On QRS detection methodologies: A revisit for mobile phone applications, wireless ECG monitoring and large ECG databases analysis

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Abstract
This review discusses the development of any QRS detection algorithm based on three assessment criteria: robustness to noise, parameter choice, and numerical efficiency. This is because of there is a need nowadays for fast and robust QRS detection algorithms to be deployed on mobile phones, and run over large ECG databases and wireless medical body area network. Till now, there is no satisfying universal solution for detecting QRS complex given the fact it was a topic of investigation for the last 30 years. The difficulty arises mainly because of the diversity of the QRS waveforms, abnormalities, low SNR and the artifacts accompanying the ECG signals. The existing QRS detection algorithms may provide an acceptable solution on small ECG segments, within a certain amplitude range, amid particular type of arrhythmia, or/and noise. These issues are discussed in comparison with the most conventional algorithms, followed by recommendations for developing a reliable QRS detection suitable for large-recorded ECG signals and battery-driven devices.

Keywords: electrocardiogram, QRS detection, ECG analysis, R peak detection, mobile applications, large ECG dataset analysis

1. Introduction

According to the World Health Organization, cardiovascular diseases (CVD) are the number one cause of death worldwide. It is the leading cause of death in Australia, and the second leading cause of disease burden [1]. In 2007, CVD was the underlying cause of 34 per cent of all deaths in Australia (46,626 deaths [2]) and it is estimated that around 1.4 million Australians experience a disability associated with the cardiovascular system. These rates are consistent with those of other western developed countries such as New Zealand, the United States (US), the United Kingdom (UK) and the Scandinavian nations [3].

CVD is the most expensive disease group in terms of direct health-care expenditure. In 2008, it cost Australia about $5.9 billion [4]. As a consequence of the direct and indirect costs of CVD, medical researchers have placed significant importance on cardiac health research. This has produced a strong focus on preventative, medicinal and technological advances, both in Australia and abroad. One such research pathway is leading researchers towards improving the conventional cardiovascular-diagnosis technologies used in hospitals/clinics.

The most commonly performed cardiac test is ECG as it is a useful screening tool for a variety of cardiac abnormalities, simple, risk-free and inexpensive. The advances in technology have done much change to the way we collect, store and diagnose ECG signals, especially the use of mobile phones to replicate these processes. It is expected that Holter devices will be replaced by mobile phones in the near future. The reason is Holter device does not detect arrhythmias automatically in realtime and it does not provide realtime information to the hospital/doctor/patient when critical heart condition occurs.

On the other hand the advances in memory/storage technology have enabled us to store more ECG signals than ever before. Therefore, scientists are collecting more information in order to understand the mechanism of the cardiovascular diseases which will ultimately lead to effective treatments.

Certainly, analysing ECG signals collected by a mobile phone needs to be fast as we have limitation in terms of phone memory and processor capability. The same holds for analysing large ECG recordings collected over one or more days.

Recently, scientists are more interested in developing an efficient algorithm to run within a mobile phone to determine the quality of collected ECG signals. The 2011 PhysioNet/Computing in Cardiology Challenge has been established to encourage the development of software that can run in a mobile phone, recording an ECG and providing useful feedback about its quality.

PhysioNet provided a large set of ECG records for use in the Challenge, together with an open-source sample application that can run on an Android phone, and can classify ECGs as acceptable or unacceptable. Therefore, the next step is analysing the acceptable ECG signal for diagnosis without relying on an expert for interpretation. If this possibility becomes reality it will help the developing nations and rural population to benefit from inaccessible expertise.

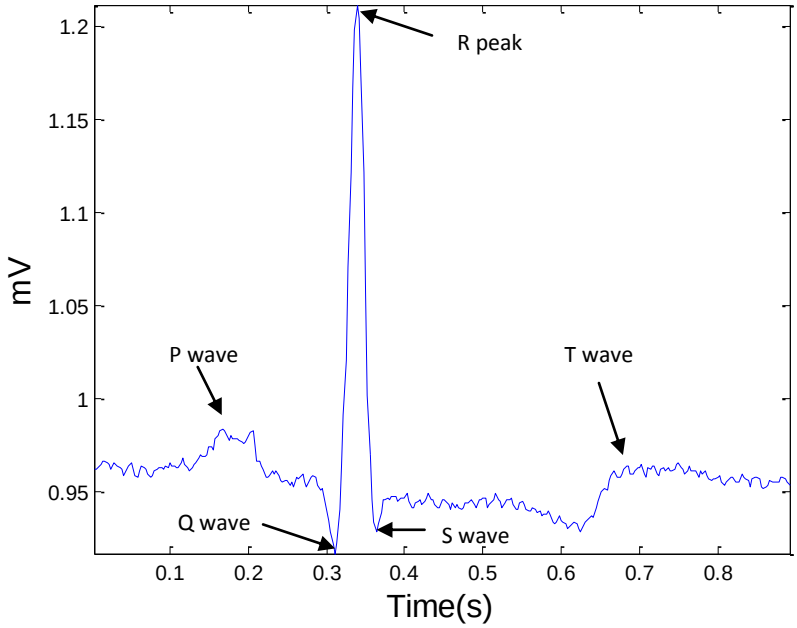


Figure 1. Main Events in ECG signals. A typical ECG tracing of the cardiac cycle (heartbeat) consists of a P wave, a QRS complex, and a T wave.

ECG signals contain features that reflect the way the heart is working. These features represent the physiological events that are the sequence of depolarisation and repolarisation of the atria and ventricles. Each beat in the ECG signal contains three

main events: the P wave, the QRS complex, and the T wave; as shown in Figure 1. Each event (wave) has a peak. The analysis of ECG signals for monitoring or diagnosis requires the detection of these events. Once an event has been detected, the corresponding signal can be extracted and analysed in terms of its amplitude (peak), morphology, energy and entropy distribution, frequency content, intervals between events.

The automatic detection of the P, QRS and T events is critical for reliable cardiovascular assessments, such as diagnosing cardiac arrhythmias [5-9], understanding the autonomic regulation of the cardiovascular system during sleep and hypertension [10, 11], detecting breathing disorders such as Obstructive Sleep Apnea Syndrome [12, 13], and monitoring other structural or functional cardiac disorders. Once the QRS, P and T events are detected accurately, a more detailed examination of ECG signals can be performed.

The detection of QRS complexes has been extensively investigated in the past two decades. Many attempts have been made to find a satisfying universal solution for QRS complex detection. Difficulties arise mainly because of the diversity of the QRS waveforms, abnormalities, low SNR and the artifacts accompanying the ECG signals.

Conversely, P and T event detection has not been investigated as much as QRS detection. The P and T event detection problem is still far from being resolved [14]. Reliable P- and T-wave detection is more difficult than QRS complex detection for several reasons, including low amplitudes, low SNR, amplitude and morphology variability, and possible overlapping of the P-wave and the T-wave.

Any cardiac dysfunction associated with excitation from ectopic centres anywhere in the myocardium may lead to premature complexes (atrial or ventricular), which change the morphology of the waveform and the duration of the RR interval. The occurrence of multiple premature complexes is considered clinically important, as it is an indication for disorders in the depolarisation process preceding the critical cardiac arrhythmia. The detection of premature ventricular complexes has been extensively discussed in the literature, since they are associated with an increased risk of ventricular tachycardia or ventricular flutter/fibrillation, which can lead to sudden cardiac death [15]. The detection of premature atrial beats has not been widely investigated, although they can be used to predict supraventricular tachycardia, paroxysmal atrial fibrillation [6, 16] and postoperative atrial fibrillation [7]. Therefore, the atrial premature beats detection problem is also considered at the end of this chapter.

There is a body of evidence to suggest that averaging multiple detectors, even in a simple voting structure, is superior to any single algorithm [17, 18]. While this is not the main objective of this review, discussing the current detection algorithms will help in investigating this concept.

The motivation behind this review is to evaluate algorithms that detect the QRS complexes in arrhythmia ECG signal to be deployed on mobile phones and analyse large ECG signals in a time-efficient manner. The same criterion holds for the detection of P and T wave. To obtain a fast and robust assessment of ECG analysis performance, algorithms will be evaluated against the following aspects:

1. **Robustness to noise**: there are many sources of noise (e.g. powerline interference, muscle noise and motion artifacts). Therefore, the developed algorithms should be robust to these noises.
2. **Parameter choice**: The choice of parameters should lead to accurate detection. Parameters should not have to be manually adjusted for different recordings.
3. **Numerical efficiency**: The developed algorithm may have a large number of iterations, parameters to adjust, features extracted, or classification steps. It is desirable to provide numerically efficient (simple, fast, and fewer calculations required) algorithms. Of course, computers are very fast today, so numerical efficiency is less important than it used to be. However, if a

simple and fast algorithm can achieve good results, there is no need for complicated algorithms. In particular, when the algorithm is used online (in a slightly modified form from the offline version) in an embedded system, numerical efficiency would still be relevant.

Aas shown in Figure 2, any automated QRS detection algorithm structures can be divided into two stages: QRS enhancement and QRS detection [19].

