QRS Complex Detection and Analysis of Cardiovascular Abnormalities: A Review

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Abstract: *The ability to evaluate various Electrocardiogram (ECG) waveforms is an important skill for many health care professionals including nurses, doctors, and medical assistants. The QRS complex is a vital wave in any ECG beat. It corresponds to the depolarization of ventricles. The duration, the amplitude and the complex QRS morphology are used for the purpose of cardiac arrhythmias diagnosis, conduction abnormalities, ventricular hypertrophy, myocardial infarction, electrolyte derangements etc. In this review, the different algorithms and methods for QRS complex detection have been discussed. Moreover, this review conceptualizes the challenge by discussing the effect of QRS complex on various critical cardiovascular conditions.*

Keywords: *QRS complex, Cardiac arrhythmia, Conduction abnormalities, Ventricular hypertrophy, Myocardial infarction.*

Introduction

QRS complex is the most prominent feature in the Electrocardiogram (ECG) signal and corresponds to the ventricular excitation [26]. The importance of QRS detection results from the wide use of the timing information of this component, e.g., in heart rate variability analysis, ECG classification, and ECG compression. In most cases, the temporal location of the R-wave is taken as the location of the QRS complex [23].

The Autonomic nerve system (ANS) controls the Heart rate and the RR interval by changing the firing rate of the SA node and the time interval of the Plateau period of the Action potential (AP) as well as the conduction velocity of the muscles. The QRS complex is considered to be fairly constant and does not change with the change of heart rate as it reflects the time that passes between the depolarization of first ventricle muscle and the last one and because the AP is carried on the ventricle through the high speed Purkinje fibers and travels only a short distance in the ventricle between the endocardium and the epicardium. The QT period is closely related to the Plateau period of the Ventricle AP. This is controlled by the ANS and changes with the Heart rate. Several formulae were developed to link between the QT interval and the Heart rate. The recent and the most accurate one is the Framingham correction formula [40]. The formula linearly normalizes the QT interval to 60 BPM Heart rate according to the relation

$$QTLC = QT + 0.154*(1 - RR), \quad (1)$$

where QTLC is the linearly corrected QT interval duration in seconds, QT is the original QT intervals in seconds, and RR is the original interval between two successive R-waves in seconds [40].

Manual and automated QT interval measurement and sources of variation in the QT readings were described by Simova and Christov [42].

As the ANS modulates the cardiac pacemaker and provides beat by beat regulation of the cardiovascular system [47], the analysis of Heart rate variability (HRV) can be used clinically to assess the ANS providing separate measures of the sympathetic and parasympathetic nervous systems [22]. The ECG recording may contain various challenging problems such as segment with high noise content, sudden change in QRS amplitude and morphology, or muscle and electrode artifact which are not often detected correctly. Hence, reliable and correct detection of QRS complexes, under various backgrounds, is very important in any algorithm used for ECG analysis. The correct performance of these systems depends on several important factors such as quality of ECG signal, the applied detection rule, the learning and used testing dataset [21, 25].

Methodologies

Slope vector waveform algorithm

Köhler et al. [23] proposed a Slope vector waveform (SVM) algorithm for the detection of QRS complexes in electrocardiographic signals that is based on a feature obtained by counting the number of zero crossings per segment. At first, a low-pass filter with cut-off frequency 45 Hz is used to filter high-frequency noise, and SVW algorithm is considered following filtering. The process of SVW is divided into two steps: *variable stage differential* and *non-linear transform*.

For non-linear enhancement, the enhancement function used in [23] is written as:

$$F(x) = x^2 + a_3 x^3 + 8x^4, \; x \in [0, 1], \tag{2}$$

where a_3 is the coefficient that relies upon expected signal-to-noise ratio ratio.

It is well known that zero crossing methods are robust against noise and are particularly useful for finite precision arithmetic. Their suggested new detection method inherits this robustness and provides a high degree of detection performance even in cases of very noisy electrocardiographic signals. Furthermore, due to the simplicity of detecting and counting zero crossings, their proposed technique provides a computationally efficient solution to the QRS detection problem. They have confirmed the performance of the algorithm by a sensitivity of 99.70% (277 false negatives) and a positive predictivity of 99.57% (390 false positives) against the MIT-BIH arrhythmia database [23].

Fuzzy c-means algorithm

Deelport and Liesch presented an application of Fuzzy c-means algorithm (FCM) for the detection of QRS complexes, using the entropy criteria for the generation of the feature signal [12]. This method is suitable for the detection of all kind of morphologies of QRS complexes suggested by Mehta et al. [25] the FCM algorithm, which is best known fuzzy clustering algorithm, produces constrained soft partition. In order to produce constrained soft partition, the objective function J_1 of hard c-means has been extended in two ways: (1) the fuzzy

membership degree in cluster has been incorporated in the formula and (2) an additional parameter *m* has been introduced as a weight exponent in fuzzy membership. The extended objective function, denoted by J_m, is:

$$J_m(P,V) = \sum_{i=1}^{k} \sum_{x_k \in X} (\mu_{C_i}(x_k))^m \| x_k - v_i \|^2, \quad (3)$$

where *P* is fuzzy partition of dataset *X* formed by C_1, C_2, …, C_k and *k* is number of clusters. The parameter *m* is weight that determines the degree to which partial members of cluster affect the clustering result.

