%) = 1.85\%$ for MITDB.

$$S_p(\%) = \frac{TP}{TP + FP} \times 100 \tag{7}$$

$$S_e(\%) = \frac{TP}{TP + FN} \times 100 \tag{8}$$

where, TP = True positive (properly detected beats), FN = False negative (failed to detect a real beat), FP = False positive (detects a beat when no beat is present).

The evaluation of the detection performance is computed using Specificity (S_p) and Sensitivity (S_e) [3], which are normally computed using (7) and (8). For FANTASIA both S_e and S_p found to be 100% where as $S_e = 100\%$ and $S_p = 98.18\%$ for MITDB (Table 1).

3 Feature Extraction from QRS Complex

3.1 Continuous Wavelet Transform Using FFT Algorithm (CWTFT)

The mean of the detected QRS complexes is segmented from the ECG signal and analyzed using CWTFT. CWT can be computed using the product of Fourier Transforms (Inverse Fourier Transform (IFT)), from the below (9) equation

Table 1 Energy power spectral distribution of QRS complex

FANTASIA	Power		Energy		MITDB	Power		Energy	
	F_domain	T_domain	Max (%)	Sca_Max		F_domain	T_domain	Max (%)	Sca_Max
f1o01m	0.9666	0.9135	0.4812	39.2000	101	0.0661	0.0890	0.5387	36.8000
f1o05m	0.9717	0.8902	0.4889	39.2000	105	0.3123	0.1436	0.6048	50
f1o08m	0.9672	0.9126	0.3985	39.2000	107	0.2900	0.2371	0.5552	38.2000
f1o10m	0.3629	0.2291	1.1681	19.4000	108	0.0705	0.0310	0.5373	36.3000
f1y01m	0.4764	0.2122	1.2507	17.4000	109	0.1344	0.0977	0.7259	50
f1y02m	0.2925	0.1944	1.1319	18.4000	111	0.0954	0.1010	0.7132	50
f1y03m	0.3654	0.1717	1.4919	15.5000	112	0.1459	0.1452	0.5266	36.8000
f1y04m	0.1725	0.1440	0.6246	29	117	0.2111	0.2336	0.5990	31
f1y05m	0.1102	0.1124	0.5895	29	119	0.0548	0.0698	0.6413	50
f1y06m	0.4842	0.2460	1.6021	14.5000	121	0.3989	0.1880	0.6975	47.4000
f1y07m	0.1835	0.1557	0.8417	23.2000	123	0.0918	0.1408	0.4991	40.7000
f1y08m	0.4324	0.2092	1.4796	15.5000	124	0.2284	0.1754	0.7395	50
f1y09m	0.2414	0.1127	0.5425	35.8000	200	0.0613	0.0639	0.5255	42.6000
f1y10m	0.5812	0.2779	1.4890	15.5000	202	0.2512	0.1345	0.6968	50
f2o01m	0.4469	0.2339	1.2997	16.5000	203	0.2671	0.1339	0.5146	33.4000
f2o02m	0.5237	0.2477	0.9863	23.2000	205	0.1201	0.1080	0.4952	39.7000
f2o03m	0.1437	0.1732	0.7645	26.1000	207	0.5461	0.2787	0.6694	34.8000

(continued)

Table 1 (continued)

FANTASIA	Power		Energy		MITDB	Power		Energy	
	F_domain	T_domain	Max (%)	Sca_Max		F_domain	T_domain	Max (%)	Sca_Max
f2o04m	0.4680	0.2551	1.2254	17.4000	208	0.1184	0.1106	0.5224	44.5000
f2o06m	0.4842	0.2460	1.6021	14.5000	210	0.2389	0.1445	0.6647	50
f2o07m	0.2220	0.1670	0.8252	25.2000	212	0.2795	0.1707	0.5330	41.6000
f2o09m	0.4420	0.2716	1.1316	18.4000	213	0.0902	0.1233	0.5099	46.5000
f2o10m	0.2584	0.1711	0.8801	23.2000	214	0.1906	0.1198	0.7076	50
f2y01m	0.4297	0.2505	1.3612	15.5000	221	0.2310	0.0988	0.4771	35.3000
f2y02m	0.5237	0.2477	0.9863	23.2000	222	0.1022	0.1557	0.6405	30
f2y03m	0.5182	0.2448	1.4546	15.5000	223	0.1322	0.1730	0.5940	46.5000
f2y06m	0.1144	0.1471	0.6274	30	228	0.2221	0.1288	0.5590	35.8000
f2y07m	0.2789	0.1803	0.9732	21.3000	230	0.0292	0.0654	0.4499	45.5000
f2y08m	0.2898	0.1679	0.8171	25.2000	232	0.0223	0.0580	0.4796	45.5000
f2y09m	0.2507	0.1620	0.7709	26.1000	233	0.2602	0.2651	0.7185	31
f2y10m	0.2082	0.1060	2.0152	11.6000	234	0.2442	0.1433	0.5171	41.6000

Database	Total beats	Total TP (beats)	Total FP (beats)	Total FN (beats)	Total failed detection (%)	Sensitivity (%)	Specificity (%)
FANTASIA	4000	3989	11	09	0.50	99.72	99.77
MITDB	4000	3971	17	13	0.75	99.67	98.18