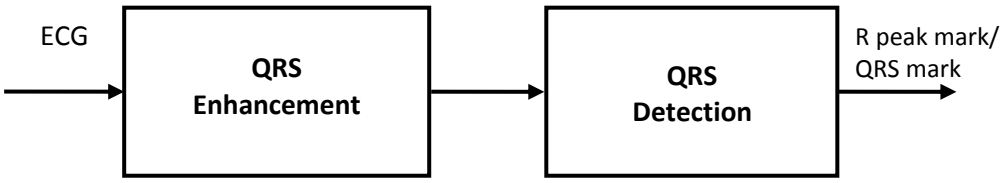


Figure 2. QRS detection structure. It consists of two stages: QRS enhancement (i.e. filtering) and QRS detection (or classification).

The QRS enhancement stage is used to enlarge the QRS complex compared to the other ECG features (P, T, and noise). The QRS enhancement stage is occasionally called pre-processing or feature extraction. The QRS detection stage is used to demarcate the QRS complex by providing the onset and offset of the QRS complex. If the R peak is required to be detected, an extra step is needed to determine the maximum amplitude value within the detected QRS complex.

This review is structured as follows. In the next section we discuss types of QRS enhancements techniques in time domain. Section 3 elaborates on the QRS enhancements in frequency domain, while Section 4 shows the QRS enhancements in time-frequency domain. Section 5 compares different QRS detection methods. Finally a conclusion and discussion is covered in Section 6.

2. QRS Enhancement in Time Domain

This section presents several signal processing techniques used to emphasise the QRS detection area. It is an important stage before detecting the QRS complex.

2.1 First Derivative Only

The differentiator is commonly used as a high-pass filter, to modify the phase of the ECG signals and to create zero crossings in the location of the R peaks.

Usage in algorithms

This first-derivative-only step has been used extensively in literature to detect QRS complexes as follows:

- first derivative of ECG signal followed by threshold [20-22] (thresholding will be discussed in Section 5.1)
- amplitude threshold applied to ECG signal followed by First derivative of ECG signal [23, 24] (see Section 2.2), followed by threshold
- first derivative combined with second derivative of ECG signal [25, 26] (see Section 2.3), followed by threshold
- first derivative of ECG signal followed by digital filters [27] (see section 2.4), followed by threshold

- digital filter applied to ECG signal followed by first derivative [28], followed by threshold
- mathematical Morphology filtering applied to ECG signal followed by first derivative [29] (see Section 2.5), followed by threshold
- first derivative can be used before applying Hilbert transform [30-32] (see Section 3.1), followed by threshold
- first derivative can be used before applying Wavelet transform [33] (see Section 4.2), followed by threshold

Assessment criteria:

1. **Robustness to noise:** the first derivative does not remove high-frequency noise; however, it helps to reduce the motion artifacts and base line drifts [33].
2. **Parameter choice:**
   - The processed ECG segments have equally fixed lengths and thresholds [20-22].
   - As mentioned above, researchers have introduced several differentiators without mentioning the reason behind their choices [20-22].
3. **Numerical efficiency:** amplitude and first derivative class of algorithms is simple and contains one equation for features extraction. Most cases used Okada's equation. The complexity of this class will increase if segmentation is applied. The order of complexity depends on the number of processed segments for each record.

2.2 Amplitude and First Derivative

In older algorithms, the amplitude threshold is applied before any differentiation to the signal is applied in order to horizontally cut the ECG signal to reduce the P and T waves' influence compared to the R wave. The first derivative is applied after the amplitude threshold to steep up the slope of the QRS complex, where the amplitude threshold is calculated as a fraction of the measured ECG signal .

Usage in algorithms:

This amplitude and first derivative step has been used in literature to detect QRS complexes as follows:

- amplitude threshold is applied to the ECG signal, followed by the first derivative of the ECG signal [23, 24] and then the threshold.

Assessment criteria:

1. **Robustness to noise:** the signal noise is not removed properly and is not considered by the first-derivative-only class of algorithms for features extraction.
2. **Parameter choice:**
   - The processed segments have equally fixed lengths [23-27, 34].
   - The value of the β ratio must be adjusted once before the ECG signal analysis takes place. It is a fixed threshold through the entire ECG signal analysis [23-27, 34].
   - As mentioned above, researchers have introduced several differentiators by without mentioning the reason behind their choices [23-27, 34].
   - The choice of the processed ECG segment length is determined experimentally [23-27, 34].
   - Friesen et al. [35] used ECG data with a fixed length of 33 seconds. Their algorithm scored a high accuracy because they processed small

segments of ECG signals. It is expected that the performance of this algorithm on longer ECG signals will be poor unless the long ECG signals are separated into smaller segments. In this case, the performance will be better; however, there is a possibility of losing beats at the beginning and end of each processed ECG segment.

3. **Numerical efficiency:** amplitude and first derivative class of algorithms is simple and contains one equation for features extraction. Most cases used Okada's equation. The complexity of this class will increase if segmentation is applied. The order of complexity depends on the number of processed segments for each record.

2.3 First and Second derivative

Some algorithms compute the first and second derivatives of the measured ECG signals independently. A linear combination of the magnitudes of the first and second derivative is used to emphasise the QRS complex area compared to the rest of the ECG features.

Usage in algorithms

The first and second derivatives step has been used in literature to detect QRS complexes as follows:

- first derivative combined with second derivative of ECG signal [25, 26], followed by threshold.
- second derivative can be used before applying Hilbert transform [30, 32] (see Section 3.1), followed by threshold.

Assessment criteria

1. **Robustness to noise:** the signal noise is not removed properly and is not considered by the first-derivative-only class of algorithms for features extraction.
2. **Parameter choice:**
   - The processed segments have equal and fixed lengths [23-27, 34].
   - The parameters used are fixed.
   - The choice of the first and second derivatives equations is experimentally conducted [25, 26]. Moreover, authors do not justify the combination of the first and second derivatives.
   - As mentioned above, researchers have introduced different differentiators without mentioning the reason behind their choices [25, 26].
3. **Numerical efficiency:** first- and second-derivative classes of algorithms are simple and contains up to four equations for features extraction. The complexity of this class derives from the ECG segmentation. The order of complexity depends on the number of processed segments for each record.

2.4 Digital Filters

Algorithms based on more complicated digital filters were published in [20, 27, 35-40].

A multiplication of backward difference (MOBD) algorithm is proposed in literature [41, 42] as digital filter to detect QRS complexes, which is basically an AND-combination of adjacent magnitude values of the derivative.

Commonly, a bandpass digital filter used in detecting QRS complexes, especially the one introduced by Pan and Tompkins [28].

There have been more sophisticated digital filters published in literature [27, 28, 43-50], as described briefly below.

Usage in Algorithms

Digital filters have been used extensively in literature to detect QRS complexes as follows:

- first derivative of ECG signal followed by digital filters followed by threshold [27].
- bandpass filter applied to ECG signal followed by first derivative, followed by threshold [28]
- bandpass filter applied first before Hilbert transform (see Section 3.1), followed by threshold [51]
- bandpass filter can be followed by first derivative before applying Wavelet transform (see Section 4.2), followed by threshold [33]
- Bandpass filter applied to ECG signal followed by matching filter (see Section 4.3), followed by threshold [52]

Assessment criteria:

1. **Robustness to noise:** the digital filter can increase the SNR ratio according to the nature of the used filter and its order.
2. **Parameter choice:**
   - The processed segments have equal and fixed lengths [23-27, 34].
   - The parameters used are fixed.
   - The choice of the differentiator in the digital filters works as a notch filter.
   - In the digital filters algorithms, the low-pass filter is usually a symmetrical amplification. The values of amplifications are determined experimentally.
   - The mathematical operations used are not justified by authors (e.g. squaring, difference, multiplication).
3. **Numerical efficiency:** the digital filters class of algorithms is simple and contains up to four equations for features extraction. The complexity of this class will increase if segmentation is applied. The order of complexity depends on the number of processed segments for each record.

2.5 Mathematical Morphology

The use of mathematical morphology operators for QRS detection was described in [53]. Mathematical morphology originates from image processing and was proposed for ECG signal enhancement in [54]. The successful removal of noise from the ECG is reported therein.

Usage in algorithms

The mathematical morphology algorithm has been used in literature to detect QRS complexes as follows:

- mathematical morphology filtering applied to ECG signal, followed by threshold [55].
- mathematical morphology filtering applied to ECG signal, followed by first derivative, followed by threshold [29].

Assessment criteria

1. **Robustness to noise:** the signal noise is partially addressed by the mathematical morphology class of algorithms. The use of a low-pass filter improves the SNR.
2. **Parameter choice:**
   - The processed segments have equal and fixed lengths [23-27, 34].
   - The structuring element is fixed during the ECG analysis.
   - The length of the structuring element used is three which a fixed value.

- The length of the structuring element is determined experimentally. The length of the operating structure element must be shorter than the product of the length of the signal wave and the sampling frequency [55]. Therefore, the length of the structuring element can be different to three.
- The authors to not justify the multiplication operations used [23-27, 34].