Overview of FCM

FCM (*X*, *c*, *m*, ε)

X: unlabeled dataset;

c: the number of cluster to be formed;

m: the parameter in objective function;

ε: threshold for the convergence criteria;

1. Initialize the prototype $V = \{v_1, v_2, \ldots, v_k\}$;
2. Repeat steps 3, 4 and 5 until,

$$\sum_{i=1}^{c} \| v_i^{prevoius} - v_i \| \leq \varepsilon ; \quad (4)$$

3. $V^{previous} \leftarrow V$;
4. Compute the membership function using Eq. (3);
5. Update the prototype, v_i in *V* using Eq. (4).

The performance of the algorithm was validated using original 12-lead ECG recording from the standard ECG database and the onset and offset of the QRS complexes are found to be within tolerance limit given by CSE library [25].

Pan-Tompkins and wavelet algorithms

The basic idea is to run both algorithms in parallel. When both methods disagree whether to predict a QRS complex in a particular time window, Meyer et al. [26] applied a data-driven strategy for deciding whether or not to accept the candidate QRS complex. More precisely, in cases of disagreement, they suggest to locally rerun the Pan-Tomkins (PT) method with a modified threshold, accepting the result of the local rerun as the final decision. The local decisions can formally be seen as the majority vote of a (three-component) ensemble classifier, where, the third classifier repeats one of the first two classifications, however, with modified threshold. Meyer et al. [26] introduced two parameters α and β to control the threshold adjustment, which are both estimated on training data. By varying α and β, in theory, interpolate between the predictions of the individual algorithms and Boolean combinations like union and intersection [26].

In Fig. 1 the PT method detects peaks at time points 50, 219, and 386 (dashed lines), and the wavelet method at time points 219, 386, and 472 (dotted lines); dashed-dotted lines refer to QRS complexes predicted by both algorithms [26]. In Fig. 2 the PT algorithm detects peaks at time point's 50, 275, and 498 (dashed lines), and wavelet at time points 41, 139, 368, and 498 (dotted lines); dashed-dotted lines: prediction by both algorithms [26].

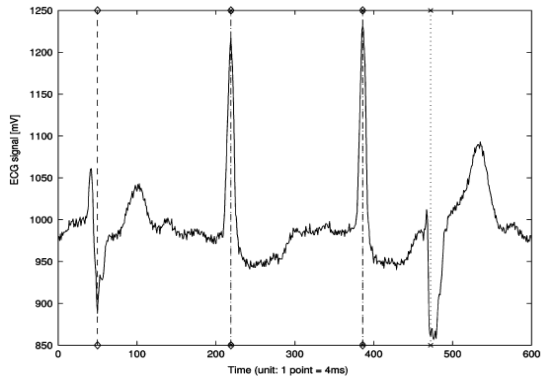

Fig. 1 Example for automatic QRS complex detection

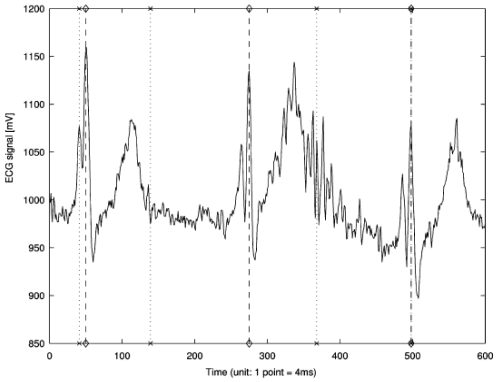

Fig. 2 Second example for automatic QRS complex detection

Difference operation method

Yeh and Wang [48] proposed a simple and fast algorithm, termed the Difference operation method (DOM) for detecting the QRS complex. The proposed DOM includes two stages. The first stage is to find the point *R* by applying the difference equation operation to the ECG signal. The second stage looks for the points *Q* and *S* according to the point *R* to find the QRS complex. The DOM method can detect the QRS complex easily without any complex mathematical calculation, such as cross-correlation, Fourier transformation, etc. The time complexity for DOM is $O(n)$, where n is the number of sampling points (that is, more sampling points need more processing time). The MIT-BIH arrhythmia database [27] is experimented to evaluate the effectiveness of the proposed DOM and it has only 0.19% failure rate which is much better than the other popular methods.

Combined adaptive threshold

A real-time detection method is proposed, based on comparison between absolute values of summed differentiated electrocardiograms of one of more ECG leads and adaptive threshold. The threshold combines three parameters: an adaptive slew-rate value, a second value which rises when high-frequency noise occurs, and a third one intended to avoid missing of low amplitude beats [9].