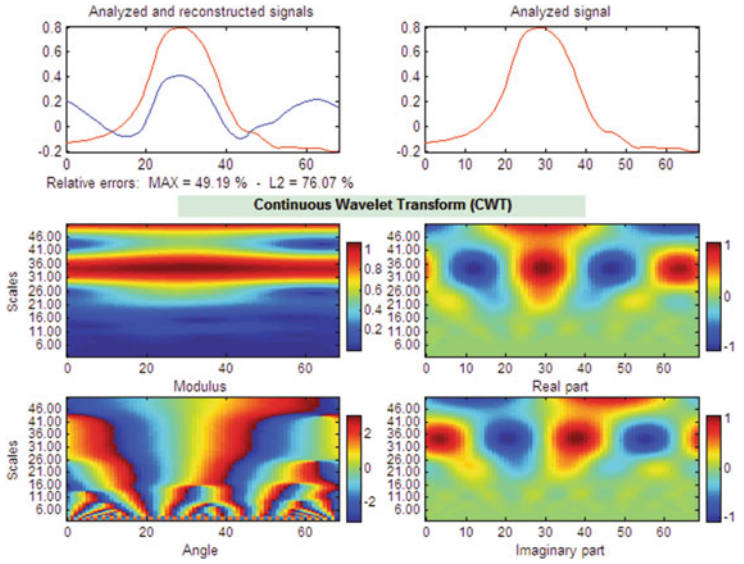

Fig. 4 CWTFT of QRS complex for MITDB data #203

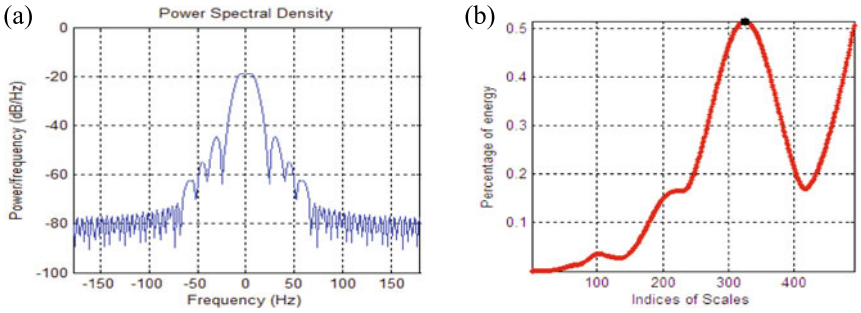

Fig. 5 **a** Max power, **b** energy estimation

$$C(x, y; g(t), \psi(t)) = \frac{1}{2\Pi} \int_{\infty}^{-\infty} \hat{g}(\omega)\sqrt{x}\widehat{\psi} * (x\omega)e^{j\omega y}d\omega \tag{9}$$

Using period-gram (PSD) and CWTFT power energy distribution (Fig. 4) of each signal of both the databases is computed in Table 1 where the power (Fig. 5a) (frequency and time domain) and energy (maximum percentage (Fig. 5b) and scale maximum) are tabulated.

Table 2 Analysis of variance of QRS complex for frequency domain power of FANTASIA and MITDB

Source	DF	Adj SS	Adj MS	F-value	p-value
Factor	1	0.7491	0.74910	21.91	0.000
Error	58	1.9827	0.03418		
Total	59	2.7318			

Table 3 Analysis of variance of QRS complex for maximum energy percentage of FANTASIA and MITDB

Source	DF	Adj SS	Adj MS	F-value	p-value
Factor	1	3.105	3.10451	35.97	0.000
Error	58	5.006	0.08630		
Total	59	8.110			

3.2 One-Way ANOVA

One-way ANOVA is implemented to determine whether there are statistically significant differences among the means of several populations (i.e., power and energy of healthy and arrhythmic QRS complex).

Table 2 shows that there is a significant difference (i.e., p-value = 0.000) in between the frequency domain power of QRS complex of healthy and arrhythmic signals. In the frequency domain power of FANTASIA and MITDB, the intervals (at 95% CI) for the means of these two data sets do not overlap which suggests that the population means for these levels are different.

Table 3 shows that there is a significant difference (i.e., p-value = 0.000) in between the maximum energy percentage of QRS complex of healthy and arrhythmic signals. In between the maximum energy percentage of FANTASIA and MITDB, the intervals (at 95% CI) for the means of these two data sets do not overlap which suggests that the population means for these levels are different. The same results are obtained with the time domain power and maximum scale energy parameters.

4 Conclusions

The PSD and CWTFT compute the average power and distribution of energy power at different scales for normal and arrhythmic QRS complex. The mean energy power spectral parameter of QRS complexes of healthy subjects (FANTASIA) and arrhythmic (MITDB) signals proves to be lying in a different domain, which are validated with one-way ANOVA (p-value < 0.05). The proposed methodology also considers the critical role of a detection method for QRS complex where the failed detection percentage is found to be $F_d(\%) = 0$ for FANTASIA and $F_d(\%) = 1.85\%$ for MITDB databases. Moreover, the high-frequency noise components are eliminated using SWT (i.e., 50 Hz power line interference embedded with FANTASIA). This proposed approach for analyzing QRS complex certainly formulates a new way

of considering research possibility to detect arrhythmia segregating from healthy signals. The further research lies in testing this methodology with different erratic signals and extending the possibility of finding changes in ischemic heart disease (IHD) by analyzing QRS, ST-segment, and T wave.

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