3. **Numerical efficiency:** the mathematical morphology class of algorithms is simple and contains at least 15 equations for features extraction. The complexity increases with the number of processed ECG segments. Certainly, the order of complexity is higher than the derivative-based algorithms and digital filter algorithms.

2.6 Empirical Mode Decomposition

The Empirical Mode Decomposition (EMD) has been introduced by Huang *et al* [56] for nonlinear and non-stationary signal analysis. The key part of this method is that any complicated data set can be decomposed into a finite and often small number of Intrinsic Mode Functions (IMFs) that admits well behaved Hilbert transforms.

Usually when the raw ECG signals get decomposed into number of IMFs, the combination of the IMFs produces a signal where QRS is more salient. This process can be considered as an adaptive filtering, similar to the use of Wavelet transform.

Usage in algorithms

The empirical mode decomposition algorithm has been used in literature to detect QRS complexes as follows:

- Empirical Mode Decomposition filtering applied to ECG signal followed by threshold [57].
- Empirical Mode Decomposition filtering applied to ECG signal followed by singularity and threshold [58],[59]
- High-pass filter applied to ECG signal, followed by EMD filtering, followed by threshold [59].

Assessment criteria:

1. **Robustness to noise:** the first several IMFs can filter out the noise and preserve the QRS content compared to the other ECG features [58]. Therefore the first several IMFs are mainly caused by the QRS complex and improve the SNR.
2. **Parameter choice:**
   - The processed segments have equally fixed lengths [58].
   - The number of IMFs depends on the length of the ECG segment. If the segment length is increased, the number of IMFs will increase.
   - The length of the ECG segment is not determined experimentally.
   - The choice of IMFs is determined by trial-and-error methodology.
3. **Numerical efficiency:** the EMD class of algorithms is simple and contains at least nine steps with several equations for features extraction. The complexity increases with the number of processed ECG segments. Certainly, the order of complexity is higher than the derivative-based algorithms and digital filter algorithms.

3. QRS Enhancement in the Frequency Domain

3.1 Hilbert Transform

The use of the Hilbert transform for QRS detection is proposed in [60, 61], and it is usually used to rectify the phase in order to create a signal with outstanding peaks in the location of the R peaks [30-32].

Usage in algorithms

The Hilbert transform has been used in literature to detect QRS complexes as follows:

- first derivative can be used before applying Hilbert transform followed by threshold [30-32]
- bandpass filter applied before Hilbert transform, followed by threshold [51]
- wavelet transform (see Section 4.2) applied before Hilbert transform, followed by threshold [62].

Assessment criteria

1. **Robustness to noise:** the Hilbert transform does not improve the SNR itself. Therefore, some researchers filter the signal before applying the Hilbert transform to the signal. Benitez et al. [31] used bandpass filter 8−20 Hz to remove muscular noise and maximise the QRS.
2. **Parameter choice:**
   - The processed segments have equally fixed lengths [31, 63].
   - When the FFT approach was implemented in calculating the Hilbert transform, no dependence of the envelope on the frame width was detected for frames of 512−2,048 points.
   - The length of the ECG segment is not determined experimentally.
   - The choice digital filters and moving average are determined experimentally.
3. **Numerical efficiency:** the Hilbert transform algorithm contains at least nine steps with several equations for features extraction. However, the primary disadvantage of this method is the increased computational burden required for FFT calculations compared to the time domain approaches. Hilbert transform techniques generally have a large computation overhead [63]. Moreover, the complexity increases with the number processed ECG segments.

4. QRS Enhancement in the Time-Frequency Domain

4.1 Filter Banks

Filter banks decompose the bandwidth of the input ECG signal into subband signals with uniform frequency bands. The subbands can be downsampled since the subband bandwidth is much lower than that of the input signal. The subbands provide information from various frequency ranges; thus, it is possible to perform time- and frequency-dependent processing of the input signal.

Similar to EMD, a variety of features are indicative of the QRS complex can be designed by combining sub-bands of interest reported in [64].

These features have values that are proportional to the energy of the QRS complex. Finally, heuristic beat-detection logic can be used to incorporate some of the above features that are indicative of the QRS complex.

Usage in algorithms

The filter banks have been used in literature to detect QRS complexes as follows:

- filter banks applied to ECG signal followed by threshold [64, 65].
- wavelet transform (see Section 4.2) applied to ECG signal, followed by filter banks, followed by correlation [66].

Assessment criteria

1. **Robustness to noise:** the filter banks significantly improve the SNR for Gaussian noise compared to the mean and median averaging methods [67]. For muscle noise, the filter banks improve the SNR comparatively better than the mean and median averaging methods [67].
2. **Parameter choice:**
   - The length of the filter, number of subbands, transition-band width and stop-band attenuation have fixed values [68]. For example, the length of each of the finite impulse response (FIR) filters used by Afonso et al. [67] was 32. The input noisy ECG is decomposed by the analysis filters into eight uniform subband frequencies. The sub-band signal in the (0—12.5 Hz) range is not modified. The subband signal in the (12.5—25 Hz) range is attenuated in the period outside the QRS complex. Any high-frequency components outside the QRS complex are modelled as noise. Thus, in the remaining six sub-bands (25—100 Hz*)*, the signal is nulled in periods outside the QRS complex.
   - The filter bank complexity depends on four parameters [68]: length of filter, number of sub-bands, transition-band width and stop-band attenuation. Theses parameters are determined experimentally.
   - The main difficulty is choosing the optimal bank filters and their optimal combination in order to emphasise the QRS complexes.
3. **Numerical efficiency:** The drawback of using filter banks is a relatively high computational cost due to the involvement of a large amount of multipliers in the FIR filters [65].

4.2 Wavelet Transform

Wavelets are closely related to filter banks and EMD. It is defined as an integral transform, usually implemented using a dyadic filter bank where the filter coefficients are directly derived from the wavelet function used in the analysis [69, 70].

Usage in algorithms

The WT transform has been used in literature to detect QRS complexes as follows:

- WT applied to ECG signal, followed by threshold [71, 72]
- first derivative can be used before applying Wavelet transform followed by Zero crossing (see section 5.6), followed by threshold [73]
- WT applied first before Hilbert transform, followed by threshold [74]
- WT applied to ECG signal, followed by filter banks, followed by correlation [75]
- WT applied to ECG signal, followed by neural networks (see Section 5.2) [73]
- Wavelet transform applied to ECG signal, followed by singularity (see 5.7) and zero crossing (see Section 5.6), followed by threshold [74]

Assessment criteria:

1. **Robustness to noise:** WT does not increase the SNR, but the SNR can be improved by selecting the coefficients with the largest amplitude [75].
2. **Parameter choice:**
   - Choosing the mother wavelet is usually determined by the shape of the wavelet, which should be closer to the QRS complex shape, and it depends on the researcher's methodology in detecting the QRS complex.
   - One mother wavelet (i.e. Haar, Daubechies, Biorthogonal, Mexican hat must be chosen once during the entire ECG analysis.

- Choosing the length of the processed ECG segment does varies in literature. Ahmed *et al* (2000) split the ECG signals into 2.4-seconds segments while Zheng and Li split the signals into 11 seconds.
- Choosing the wavelet scale for varies in literature. Szilagyi and Szilagyi [76] used scales 2^3 and 2^4, which reflect the QRS complex, while Xu et al. [77] used scales from 2^2 to 2^4 to detect QRS complexes.
- Choosing the sampling frequency of the processed ECG signal;. Martinez *et al* (2004) recommended to resample the signal at 250 Hz.

3. **Numerical efficiency:** if the ECG is segmented (this is usually the case), the length of the segment reflects the tradeoff between the accuracy and computational time-consumption of the algorithm [71]. In general, WT, similar to filter banks, is relatively high in computational cost [78].

5. QRS Detection

After extracting the QRS features using the discussed algorithms, the next step is to detect QRS complexes. This step comes after extracting the ECG features that contain QRS that is more emphasised compared to the noise and other ECG features.

5.1 Threshold

Thresholding can be applied to time-domain [23, 24] and time-frequency ECG signals. The use of a fixed threshold to detect QRS complexes is simple and efficient for stationary ECG signals with normal beat morphology. Due to severe baseline drifting and movement of patients, an ECG signal waveform may vary drastically from one heartbeat to the next, as shown in Figure 3. Therefore, the probability of missing QRS complex is high. With adaptive thresholding, the probability of missing QRS complexes decreases. Adaptive thresholding mainly uses multiple thresholds empirically.