Two algorithms were developed: Algorithm 1 detects the current beat present in the ECG signal and Algorithm 2 has an RR interval analysis component. The algorithms are self-adjusting to the thresholds and weighting constants, regardless of resolution and sampling frequency used. They operate with any number *L* of ECG leads, self synchronize to QRS or beat slopes and adapt to beat-to-beat intervals. The algorithms were tested by an independent expert, thus excluding possible author's influence, using all 48 full-length ECG records of the MIT-BIH arrhythmia database. The results were: sensitivity *Se* = 99.69% and specificity *Sp* = 99.65% for Algorithm 1 and *Se* = 99.74% and *Sp* = 99.65% for Algorithm 2 [9].

Empirical modal decomposition

Hadj Slimane and Naït-Ali [16] proposed Empirical modal decomposition (EMD) which is defined by a process called sifting. It decomposes a given signal $x(t)$ into a set of AM-FM components, called Intrinsic mode functions (IMF). Therefore, K modes $d_k(t)$ and a residual term $r(t)$ [11, 29] are obtained and expressed by:

$$X(t) = \sum_{k=1}^{s} d_k(t) + r(t), \quad k = 1, 2, \ldots, s. \tag{5}$$

The EMD algorithm is summarized by the following steps:
1. Start with the signal $d_l(t) = x(t)$, $k = 1$. Sifting process $h_j(t) = d_k(t)$, $j = 0$;
2. Identify all local extrema of $h_j(t)$;
3. Compute the upper (*EnvMax*) and the lower envelopes (*EnvMin*) by cubic spine lines interpolation of the maxima and the minima;
4. Calculate the mean of the lower and upper envelopes,

$$m(t) = \frac{1}{2}\left(EnvMin(t) + EnvMax(t)\right); \quad (6)$$

5. Extract the detail $h_{j+1}(t) = h_j(t) - m(t)$;
6. If $h_{j+1}(t)$ is an IMF, go to step 7, else, iterate steps 2 to 5 upon the signal $h_{j+1}(t)$, $j = j + 1$;
7. Extract the mode $d_k(t) = h_{j+1}(t)$;
8. Calculate the residual $r_k(t) = x(t) - d_k(t)$;
9. If $r_k(t)$ has less than 2 minima or 2 extrema, the extraction is finished $r(t) = r_k(t)$.
Else, iterate the algorithm from step 1 upon the residual $r_k(t)$, $k = k + 1$.

This algorithm requires the following stages: a high-pass filter, signal EMD, a non-linear transform, integration and finally, a low-pass filter is used. In order to evaluate the proposed technique, the well known ECG MIT-BIH database has been used. Moreover it is compared to a reference technique, namely Christov's detection method [9]. The proposed algorithm allows achieving high detection performances [16].

Short-time Fourier transform based technique

Uchaipichat and Inban [44] have proposed the Short-time Fourier transform (STFT) which was employed in ECG filtering stage. The narrow rectangular window was used to transform ECG signals into time-frequency domain. The temporal information at 45 Hz from spectrogram was analyzed for detecting QRS locations. The automated thresholding combined with local maxima finding method was modified to find the QRS location [44].

The STFT is the technique for non-stationary signal analysis that transforms signal information from time domain into time-frequency domain. The main concept of the STFT is to consider a non-stationary signal as a stationary signal over short periods of time within a window function [15, 17]. The computation of STFT can be defined as:

$$T(f,\tau) = \int_{-\infty}^{\infty} \left[x(t)w(t-\tau)\right] e^{-j2\pi ft} dt \ , \quad (7)$$

where $w(t - \tau)$ is the window function. From Eq. (1) the STFT maps signal $x(t)$ into two-dimensional function in time, τ, and frequency, f. The energy surface distribution of STFT called spectrogram can be computed by

$$E(f,\tau) = |T(f,\tau)|^2 \ . \quad (8)$$

The rectangular window was used in this study. The narrow window width of 16-point was used because the high resolution in time is required to detect QRS complex. The data used in their study was MIT-BIH Arrhythmia database. As the results, their proposed technique achieved the detection rate better than 99% [44].

Discrete wavelet transform

Behbahani and Dabanloo have proposed multiresolution wavelet and thresholding methods for automatic QRS Complex detection [7]. A wavelet has its energy concentrated in time. Sinusoids are useful in analyzing periodic and time-invariant phenomena, while wavelets are well suited for the analysis of transient, time-varying signals, thus well suited for ECG signals. Basically wavelet transform is the convolution operation of the subject signal $f(t)$ and the wavelet function $\psi(t)$. The Discrete wavelet transform (DWT) is expressed as:

$$X_{j,k} = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)dt \ . \tag{9}$$

The approximation coefficient of the signal $f(t)$ is represented as:

$$A_{j,k} = \int_{-\infty}^{\infty} f(t)\phi_{j,k}(t)dt \ , \tag{10}$$

where $\phi(t)$ is scaling function, j and k are scale and location respectively. For a range of scale n, the original signal $f(t)$ under DWT can be represented as:

$$f(t) = f_n(t) + \sum_{j=1}^{n} d_j(t) \ , \tag{11}$$

where $f_n(t)$ is mean signal approximation and is given by

$$f_n(t) = A_{n,k}\phi_{n,k}(t) \tag{12}$$

and $d_j(t)$ is detail signal approximation in scale j.

Automatic extraction of time plane features is important for cardiac disease diagnosis. This paper presented a multi-resolution wavelet transform based system for detection and evaluation of QRS complex. In first step, Behbahani et al. [7] have implemented the selective confident method to find the QRS complex, at next step threshold method is applied to find the QRS complex and finally applied the composition of first step algorithm and thresholding method which shows robust ability of finding QRS compared to other methods. Achieved overall accuracy of QRS detection for only d_4 scale without threshold is 84.48%, the composition of d_3, d_4, d_5 without threshold 93.23%, only d_4 with threshold 90%, and d_3, d_4, d_5 with threshold 98.2% [7].

QRS complex analysis: cardiovascular conditions

A disturbance in the conduction of excitation from the atria to the ventricles is revealed by the prolongation of the P-R intervals. Any electrocardiographic lead, which records the P- and QRS-wave, can be used to diagnose atrioventricular conduction defects. The electro-cardiogram can reflect many types of conduction defects. One of these is the atrial arrhythmias which may be compatible with life but the severe and dangerous one is the ventricular fibrillation where death is ensued if proper step against fibrillation not being taken [22].

Analysis of HRV data from patients with congestive heart failure shows a decrease in spectral power at all frequency ranges [41]. This finding provides very important evidence that cardiac parasympathetic function is depressed in patients prone to sudden cardiac death [22]. Pueyo et al. stated in their article about the effect of QRS slopes upon ischemia [34]. Myocardial ischemia precedes infarction and is manifested by reduced blood flow to the heart, and may be caused by narrowing or occlusion of a coronary artery during a short period of time. Ischemia is sometimes accompanied with pain (angina pectoris) and sometimes without (silent ischemia), thus making its diagnosis more difficult. During the first instants of acute coronary occlusion, ischemia is manifested in the ECG by changes in the ventricular repolarization period (i.e., ST segment and T-wave). Alterations during the ventricular depolarization (QRS complex) have traditionally been associated with the onset of the necrotic process. However, early animal studies demonstrated changes in QRS morphology due to slowing of intra myocardial conduction during ischemia [17-19]. Later on, similar results have been obtained in clinical studies with patients undergoing percutaneous trans-luminal coronary angioplasty (PTCA). During this procedure, a balloon is inserted and inflated inside a coronary artery to induce controlled ischemia, whereas, upon release, the blood flow to the cardiac cells is restored. Wagner et al. [46] reported on changes in QRS amplitudes during PTCA. Some changes occurred during the early part of inflation being secondary to ST segment changes. However, primary changes occurred during the later part which was believed to reflect conduction delays. Since such changes disappeared after balloon deflation, they were associated with ischemia. In another study with patients undergoing elective PTCA in one of the major coronary arteries [33], the time course of ischemia was analyzed during both depolarization and repolarization. It was shown that QRS changes occur later in time than ST and T changes, indicating that more severe ischemia is required to cause depolarization changes. Recent studies have suggested that a decrease in high-frequency content (150-250 Hz) of the QRS complex is a better marker of ischemia than the traditional ST index [19, 26, 34]. However, the reduction in RMS voltage of the high-frequency QRS components (HF-QRS) exhibits large inter individual variation, disqualifying this index for separation of subjects with and without Coronary artery disease (CAD) [18] and subjects with and without previous MI [36]. The main clinical application of HF-QRS is thus restricted to the monitoring of ischemia in a given patient [1, 4, 31], unless a baseline HF-QRS value is available for the patient. In addition to the RMS voltage, the high-frequency QRS components have been quantified by the presence of so-called reduced-amplitude zones (RAZ). Abboud et al. introduced an RAZ index which, in contrast to the RMS voltage, was able to separate healthy subjects from CAD patients [2]. It is known that myocardial ischemia, in its advanced phase, modifies the electrophysiological properties of the ventricular cells by reducing the upstroke slope and the amplitude of the action potential, due to an increase in the potassium level of the extracellular space [10, 19, 45]. These alterations may be manifested as a widening of the QRS complex and a decrease in its amplitude. Accordingly, Pueyo et al. [34] hypothesized that the reduction in the upward and downward slopes of the QRS complex serve as measurements of ischemia-induced alterations and the approach avoids the problem of filter ringing, which smears the signal so that the nature of the localized HF-QRS features is masked. Furthermore, the proposed slope indices do not require signal averaging, but are computed directly from the ECG, thus constituting more robust indices. To further investigate this, Pueyo et al. [34] measured the QRS slopes and HF-QRS both before and during PTCA recordings and compared the abilities of the indices as well as some other traditional ECG indices, to detect ischemia-induced alterations. Pueyo et al. concluded that QRS slope information can be used as an adjunct to the conventional ST segment analysis in the monitoring of myocardial ischemia [34].