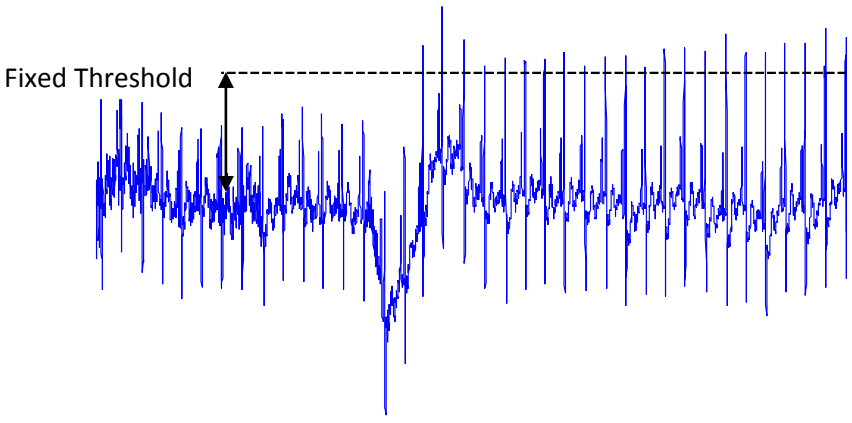


Figure 3 Fixed threshold in ECG segment. The measured ECG signals carry significant clinical information for a cardiologist, especially R peak detection in ECG signals. R-peak detection generally uses the threshold value, which is fixed. The QRS cannot be detected below the fixed threshold value. Moreover, the fixed threshold will affect the detection of P and T waves.

Usage in algorithms

The threshold step has been used in literature as the last stage for most of the QRS detection algorithms [20-22] [23-26] [30-33] [29]

Assessment criteria

1. **Robustness to noise:** The performance of the threshold approach will be affected by low SNR signals [28, 35].
2. **Parameter choice:**
   - The threshold is a fixed value [21, 25, 27, 28].
   - The threshold is experimentally defined [21, 25, 27, 28]. The real difficulty derives from choosing the optimal threshold.
3. **Numerical efficiency:** the threshold approach is simple. It is an IF-THEN-ELSE statement. Therefore, it is considered computationally efficient by researchers [21, 25, 27, 28].

5.2 Neural Networks

Artificial neural networks (ANNs) mimic the biological neural process, similar to the human brain, by modelling the neurological information processing by means of a mathematical paradigm. Different types of ANNs have been used in literature to classify classical linear and non-linear approaches. However, mostly the multilayer perceptrons (MLP), radial basis function (RBF) networks and learning vector quantization (LVQ) networks are used in the analysis of ECG signals.

RBF networks are closely related to fuzzy-logic methods [78]. The advantage of RBF networks over MLP networks is, similar to fuzzy-logic methods, the possibility to interpret the parameters. This makes the results more predictable and hence reliable.

The LVQ network consists of an input layer, a competitive layer and a linear layer. The competitive layer automatically learns to classify input vectors into sub-classes, where the maximum number of subclasses N equals the number of competitive neurons. In this layer, classification is accomplished on the basis of the Euclidian distance between the input vector and the weight vector of each of the competitive neurons. Finally, the linear layer combines the subclasses of the first layer with the user-defined target classes.

To accomplish the classification, the parameters of the network need to be trained. Whereas the MLP and RBF networks are trained by supervised learning algorithms, the LVQ network is adjusted in an unsupervised manner. Appropriate training algorithms are described in the literature; for example, in [79, 80]

The application of neural networks in the field of ECG waveform classification is reported in [19, 43, 81-89]. Some of these algorithms [19, 87, 89, 90] are also concerned with the QRS detection problem.

Usage in algorithms

The neural networks (NNs) have been used in literature to detect QRS complexes as follows:

- WT applied to ECG signal, followed by NNs [73]
- wavelet applied first to ECG signal, followed by Hidden Markov Model (HMM; see Section 5.3) [91]
- NNs (used as a filter) applied to ECG signal, followed Matched Filter (see Section 5.4) [90]

Assessment criteria

1. **Robustness to noise:** NNs are highly sensitive to noise [92]. The performance of the classifier can be significantly reduced if the NNs is constructed with a proper architecture and trained with appropriate data.
2. **Parameter choice:**
   - The type of the NNs must be chosen and adjusted before the analysis.

- Number *N* of inputs to NNs: to have just one single NN with a fixed number *N* of inputs, with each one receiving one of the samples from the window. The number of samples per window must then be fixed [93].
- There is a range of samples to be selected as the number of NN inputs, for example, García-Berdonés et al. [93] used 20 samples as the number of inputs.
- Choosing the number of neurons in the NN hidden layer still remains a challenge. There is no definite way of determining the right number of neurons in hidden layer.

3. **Numerical efficiency:** the training phase can be a numerically inefficient as it is an iterative process for adjusting the NN's weights [94]. If the number of hidden neurons is too large, the NN will need more storage and the computational load for training.

5.3 Hidden Markov Model

HMMs models have proved to be a powerful and flexible class of statistical model for describing many different types of sequential data [92]. Coast and Cano [95] were first to prove that HMM is a promising technique for detecting QRS complexes in ECG signals.

The objective of the algorithm is to infer the underlying state sequence from the observed signal. The advantage of this detection method is that not only is the QRS complex determined, but the P- and T-waves are also detected.

Usage in algorithms

The HMM has been used in literature to detect QRS complexes as follows:

- bandpass filter applied to ECG signal, followed by HMM [95, 96]
- wavelet applied to ECG signal, followed by HMM [91]

Assessment criteria

1. **Robustness to noise:** HMM is sensitive to noise, baseline wander, DC drift and heart rate variation [97].
2. **Parameter choice:**
   - Determining the number of states, transition probabilities and output function has been done experimentally.
   - The parameters of a HMM cannot be directly estimated from training data using maximum likelihood estimation formulas, since the underlying state sequence that produced the data is unknown [95].
   - HMM parameters are to be fixed.
3. **Numerical efficiency:**
   - The problems of the method include a necessary manual segmentation for training prior to the analysis of a record, its patient dependence, and the considerable computational complexity, even when the computationally efficient Viterby algorithm [98] is applied.
   - The number of parameters that need to be set in an HMM is large—there are usually from 15 to 50 parameters that need to be evaluated.

5.4 Matched Filters

There are linear matched filtering approaches as, for example, reported in literature [99-102]. A bandpass filter is usually recommended before using the matched filter to improve the SNR. Moreover, real-time computations of matched filters are reported in [99] and [101].

Usage in algorithms

The matched filters have been used in literature to detect QRS complexes as follows:

- Matched filters applied to ECG signal [103]
- Digital filter applied to ECG signal, followed by matched Filters [100, 104]
- NNs (used as a filter) applied to ECG signal, followed matched Filter [90]

Assessment criteria

1. **Robustness to noise:** the matched filter improves the SNR [105].
2. **Parameter choice:**
   - fixed template length.
   - The template length and filter are determined experimentally.
3. **Numerical efficiency:**
   Template multiplication is computationally inexpensive due to the sample by sample comparison. In general, it is computationally expensive because of the sample-by-sample moving comparison with the template along the ECG signals.

5.5 Syntactic Method

A syntactic algorithm has been used for ECG signal analysis in [106-108]. A syntactic method is assumed to be a concatenation of linguistically represented primitive patterns; that is, strings. Using a grammar, this string representation is parsed for strings coding a search pattern. Therefore, a syntactic algorithm for pattern recognition essentially requires the definition of primitive patterns, a suitable linguistic representation (alphabet) of the primitive patterns, and the formulation of a pattern grammar. In ECG processing, the signal is split into short segments of a variable or fixed length. Each segment is then represented by a primitive, and then coded using the predefined alphabet. Most algorithms use line segments as primitives for the signal representation. In [108] the set of line primitives is extended by peaks, parabolic curves and additional attributes.

Usage in algorithms

The syntactic method is applied to an ECG signal to detect a QRS complex by itself [106-108].

Assessment criteria

- **Robustness to noise:** the syntactic method is sensitive to noise [108].
- **Parameter choice:**
  - The length of the segment is fixed. Belforte et al. [106] used 30-seconds duration per segment.
  - Four fixed attributes used the syntactic method [107]: degree of curvature, arc length, chord length and arc symmetry, which are determined experimentally.
- **Numerical efficiency:**
  The syntactic method has a high computational cost compared to the discussed approaches. Measurements of the various parameters have to be performed; powerful grammars capable of describing syntax as well as semantics are needed as a model for the formulation of a pattern grammar.

5.6 Zero Crossing

Kohler *et al* (2001) proposed the QRS detection based on zero crossing counts. A bandpass filter is usually applied first to the ECG signal.

Usage in algorithms

The zero-crossing technique has been used in literature to detect QRS complexes as follows:

- bandpass filter applied to ECG signal, followed by zero crossing [109]
- WT applied to ECG signal, followed by zero crossing, followed by threshold [110, 111]
- WT applied to ECG signal, followed by singularity and zero crossing, followed by threshold [74]

Assessment criteria:

1. **Robustness to noise: t**he zero crossing is sensitive to noise [109].
2. **Parameter choice:**
   - The threshold used for counting the number of zero crossings per segment is fixed [109] and determined experimentally.
   - Choosing the wavelet scales to search for zero-crossing varies in literature [111, 112].
3. **Numerical efficiency:** the zero-crossing approach is simple but computationally inefficient. This is because of the time consuming stages in the maximum/minimum search for the temporal localisation of the R wave [109].

5.7 Singularity

Mallat and Hwang [112] introduced the singularity algorithm. To detect the QRS complex, the R peak must be detected first. The detection of R peaks is performed by scanning for simultaneous modulus maxima in the relevant scales of the WT. For a valid R peak, the estimated Lipschitz regularity must be greater than zero.

Besides the condition on the Lipschitz regularity, the algorithm applies further heuristic decision rules such as conditions on the sign and the timing of the peak occurrence within the different scales. Once the R peak is detected, the Q and S waves can be detected. The onset of the QRS complex (Q wave) corresponds to the first modulus maximum before the R wave, and the offset of QRS complex (S wave) corresponds to the first modulus maximum after the R wave.

Many other QRS detection algorithms based on local maxima are presented in [113], [114] and [115]. In [74], characteristic points are detected by comparing the coefficients of the discrete WT on selected scales against fixed thresholds.

Usage in algorithms

The singularity technique has been used in literature to detect QRS complexes as follows:

- EMD filtering applied to ECG signal, followed by singularity and threshold [58]
- WT applied to ECG signal followed by singularity and zero crossing, followed by threshold [74]

Table 1. Comparison based on techniques used in the QRS enhancement and detection stages, and subjective numerical efficiency. SE and +P stand for sensitivity and positive productivity respectively.

Publication	QRS Enhancement	QRS detection	Database	Number of beats	Numerical Efficiency	SE (%)	+P (%)

Pan and Tompkins [28]	First derivative + squaring + bandpass filter	Multiple thresholds	MIT-BIH	116137	Medium	99.76	99.56
Kadambe et al. [116]	First derivatives + moving averages	Threshold	CSE-3	17988	High	98.5	99.18
Arzeno et al. and Benitez et al. [30, 31]	First derivative + Hilbert transform	Threshold	MIT-BIH	109257	Medium	99.13	99.31
Arzeno et al. [30]	First derivative + Hilbert transform	Two thresholds	MIT-BIH	109517	Medium	99.29	99.24
Arzeno et al. [30]	First derivative + squaring + bandpass filter	Multiple thresholds	MIT-BIH	109504	Medium	99.68	99.63
Arzeno et al. [30]	First derivative + squaring + bandpass filter	Variable thresholds comparison	MIT-BIH	109436	Medium	99.57	99.58
Arzeno et al. [30]	Second derivative + squaring + bandpass filter	Variable thresholds comparison	MIT-BIH	108228	Medium	98.08	99.18
Ayat et al. [117]	Bandpass Filter + First Derivative + Moving average	Threshold	MIT-BIH	N/R	High	99.74	99.81
Ayat et al. [117]	Bandpass Filter + First Derivative + Moving average	Threshold	AHA	N/R	High	99.47	99.73
Moraes et al. [118]	Low pass filter + First derivative + modified spatial velocity	Threshold	MIT-BIH	109481	Medium	99.69	99.88
Chouhan and Mehta [119]	Digital filters	Threshold	MIT-BIH	102654	Medium	99.55	99.49
Hamilton [120]	Digital filters	Multiple thresholds	MIT-BIH	109487	Medium	99.77	99.64
Lee et al. [121]	WT	Multiple thresholds + zero Crossing	MIT-BIH	104182	Medium	99.89	99.94
Chen et al. [122]	WT	Multiple thresholds + zero Crossing	MIT-BIH	109428	Medium	99.8	99.86
Adnane et al. [123]	Filter banks	Multiple thresholds	MIT-BIH	90909	Low	99.59	99.56
Martinez et al. [124]	Continuous WT	Threshold	MIT-BIH	109837	Medium	99.91	99.72
Afonso et al. [125]	Discrete WT + Cubic Spline Interpolation + moving average	Threshold	MIT-BIH	N/R	Low	98.68	99.59
Ghaffari et al. [126]	Hybrid Complex WT	Threshold	MIT-BIH	24000	Low	99.79	99.89
Ghaffari et al. [126]	Complex Frequency B-Spline WT	Threshold	MIT-BIH	24000	Low	99.29	99.89
Ghaffari et al. [126]	Complex Morlet WT	Threshold	MIT-BIH	24000	Medium	99.49	99.29

Assessment criteria:

1. **Robustness to noise:** the singularity approach is sensitive to noise [127].
2. **Parameter choice:**
   - Choosing the wavelet scales to search for singular points is performed experimentally [127, 128].
   - The threshold used for detecting R peaks per segment is fixed [127].

- The threshold used for detecting R peak counts per segment is determined experimentally.

3. **Numerical efficiency:** the singularity approach load is more complicated than the zero-crossing approach. It is computationally inefficient because of the consuming stages in the search and the optimisation to detect R waves in ECG segments [74, 127].

6. Discussion and conclusions

Performance of QRS detection algorithm is typically done using two statistical measures: $SE=TP/(TP+FN)$ and $+P=TP/(TP+FP)$, where *TP* is the number of true positives (QRS complexes detected as QRS complexes), *FN* is the number of false negatives (QRS complexes has not been detected as QRS complexes), and *FP* is the number of false positives (non-QRS complexes detected as QRS complexes). The sensitivity *SE* reports the percentage of true beats that were correctly detected by the algorithm. The positive predictivity $+P$ reports the percentage of beat detections that were true beats.

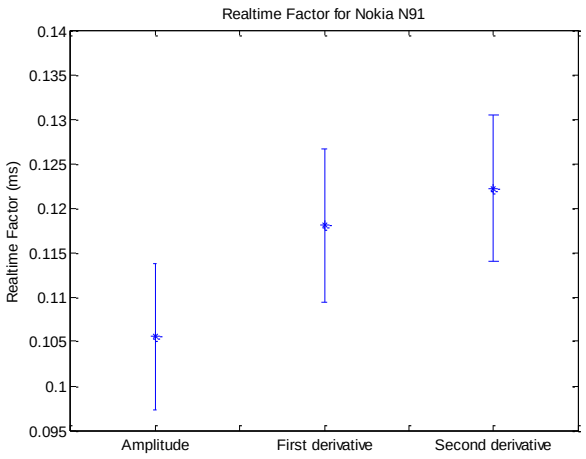
The performance of current QRS detection algorithms is not completely assessed in terms of robustness to noise, parameter choice, and numerical efficiency. Moreover, many of the QRS algorithms were not tested against a standard database or any database at all. Many researchers scored high detection performance using few records. This issue makes the results difficult to compare and evaluate.

Few algorithms from the literature demonstrate the idea of scoring high performance using few ECG recordings:

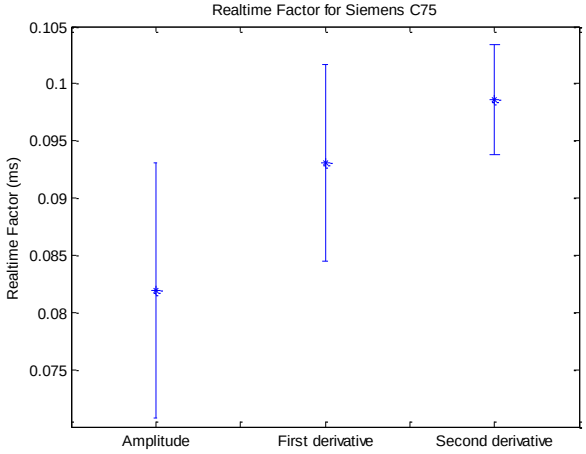
- Xue et al. reported sensitivities of 99.84 per cent and 99.09 per cent and positive predictivity of 99.61per cent and 98.59 per cent based on just two records—numbers 105 and 108—from the MIT−BIH Arrhythmia Database [129].
- Lee et al. [121] scored 0.15 per cent false detections based on 46 files from the MIT−BIH Arrhythmia Database [129], excluding files 214 and 215.
- Several publications have listed the use of all files in the MIT−BIH Arrhythmia Database, excluding patients with pacemakers. For example, Fard et al. [128] achieved a sensitivity of 99.22 per cent and specificity of 99.73 per cent after excluding records (108, 200, 201 and 203) of patients with pacemakers.
- Alvarado et al. [130] reported a sensitivity of 99.87 per cent and a positive predictivity of 99.82 per cent after using nine files out of 48 from the MIT−BIH Arrhythmia database.
- [29] scored accuracy of 99.67 per cent after using five files out of 48 from MIT−BIH Arrhythmia database.
- [33] scored accuracy of 99.69 per cent after using nine files out of 48 from MIT−BIH Arrhythmia Database.
- Chen et al. [122] excluded segments with ventricular flutter in record 207 of MIT−BIH Arrhythmia Database (2 min 24 s).

As discussed above, the number of records affects the overall accuracy of all detection algorithms. This means that there is an extra problem added to the previous three problems (robustness to noise, parameter choice, and numerical efficiency), which is the number of records used in testing the developed algorithm.