Altuve et al. [3] have stated in their article about Apnea-Bradycardia Characterization in Preterm Infants by analyzing QRS complex of ECG signal. The repetition of these episodes has been associated with a poor neuromotor prognosis at 3 years [20] and has been identified as a predisposing factor to sudden-death syndrome in newborns [5]. Furthermore, these episodes extend the hospitalization periods and occasionally require telemonitoring at home. Therefore, in neonatal intensive care units, preterm infants undergo continuous cardiorespiratory monitoring to detect apnea-bradycardia episodes and to initiate quick nursing actions. Manual stimulation is the most common way to stop apnea-bradycardia episodes in preterm newborns, however, the intervention delay measured from the activation of the monitoring alarm to the application of the therapy remains long [32]. The cardiac cycle length (RR interval) extracted from the electrocardiogram (ECG) is generally used to detect apnea-bradycardia episodes. However, other parameters extracted from the ECG, like R-wave amplitude and QRS complex duration, could be also integrated in a new detection approach. Therefore, in this paper, three time series (RR, R-wave amplitude and QRS complex duration) were studied for periods at rest, before, during and after apnea-bradycardia episodes. To extract these series from the ECG, a QRS detector algorithm [30] followed by an ECG segmentation method [13] were applied. However, these methods were conceived for the analysis of adult ECG and should be adapted to the specific characteristics of the newborn's ECG. Evolutionary algorithms were chosen to realize these important steps.

Altuve et al. [3] have proposed an automatic beat detection and segmentation methods which have been adapted to the ECG signals from preterm infants, through the application of two evolutionary algorithms. ECG data acquired from 32 preterm infants with persistent apnea-bradycardia have been used for quantitative evaluation. The adaptation procedure led to an improved sensitivity and positive predictive value, and a reduced jitter for the detection of the R-wave, QRS onset, QRS offset, and iso-electric level. Additionally, time series representing the RR interval, R-wave amplitude and QRS duration, were automatically extracted for periods at rest, before, during and after apnea-bradycardia episodes. Significant variations ($p < 0.05$) were observed for all time-series when comparing the difference between values at rest versus values just before the bradycardia event, with the difference between values at rest versus values during the bradycardia event. These results reveal changes in the R-wave amplitude and QRS duration, appearing at the onset and termination of apnea-bradycardia episodes, which could be potentially useful for the early detection and characterization of these episodes [3].

In patients with Brugada syndrome (BS), the presence of fragmented QRS was shown to predict occurrence of spontaneous ventricular arrhythmias and cardiac arrest [28]. Batchvarov et al. [6] used Principal component analysis (PCA) of the QRS complex to assess depolarization heterogeity during Ajmaline test in 96 patients with suspected BS. PCA was performed on 15-lead ECGs (12 leads +V1, V2 and V3 from 3rd inter costal space, V1 h to V3 h using a) V1, V2 and V3 (QRS-PCA stand), b) V1 h, V2 h and V3 h (QRS-PCA high), and c) V1 to V3, V1 h to V3 h (QRS-PCA total). Among patients with positive tests ($n = 23$), those with symptoms ($n = 6$) had higher QRS-PCA high before ($p = 0.003$) and during maximum drug effect ($p = 0.001$) than those without symptoms ($n = 17$). Following Ajmaline test [6], QRS-PCA decreased significantly in patients with negative ($n = 73$) ($p = 0.00004$), but not in those with positive tests ($p = 0.098$). Symptomatic patients with non-diagnostic resting ECGs have increased depolarization heterogeneity. PCA could detect depolarization heterogeity and thus help the diagnosis and risk stratification of patients with BS [6].

Time-domain Ventricular late potentials (VLP) analysis has established the clinical value for stratifying the risk of development of sustained ventricular arrhythmias in patients recovering from myocardial infarction, and for the identification of patients with ischemic heart disease and unexplained syncope [8]. Recently, the VLP parameters have also been applied to assess the risk of ventricular arrhythmias for symptomatic and asymptomatic patients with BS [43], Chagas disease patients [35] and patients with arrhythmogenic right ventricular cardiomyopathy [14]. Lin [24] proposed a Finite-impulse-response (FIR) prediction model to analyze the Unpredictable intra-QRS potentials (UIQP) for identifying ventricular tachycardia patients with high-risk ventricular arrhythmias. The simulation study shows that a QRS complex including Abnormal intra-QRS potentials (AIQP) has a higher UIQP and UIQP-to-QRS ratio in comparison with one without AIQP. The clinical results demonstrate that the mean UIQP-to-QRS ratios of VT patients in leads X, Y and Z were significantly larger than those of the normal subjects, and the linear and logical combination of UIQP-to-QRS ratios and ventricular late potential parameters can enhance diagnosis performance for VT patients [24].