(a)



(b)



(c)

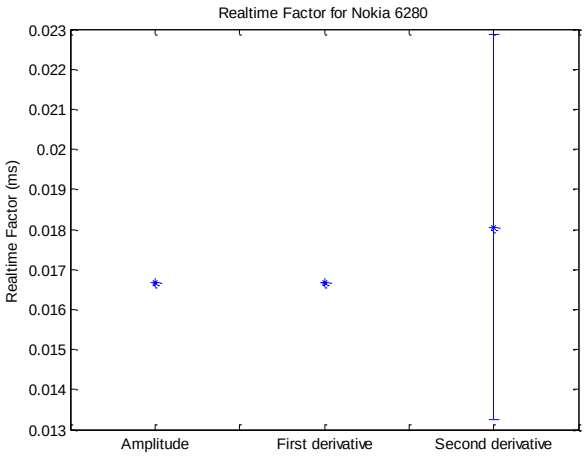


Figure 4 Realtime factors for three different mobile phones. Three QRS detection algorithms have been tested, as reported by [131]. The QRS enhancement phase was amplitude, first-derivative, and second-derivative based, while the QRS detection was thresholding. Realtime factor is the processing time needed to run the QRS detection algorithm for an individual ECG entry within one measurement window size of 60 seconds.

As discussed, some authors excluded records from the MIT−BIH Arrhythmia Databasee for the sake of reducing the amount of noise in the processed ECG signals; consequently their algorithms achieved better performance. Other researchers excluded segments with ventricular flutter [122] and paced patients [128] from their

investigations. Therefore, a robust algorithm is required to analyse ECG signals without excluding any records or particular segments.

As the essential quality is real-time monitoring with enough overhead left to perform classification, the numerical efficiency (complexity) will play a major role in the algorithm selection. The simpler the algorithm, the faster it is. However, it does not mean that a faster algorithm will be more accurate. In here, the numerical-efficiency will be considered independently of the accuracy factor.

Many QRS detection algorithms have been published; therefore, a comparison needs to be conducted. An algorithmic comparison regarding the numerical efficiency assessment criteria has been carried out subjectively. As shown in Table I, each algorithm has been categorised as low, medium or high in terms of its numerical efficiency, based on the number of iterations and the number of equations (e.g. multiplications, additions, differentiations) used. The higher the numerical efficiency, the faster the algorithm, and vice versa. Consequently, the faster the algorithm, the more suitable it is for real-time monitoring.

Table I shows that Chouhan and Mehta algorithm [119] and Hamilton [120] are highly-numerically efficient, and the use of first derivative with/out moving average in the QRS enhancement phase is promising. Moreover, applying a dynamic threshold in the QRS detection phase can be efficient. However, these two algorithms tested on small ECG segments and their performance is lower than other algorithms.

With advances in computation, the demand for numerical efficiency gets lower and lower. Perhaps this is the case when the ECG signals are collected and analysed in hospitals, but it is not the case for portable ECG devices which are battery driven, especially the use of mobile phone for collecting ECG signals for patient monitoring. Therefore, there is a need for developing numerically efficient algorithms to accommodate the new wave of mobile ECG device and to analyse long-term recorded signals in a time-efficient manner.

Sufi et al. [131] investigated three QRS algorithm suitable for mobile phones. The QRS enhancement phase of their algorithms were amplitude, first-derivative, and second-derivative based while the QRS detection phase was a threshold based. For sure, they used simple methodologies for QRS enhancement and detection to be implemented over mobile phones. This simplicity has been confirmed in table I when we found the first derivative and threshold are efficient combination for detecting QRS if developed properly.

It turns out that Nokia 6280 consumes the least processing time, shown in Figure 4. As expected the amplitude based QRS enhancement technique was faster than the first-derivative and second derivative based techniques. In their study the quality of ECG signals has been discussed and data used was clean. However, their result is a foundation step for monitoring ECG signals using mobile phone, but it had some limitation in terms of memory and processing time.

Nowadays, smartphones have advanced processing and storage capabilities, which include a powerful CPU, memory and a GPU with high-speed data access via Wi-Fi or mobile broadband [132]. Therefore, implementing the discussed QRS detection algorithms over smartphone is becoming more feasible. Moreover, the consideration of the assessment critera (robustness to noise, parameter choice, and numerical efficiency) will improve the quality of diagnosis with respect to processing time.

Another aspect that has been ignored in literature is the clinical utility of the discussed ECG algorithms. It is rare to find an article that addresses the usefulness of the developed detector(s) in a clinical setting. As far as we are aware, there is no evidence that shows whether the discussed algorithms are currently implemented in practice (such as clinics or/and hospitals).

In conclusion, this overview provides a valuable indication of the required algorithms based on literature and our experience. The use of first-derivative methodology is recommended as it is highly-numerically efficient for the QRS enhancement phase, but it is sensitive to noise and arrhythmia; therefore, an adaptive

thresholding is needed in the classification phase. Both of these suggested methodologies are simple and computationally efficient to detect QRS complexes for mobile-phone applications. The simplicity and efficiency are required in developing QRS detection algorithms for processing long-term recordings and large databases, and expanding our telemedicine capabilities in the near future.

Acknowledgement

The author would like to thank Dr Gari Clifford for helpful discussions.

References

1. Australian Institute of Health and Welfare 2008, *Australia's Health 2008*, Australian Institute of Health and Welfare, Canberra.
2. Australian Bureau of Statistics 2009, *Causes of Death*, Australian Bureau of Statistics 2009, Canberra.
3. Global Cardiovascular Infobase. Ottawa, Canda: WHO Collaborating Centre on Surveillance of Cardiovascular Diseases, Surveillance and Risk Assessment Division, CCDPC, Public Health Agency of Canada and The Ottawa Hospital, University of Ottawa; [updated: 2006 March 3; cited: 2010 May 15]. Available from: http://www.cvdinfobase.ca/.
4. Australian Institute of Health and Welfare 2008, *Australia's Health*, Australian Institute of Health and Welfare, Canberra.
5. Tsipouras, M.G., Fotiadis, D.I., and Sideris, D. *Arrhythmia classification using the RR-interval duration signal*. Proceedings of Computers in Cardiology, 2002.
6. Tran, T., McNames, J., Aboy, M., and Goldstein, B., *Prediction of paroxysmal atrial fibrillation by analysis of atrial premature complexes.* Biomedical Engineering, IEEE Transactions on, 2004; **51**(4): 561-569.
7. Bashour, C.A., M. Visinescu , B. Gopakumaran,O. Wazni, F. Carangio, J.P. Yared, N. Starr, *Characterization of premature atrial contraction activity prior to the onset of postoperative atrial fibrillation in cardiac surgery patients.* CHEST, 2004; **126(4)**: 831S.
8. deChazal, P., O'Dwyer, M., and Reilly, R.B., *Automatic classification of heartbeats using ECG morphology and heartbeat interval features.* IEEE Transactions on Biomedical Engineering, 2004; **51**(7): 1196-1206.
9. Krasteva, V., Jekova, I., and Christov, I. *Automatic detection of premature atrial contractions in the electrocardiogram*. Proceedings of Electrotechniques & Electronics E+E, 2006.
10. Scholz, U.J., Bianchi, A.M., Cerutti, S., and Kubicki, S., *Vegetative background of sleep: Spectral analysis of the heart rate variability.* Physiol. Behavior, 1997; **62** (5): 1037-1043.
11. Trinder, J., Kleiman, J., Carrington, M., Smith, S., Breen, S., Tan, N., and Kim, Y., *Autonomic activity during human sleep as a function of time and sleep stage.* J. Sleep Res., 2001; **10**(4): 253-264.
12. Zapanta, L., Poon, C.S., White, D.P., Marcus, C.L., and Katz, E.S. *Heart rate chaos in obstructive sleep apnea in children*. Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEMBS '04), 2004.
13. Shouldice, R.B., O'Brien, L.M., O'Brien, C., de Chazal, P., Gozal, D., and Heneghan, C., *Detection of obstructive sleep apnea in pediatric subjects using surface lead electrocardiogram features.* Sleep, 2004; **27**: 784-792.
14. Goutas, A., Ferdi, Y., Herbeuval , J.-P., Boudraa, M., and Boucheham, B., *Digital fractional order differentiation-based algorithm for P and T-waves detection and delineation.* ITBM-RBM Elsevier, 2005; **26**(2).
15. Ruberman, W., Weinblatt, E., Goldberg, J., Frank, C., Chaudhary, B., and Shapiro, S., *Ventricular premature complexes and sudden death after myocardial infarction.* Circ J, 1981; **64**: 297-305.