Romero et al. [38] evaluated as to represent a robust measure of pathological changes within the depolarization phase i.e. ischemia-induced changes in the main three slopes of the QRS complex, upward (τ_{US}) and downward (τ_{DS}) slopes of the R-wave as well as the upward (τ_{TS}) slope of the terminal *S*-wave (Fig. 3). They proposed 4 major steps for their evaluation, i.e. 1) evaluate the normal variation of the QRS slopes in the standard 12 leads at resting state (control recordings) in a large population, with the purpose of determining reliable limits of significant QRS slope changes due to an ischemic patho-physiological process; 2) apply a normalization procedure to both control and PCI recordings to attenuate low-frequency variation in the slopes and stabilize the slope reference for better quantification of patho-physiologically significant changes; 3) test the performance of this improved method in monitoring QRS slope changes along the dynamic ECG recordings during PCI-induced ischemia on the standard 12-lead ECG and leads derived from the spatial QRS loop; and 4) determine the timing of significant changes during PCI [38].

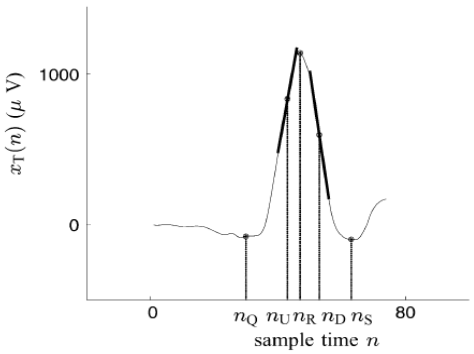

Fig. 3 Template of the simulation study and related upward and downward slopes τ_{US} and τ_{DS}

Ruschitzka et al. [39] presented in their article Cardiac-resynchronization therapy (CRT) that reduces morbidity and mortality in chronic systolic heart failure with a wide QRS complex. Mechanical dyssynchrony also occurs in patients with a narrow QRS complex, which suggests the potential usefulness of CRT in such patients. In patients with systolic heart failure and QRS duration of less than 130 msec, CRT does not reduce the rate of death or hospitalization for heart failure and may increase mortality (funded by Biotronik and GE Healthcare; EchoCRT ClinicalTrials.gov number, NCT00683696) [39].

Conclusion

The process of determining or labeling the type of cardiac dysfunction which are related with QRS complex can be challenging. By implementing automated detection algorithms, it can be easier to detect or monitor the normal and abnormal cardiac conditions. Certain vital techniques and algorithms to detect and analyze the QRS complex are discussed in this review, i.e.

- SVW algorithm which shows sensitivity of 99.70% [23];
- FCM algorithm which use multilead (i.e. 12 lead) detection of onset and offset of the QRS complexes [12];
- Pan-Tompkins and wavelet algorithms [26];
- Difference operation method which proposed a simple and fast algorithm with only 0.19% failure rate [48];
- Christov developed Combined adaptive threshold method to solve the problem remains with QRS detection accuracy in noisy ECGs [9];
- EMD [16];
- STFT based technique [44];
- DWT [7].

More over all these methods are evaluated with standard databases (i.e. MIT-BIH ECG databases).

The effect of QRS complex on various other cardiac conditions is discussed i.e. QRS-wave can be used to diagnose atrio-ventricular conduction defects [22], effect of QRS slopes upon ischemia [34], changes in QRS amplitudes during PTCA [46], effect of QRS components on CAD [18], Apnea-bradycardia characterization in Preterm Infants by analyzing QRS complex [3], presence of fragmented QRS in BS [28] & UIQP for identifying ventricular tachycardia [24]. However many techniques have been evolved for the detection and quantification of QRS complex, but the further need of research have to be done in this field to achieve more significant and analytical results. For the reader to understand the key concepts, this review analyses the QRS complex, which will help them to carry on their further research.

References

1. Abboud S. (1993). High-frequency Electrocardiogram Analysis of the Entire QRS in the Diagnosis and Assessment of Coronary Artery Disease, Prog Cardiovasc Dis, 35(5), 311-328.
2. Abboud S., B. Belhassen, H. I. Miller, D. Sadeh, S. Laniado (1986). High Frequency Electrocardiography using an Advanced Method of Signal Averaging for Non-invasive Detection of Coronary Artery Disease in Patients with Normal Conventional Electrocardiogram, J Electrocardiology, 19(4), 371-380.
3. Altuve M., G. Carrault, J. Cruz, A. Beuchae, P. Pladys, A. Hernandez (2009). Analysis of the QRS Complex for Apnea-bradycardia Characterization in Preterm Infants, Proceedings Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1, 946-949.
4. Aversano T., B. Rudikoff, A. Washington, S. Traill, V. Coombs, J. Raqueno (1994). High Frequency QRS Electrocardiography in the Detection of Reperfusion Following Thrombolytic Therapy, Clin Cardiol, 17(4), 175-182.
5. Baird T. M. (2004). Clinical Correlates, Natural History and Outcome of Neonatal Apnea, Semin Neonatology, 9(3), 205-211.