16. Hickey, B. and Heneghan, C. *Screening for paroxysmal atrial fibrillation using atrial premature contractions and spectral measures*. Proceedings of Computers in Cardiology, 2002.
17. Moody, G.B. *The PhysioNet/Computers in Cardiology Challenge 2008: T-Wave Alternans*. Proceedings of Computers in Cardiology, 2008.
18. Li, Q., Mark, R., and Clifford, G., *Robust heart rate estimation from multiple asynchronous noisy sources using signal quality indices and a Kalman filter*. Physiological Measurement, 2008; **29**: 15-32.
19. Hu, Y.H., Tompkins, W.J., Urrusti, J.L., and Afonso, V.X., *Applications of artificial neural networks for ECG signal detection and classification.* Electrocardiology, 1993; **26 (Suppl.)**: 66-73.
20. Okada, M., *A Digital Filter for the QRS Complex Detection.* IEEE Transaction on Biomedical Engineering, 1979; **26**(12): 700-703.
21. Menrad, A., *Dual microprocessor system for cardiovascular data acquisition, processing and recording*, in *IEEE Int. Conf. Industrial Elect.*, 1981.
22. Holsinger, W.P., Kempner, K.M., and Miller, M.H., *QRS preprocessor based on digital differentiation.* IEEE Transactions on Biomedical Engineering, 1971; **18**: 212-217.
23. Morizet-Mahoudeaux, P., Moreau, C., Moreau, D., and Quarante, J.J., *Simple microprocessor-based system for on-line e.c.g. arrhythmia analysis.* Medical and Biological Engineering and Computing, 1981; **19**: 497-500.
24. Fraden, J. and Neuman, M.R., *QRS wave detection.* Medical and Biological Engineering and Computing, 1980; **18**: 125-132.
25. Balda, R.A., Diller, G., Deardorff, E., Doue, J., and Hsieh, P., *The HP ECG analysis program.* In: JH van Bemmel and JL Willems, Editors, Trends in computer-processed Electrocardiograms, 1977: 197-205.
26. Ahlstrom, M.L. and Tompkins, W.J., *Automated high-speed analysis of Holter tapes with microcomputers.* IEEE Transactions on Biomedical Engineering, 1983; **30**: 651-657.
27. Engelse, W. and Zeelenberg, C. *A single scan algorithm for QRS detection and feature extraction*. Proceedings of Computers in Cardiology, 1979.
28. Pan, J. and Tompkins, W.J., *A Real-Time QRS Detection Algorithm.* IEEE Transactions on Biomedical Engineering, 1985; **32**(3): 230-236.
29. Zhang, F. and Lian, Y. *Electrocardiogram QRS Detection Using Multiscale Filtering Based on Mathematical Morphology*. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007.
30. Arzeno, N., Deng, Z., and Poon, C., *Analysis of First-Derivative Based QRS Detection Algorithms.* IEEE Transactions on Biomedical Engineering, 2008; **55**(2): 478-484.
31. Benitez, D.S., Gaydecki, P.A., Zaidi, A., and Fitzpatrick, A.P. *A new QRS detection algorithm based on the Hilbert transform*. Proceedings of Computers in Cardiology, 2000.
32. Arzeno, N.M., Poon, C.S., and Deng, Z.D. *Quantitative Analysis of QRS Detection Algorithms Based on the First Derivative of the ECG*. Proceedings of the 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2006.
33. Zhang, F. and Lian, Y. *Novel QRS Detection by CWT for ECG Sensor*. Proceedings of IEEE Biomedical Circuits and Systems Conference (BIOCAS 2007), 2007.
34. Gustafson, D., *Automated VCG interpretation studies using signal analysis techniques*, in *Draper Report No. R-1044*, 1977; Charles Stark Draper Laboratory: Cambridge, MA.
35. Friesen, G.M., Jannett, T.C., Jadallah, M.A., Yates, S.L., Quint, S.R., and Nagle, H.T., *A comparison of the noise sensitivity of nine QRS detection algorithms.* Biomedical Engineering, IEEE Transactions on, 1990; **37**(1): 85-98.
36. Christov, I.I., Dotsinsky, I.A., and Daskalov, I.K., *High-pass filtering of ECG signals using QRS elimination.* Medical & Biological Engineering & Computing, 1992; **30**(2): 253-256.
37. Laguna, P., Thakor, N.V., Caminal, P., and Jane, R., *Low-pass differentiators for biological signals with known spectra: application to ECG signal processing.* IEEE Transactions on Biomedical Engineering, 1990; **37**(4): 420-425.
38. Thakor, N., Webster, J.G., and Tompkins, W.J., *Estimation of QRS Complex Power Spectra for Design of a QRS Filter.* IEEE Transactions on Biomedical Engineering, 1984; **31**(11): 702-6.

39. Thakor, N. and Zhu, Y., *Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection.* IEEE Transactions on Biomedical Engineering, 1991; **38**(8): 785-794.
40. Chen, H.C. and Chen, S.W. *A moving average based filtering system with its application to real-time QRS detection*. Proceedings of Computers in Cardiology, 2003.
41. Sun, Y., Suppappola, S., and Wrublewski, T.A., *Microcontroller-based real-time QRS detection.* Biomedical Instrumentation and Technology, 1992; **26**(6): 477-484.
42. Suppappola, S. and Sun, Y., *Nonlinear transforms of ECG signals for digital QRS detection: A quantitative analysis.* IEEE Trans on Biomed Eng, 1994; **41**: 397-400.
43. Dokur, Z., Olmez, T., Yazgan, E., and Ersoy, O.K., *Detection of ECG waveforms by neural networks.* Med. Eng. Phys, 1997; **19**(8): 738-741.
44. Ligtenberg, A. and Kunt, M., *A robust-digital QRS detection algorithm for arrhythmia monitoring*. Computers and Biomed Res, 1983(16): 273-286.
45. Borjesson, P., Palhm, O., Sommo, L., and Nygards, E., *Adaptive QRS detection based on maximum a posteriori estimation.* IEEE Transactions on Biomedical Engineering, 1982; **29**(341-351).
46. Fancott, T. and Wong, D., *A minicomputer system for direct high speed analysis of cardiac arrhythmias in 24 h ambulatory ECG tape recording.* IEEE Transactions on Biomedical Engineering, 1980; **27**: 685-693.
47. Keselbrener, L., Keselbrener, M., and Akselrod, S., *Nonlinear high pass filter for R-wave detection in ECG signal.* Medical Engineering & Physics, 1997; **19**(5): 481-484.
48. Leski, J. and Tkacz, E., *A new parallel concept for QRS complex detector.* Engineering in Medicine and Biology Society, 1992: 555-556.
49. Nygårds, M.E. and Hulting, J., *An automated system for ECG monitoring.* Computers and Biomedical Research, 1979; **12**: 181-202.
50. Sörnmo, L., Pahlm, O., and Nygards, M.E. *Adaptive QRS detection in ambulatory ECG monitoring: A study of performance*. Proceedings of Computers in Cardiology, 1982.
51. Ulusar, U.D., Govindan, R.B., Wilson, J.D., Lowery, C.L., Preissl, H., and Eswaran, H. *Adaptive rule based fetal QRS complex detection using hilbert transform*. Proceedings of Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE, 2009.
52. Lin, C.C., Hu, W.C., Chen, C.M., and Weng, C.H. *Heart rate detection in highly noisy handgrip electrocardiogram*. Proceedings of Computers in Cardiology, 2008.
53. Trahanias, P.E., *An approach to QRS complex detection using mathematical morphology.* IEEE Transactions on Biomedical Engineering, 1993; **40**(2): 201-205.
54. Chu, C.H.H. and Delp, E.J., *Impulsive noise suppression and background normalization of electrocardiogram signals using morphological operators.* IEEE Transactions on Biomedical Engineering, 1989; **36**: 262-273.
55. Yongli, C. and Huilong, D. *A QRS Complex Detection Algorithm Based on Mathematical Morphology and Envelope*. Proceedings of the 27th Annual International Conference of the Engineering in Medicine and Biology Society, 2005.
56. Huang, N., Shen, Z., Long, S., Wu, M., Shih, H., Zheng, Q., Yen, N., C., T., and Liu, H., *The empirical mode decomposition and hilbert spectrum for nonlinear and nonstationary time series analysis.* Proc. Roy. Soc. Lond. A, 1998(454): 903-995.
57. Jing-tian, T., Xiao-li, Y., Jun-chao, X., Yan, T., Qing, Z., and Xiao-kai, Z. *The Algorithm of R Peak Detection in ECG Based on Empirical Mode Decomposition*. Proceedings of Fourth International Conference on Natural Computation, 2008.
58. Xing, H. and Huang, M. *A New QRS Detection Algorithm Based on Empirical Mode Decomposition*. Proceedings of The 2nd International Conference on Bioinformatics and Biomedical Engineering, 2008.
59. Arafat, A. and Hasan, K. *Automatic detection of ECG wave boundaries using empirical mode decomposition*. Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing, 2009.
60. Zhou, S.-K., Wang, J.-T., and Xu, J.-R. *The real-time detection of QRS-complex using the envelope of ECG*. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1988.
61. Nygards, M.E. and Sörnmo, L., *Delineation of the QRS complex using the envelope of the ECG.* Med. Biol. Eng. Comput., 1983; **21**.