6. Batchvarov V. N., I. I. Christov, G. Bortolan, E. R. Behr (2010). Principal Component Analysis of the QRS Complex During Diagnostic Ajmaline Test for Suspected Brugada Syndrome, Computing in Cardiology, 37, 501-504.
7. Behbahani S., N. J. Dabanloo (2011). Detection of QRS Complexes in the ECG Signal using Multiresolution Wavelet and Thresholding Method, Computing in Cardiology, 38, 805-808.
8. Cain M. E., J. L. Anderson, M. F. Arnsdorf, J. W. Mason, M. M. Scheinman, A. L. Waldo (1996). Signal-averaged Electro Cardiography, Journal of the American College of Cardiology, 27, 238-249.
9. Christov I. I. (2004). Real Time Electrocardiogram QRS Detection using Combined Adaptive Threshold, BioMedical Engineering OnLine, 3, 28, http://www.biomedical-engineering-online.com/content/3/1/28.
10. Cimponeriu A., C. F. Starmer, A. Bezerianos (2001). A Theoretical Analysis of Acute Ischemia and Infarction using ECG Reconstruction on a 2-D Model of Myocardium, IEEE Trans Biomed Eng, 48(1), 41-54.
11. Damerval C., S. Meignen, V. Perrier, Empirical Mode Decomposition, http://www-ljk.imag.fr/membres/ValeriePerrier/PUBLI/EMD.pdf
12. Deelport V., D. Liesch (1994). Fuzzy C-means Algorithm for Code Book Design in Vector Quantization, Electronic Letter, 30(13), 1025-1026.
13. Dumont J., A. Hernández, G. Carrault (2010). Improving ECG Beats Delineation with an Evolutionary Optimization Process, IEEE Transactions on Biomedical Engineering, 57(3), 607-615.
14. Folino A. F., B. Bauce, G. Frigo, A. Nava (2006). Long-term Follow-up of the Signal-averaged ECG in Arrhythmogenic Right Ventricular Cardiomyopathy: Correlation with Arrhythmic Events and Echocardiographic Findings, Europace, 8, 423-429.
15. Gade S., K. Gram-Hansen (1997). The Analysis of Non-stationary Signals, Sound and Vibration, 31, 40-46.
16. Hadj Slimane Z.-E., A. Naït-Ali (2010). QRS Complex Detection using Empirical Mode Decomposition, Digital Signal Processing, 20(4), 1221-1228.
17. Hamlin R. L., F. S. Pipers, H. K. Hellerstein, C. R. Smith (1968). QRS Alterations Immediately following Production of Left Ventricular Freewall Ischemia in Dogs, 4m J Physiol, 215, 1032-1040.
18. Hamlin R. L., F. S. Pipers, H. K. Hellerstein, C. R. Smith (1969). Alterations in the QRS during Ischemia of the Left Ventricular Free-wall in Goats, J Electrocardiology, 2, 223-228.
19. Holland R. P., H. Brooks (1976). The QRS Complex during Myocardial Ischemia: An Experimental Analysis in the Porcine Heart, J Clin Invest, 57, 541-550.
20. Janvier A., M. Khairy, A. Kokkotis, C. Cormier, D. Messmer, K. J. Barrington (2004). Apnea is Associated with Neurodevelopmental Impairment in Very Low Birth Weight Infants, J Perinatology, 24(12), 763-768.
21. Jekova I., V. Krasteva, I. Dotsinsky (2009). Filtering of Chest Compression Artefacts in the Electrocardiogram, Int J Bioautomation, 13(4), 19-28.
22. Khayer M. A., M. A. Haque (2004). ECG Peak Detection using Wavelet Transform, Proceedings of 3rd International Conference on Electrical & Computer Engineering ICECE 2004, Dhaka, Bangladesh, 28-30.
23. Köhler B. U., C. Hennig, R. Orglmeister (2003). QRS Detection Using Zero Crossing Counts, Progress in Biomedical Research, 8(3), 138-145.
24. Lin C.-C. (2010). Analysis of Unpredictable Components within QRS Complex using a Finite-impulse-response Prediction Model for the Diagnosis of Patients with Ventricular Tachycardia, Computers in Biology and Medicine, 40(7), 643-649.

25. Mehta S. S., C. R. Trivedi, N. S. Lingayat (2009). Identification and Delineation of QRS Complexes in Electrocardiogram using Fuzzy c-means Algorithm, Journal of Theoretical and Applied Information Technology, 5, 609-617.
26. Meyer C., J. F. Gavela, M. Harris (2006). Combining Algorithms in Automatic Detection of QRS complexes in ECG Signals, IEEE Transactions on Information Technology in Biomedicine, 10(3), 468-475.
27. MIT-BIH Database Distribution, Massachusetts Institute of Technology, Cambridge, MA, 1998.
28. Morita H., K. F. Kusano, D. Miura (2008). Fragmented QRS as a Marker of Conduction Abnormality and a Predictor of Prognosis of Brugada Syndrome, Circulation, 118, 1697-1704.
29. Oukhellou L., P. Aknin, E. Delechelle (2006). Railway Infrastructure System Diagnosis using Empirical Mode Decomposition and Hilbert Transform, Proceedings of International Conference in Acoustics, Speech and Signal Processing, ICASSP 2006, Toulouse, 3, doi: 10.1109/ICASSP.2006.1660866.
30. Pan J., W. J. Tompkins (1985). A Real-time QRS Detection Algorithm, IEEE Trans Biomed Eng, 32(3), 230-236.
31. Pettersson J., E. Cairo, L. Edenbrandt, C. Maynard, O. Pahlm, M. Ringborn, L. Sommo, S. G.Warren, G. S.Wagner (2000). Spatial, Individual, and Temporal Variation of the High-frequency QRS Amplitudes in the 12 Standard Electrocardiographic Leads, Amer Heart J, 139, 352-358.
32. Pichardo R., J. S. Adam, E. Rosow, J. Bronzino (2003). Vibrotactile Stimulation System to Treat Apnea of Prematurity, Biomed Instrum Technol, 37(1), 34-40.
33. Pueyo E., J. García, G. Wagner, R. Bailón, L. Sörnmo, P. Laguna (2004). Time Course of ECG Depolarization and Repolarization Changes during Ischemia in PTCA Recordings, Methods Inf Med, 43, 43-46.
34. Pueyo E., L. Sornmo, P. Laguna (2008). QRS Slopes for Detection and Characterization of Myocardial Ischemia, IEEE Transactions on Biomedical Engineering, 55(2), 468-477.
35. Ribeiro A. L., P. S. Cavalvanti, F. Lombardi, M. C. Nunes, M. V. Barros, M. C. Rocha (2008). Prognostic Value of Signal-averaged Electrocardiogram in Chagas Disease, Journal of Cardiovascular Electrophysiology, 19, 502-509.
36. Ringborn M., O. Pahlm, G. S. Wagner, S. G. Warren, J. Pettersson (2001). The Absence of High-frequency QRS Changes in the Presence of Standard Electrocardiographic QRS Changes of Old Myocardial Infarction, Amer Heart J, 141(4), 573-579.
37. Rioul O., M. Vetterli (1991). Wavelets and Signal Processing, IEEE Signal Processing Magazine, 8, 14-38.
38. Romero D., M. Ringborn, P. Laguna, O. Pahlm, E. Pueyo (2011). Depolarization Changes during Acute Myocardial Ischemia by Evaluation of QRS Slopes: Standard Lead and Vectorial Approach, IEEE Transactions on Biomedical Engineering, 58(1), 110-120.
39. Ruschitzka F., J. Brugada, H. Krum (2013). Cardiac-resynchronization Therapy in Heart Failure with a Narrow QRS Complex, N Engl J Med, 369, 1395-1405.
40. Sagie A., M. G. Larson, R. J. Goldberg, J. R. Bengtson, D. Levy (1992). An Improved Method for Adjusting the QT Interval for Heart Rate (The Framingham Heart Study), The American Journal of Cardiology, 70(7), 797-801.
41. Sahambi J. S., S. N. Tandon, R. K. P. Bhatt (1997). Using Wavelet Transform for ECG Characterization, IEEE Engineering in Medicine and Biology Magazine, 16(1), 77-83.
42. Simova I., I. Christov (2007). Sources of Variation in the QT Readings: What should you be Aware of?, Int J Bioautomation, 6, 78-91.
43. Tatsumi H., M. Takagi, E. Nakagawa, H. Yamashita, M. Yoshiyama (2006). Risk Stratification in Patients with Brugada Syndrome: Analysis of Daily Fluctuations in

12-lead Electrocardiogram (ECG) and Signal Averaged Electrocardiogram (SAECG), Journal of Cardiovascular Electrophysiology, 17(7), 705-711.
44. Uchaipichat N., S. Inban (2010). Development of QRS Detection using Short-time Fourier Transform based Technique, IJCA Special Issue on Computer Aided Soft Computing Techniques for Imaging and Biomedical Applications – CASCT, 7-10.
45. Vandyck-Acquah M., P. Schweitzer (2004). Electrocardiographic Background, In: Dynamic Electrocardiography, M. Malik, A. Camm, (Eds.), Oxford, U.K., Blackwell Future, 217-232.
46. Wagner N. B., D. C. Sevilla, M. W. Krucoff, K. L. Lee, K. S. Pieper, K. K. Kent, R. K. Bottner, R. H. Selvester, G. S. Wagner (1998). Transient Alterations of the QRS Complex and ST Segment during Percutaneous Transluminal Balloon Angioplasty of the Left Anterior Descending Coronary Artery, Amer J Cardiology, 62, 1038-1042.
47. Wiklund U., M. Akay, U. Niklasson (1997). Short-term Analysis of Heart-rate Variability by Adapted Wavelet Transform-methods for Characterizing Autonomic Nervous System Modulation of Cardiovascular Activity, IEEE Engineering in Medicine and Biology Magazine, 113-118.
48. Yeh Y.-C., W.-J. Wang (2008). QRS Complexes Detection for ECG Signal: The Difference Operation Method, Computer Methods and Programs in Biomedicine, 91, 245-254.

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