62. Zhang, F. and Lian, Y. *Wavelet and Hilbert transforms based QRS complexes detection algorithm for wearable ECG devices in wireless Body Sensor Networks*. Proceedings of the IEEE Biomedical Circuits and Systems Conference, 2009.
63. Zhou, H.Y. and Hou, K.M. *Embedded real-time QRS detection algorithm for pervasive cardiac care system*. Proceedings of the 9th International Conference on Signal Processing, 2008.
64. Afonso, V.X., Tompkins, W.J., Nguyen, T.Q., and Luo, S., *ECG beat detection using filter banks.* IEEE Transactions on Biomedical Engineering, 1999; **46**: 192-202.
65. Zhang, F., Wei, Y., and Lian, Y. *Frequency-response masking based filter bank for QRS dection in wearable biomedical devices*. Proceedings of IEEE International Symposium on Circuits and Systems, 2009.
66. Vai, M.I. and Zhou, L.G., *Beat-to-beat ECG ventricular late potentials variance detection by filter bank and wavelet transform as beat-sequence filter.* IEEE Transactions on Biomedical Engineering 2004; **51**(8): 1407-1413.
67. Afonso, V.X., Tompkins, W.J., Nguyen, T.Q., Trautmann, S., and Luo, S. *Filter bank-based processing of the stress ECG*. Proceedings of the 17th IEEE Annual Engineering Conference in Medicine and Biology Society, 1995.
68. Mengda, L., A. P. Vinod, and S. Chong Meng Samson, *A New Flexible Filter Bank for Low Complexity Spectrum Sensing in Cognitive Radios.* Journal of Signal Processing Systems, 2009.
69. Burrus, C.S., Gopinath, R.A., and Guo, H., (eds). *Introduction to Wavelets and Wavelet Transforms* New Jersey: Prentice Hall; 1998.
70. Strang, G. and Nguyen, T., (eds). *Wavelets and Filter Banks* Wellesley, MA, USA: Wellesley-Cambridge Press; 1997.
71. Dinh, H.A.N., Kumar, D.K., Pah, N.D., and Burton, P. *Wavelets for QRS detection*. Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2001.
72. Szilagyi, L. *Wavelet-transform-based QRS complex detection in on-line Holter systems*. Proceedings of [Engineering in Medicine and Biology, 1999. 21st Annual Conf. and the 1999 Annual Fall Meeting of the Biomedical Engineering Soc.] BMES/EMBS Conference, 1999. Proceedings of the First Joint, 1999.
73. Liang-Yu, S., Ying-Hsuan, W., and Hu, W., *Using wavelet transform and fuzzy neural network for VPC detection from the holter ECG.* IEEE Transactions on Biomedical Engineering, 2004; **51**(7): 1269-1273.
74. Xiuyu, Z., Zhen, L., LinLin, S., and Zhen, J. *Detection of QRS Complexes Based on Biorthogonal Spline Wavelet*. Proceedings of the International Symposium on Information Science and Engineering, 2008.
75. Alesanco, A., Olmos, S., Istepanian, R., and Garcia, J. *A novel real-time multilead ECG compression and de-noising method based on the wavelet transform*. Proceedings of Computers in Cardiology, 2003.
76. Szilagyi, S.M. and Szilagyi, L. *Wavelet transform and neural-network-based adaptive filtering for QRS detection*. Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2000.
77. Xiaomin, X. and Ying, L. *Adaptive Threshold for QRS Complex Detection Based on Wavelet Transform*. Proceedings of 27th Annual International Conference of the Engineering in Medicine and Biology Society, 2005.
78. Bothe, H.-H., (eds). *Neuro-Fuzzy-Methoden* Berlin, Germany: Springer-Verlag; 1997.
79. Haykin, S., (eds). *Neural Networks- A Comprehensive Foundation* (2nd), Piscataway, NJ: IEEE Press; 1999.
80. Bishop, C.M. and Hinton, G., (eds). *Neural Networks for Pattern Recognition* New York: Clarendon Press; 1995.
81. Lagerholm, M., Peterson, C., Braccini, G., Edenbrandt, L., and Sornmo, L., *Clustering ECG complexes using Hermite functions and self-organizing maps.* IEEE Transactions on Biomedical Engineering, 2000; **47**(7): 838-848.
82. Barro, S., Fernandez-Delgado, M., Vila-Sobrino, J.A., Regueiro, C.V., and Sanchez, E., *Classifiying multichannel ECG patterns with an adaptive neural network.* IEEE Engineering in Medicine and Biology, 1998; **17**: 45-55.
83. Fernandez-Delgado, M. and Ameneiro, B., *MART: A multichannel ART-based neural network.* IEEE Transaction on Neural Networks, 1998; **9**: 139-150.

84. Ham, F.M. and Han, S., *Classification of cardiac arrhythmias using fuzzy ARTMAP*. IEEE Transactions on Biomedical Engineering, 1996; **43**: 425-430.
85. Maglaveras, N., Stamkopoulos, T., Diamantaras, K., Pappas, C., and Strintzis, M., *ECG pattern recognition and classification using non-linear transformations and neural networks: A review*. Int. J. Med. Informatics, 1998; **52**: 191-208.
86. Maglaveras, N., Stamkopoulos, T., Pappas, C., and Strintzis, M., *ECG processing techniques based on neural networks and bidirectional associative memories.* Journal of Medical Engineering and Technology, 1998; **22**(3): 106-111.
87. Strintzis, M.G., Stalidis, G., Magnisalis, X., and Maglaveras, N., *Use of neural networks for electrocardiogram (ECG) feature extraction, recognition and classification.* Neural Network World, 1992; **3**(4): 313-327.
88. Suzuki, Y., *Self-organizing QRS-wave recognition in ECG using neural networks.* IEEE Transactions on Neural Networks, 1995; **6**(6): 1469-1477.
89. Vijaya, G., Kumar, V., and Verma, H.K., *ANN-based QRS-complex analysis of ECG*. Journal of Medical Engineering and Technology, 1998; **4**: 160-167.
90. Xue, Q., Hu, Y.H., and Tompkins, W.J., *Neural-network-based adaptive matched filtering for QRS detection*. IEEE Transactions on Biomedical Engineering, 1992; **39**(4): 317-329.
91. Krimi, S., Ouni, K., and Ellouze, N. *An Approach Combining Wavelet Transform and Hidden Markov Models for ECG Segmentation*. Proceedings of the 3rd International Conference on Information and Communication Technologies: From Theory to Applications, 2008.
92. Clifford, G.D., Azuaje, F., and McSharry, P., *Advanced Methods And Tools for ECG Data Analysis.* Artech House Publishers, 2006; **1st edition**.
93. García-Berdonés ' C., Narváez, J., Fernández, U., and Sandovalm, F., *A new QRS detector based on neural network* Springer-Verlag, 1997; **1240**: 1260 - 1269
94. Dokur, Z. and Ölmez, T., *ECG beat classification by a novel hybrid neural network.* Computer Methods and Programs in Biomedicine, 2001; **66**(2-3): 167-181.
95. Coast, A.A. and Cano, G.G. *QRS detection based on hidden Markov modeling*. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1989.
96. Coast, D.A., Stern, R.M., Cano, G.G., and Briller, S.A., *An approach to cardiac arrhythmia analysis using hidden Markov models.* IEEE Transactions on Biomedical Engineering, 1990(37): 826-836.
97. Cheng, W.T. and Chan, K.L. *Classification of electrocardiogram using hidden Markov models*. Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1998.
98. Coast, D.A. *Segmentation of high-resolution ECGs using hidden Markov models*. Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, 1993.
99. Dobbs, S., Schmitt, N., and Ozemek, H., *QRS detection by template matching using real-time correlation on a microcomputer.* Journal of Clinical Engineering, 1984; **9**(3): 197-212.
100. Ruha, A., Sallinen, S., and Nissila, S., *A real-time microprocessor QRS detector system with a 1-ms timing accuracy for the measurement of ambulatory HRV.* IEEE Transactiona on Biomedical Engineering, 1997; **44**: 159-167.
101. Ebenezer, D. and Krishnamurthy, V., *Wave digital matched filter for electrocardiogram preprocessing*. Journal of Biomedical Engineering, 1993; **15**(2): 132-134.
102. Lindecrantz, K.G. and Lilja, H., *New software QRS detector algorithm suitable for real time application with low signal-to-noise ratios.* Journal of Biomedical Engineering, 1988; **10**(3): 280-284.
103. Kaplan, D.T. *Simultaneous QRS detection and feature extraction using simple matched filter basis functions*. Proceedings of Computers in Cardiology, 1990.
104. Hamilton, P.S. and Tompkins, W.J. *Adaptive matched filtering for QRS detection*. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1988.
105. Yaosheng, L., Ying, X., Jiongfeng, C., and Zeguang, Z. *A Comparative Study to Extract the Diaphragmatic Electromyogram Signal*. Proceedings of the International Conference on BioMedical Engineering and Informatics, 2008.

106. Belforte, G., De Mori, R., and Ferraris, F., *A Contribution to the Automatic Processing of Electrocardiograms Using Syntactic Methods.* IEEE Transactions on Biomedical Engineering, 1979; **26**(3): 125-136.
107. Ciaccio, E.J., Dunn, S.M., and Akay, M., *Biosignal pattern recognition and interpretation systems.* IEEE Engineering in Medicine and Biology Magazine, 1993; **12**(4): 106-113.
108. Trahanias, P. and Skordalakis, E., *Syntactic pattern recognition of the ECG.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 1990; **12**(7): 648-657.
109. Köhler, B.-U., Hennig, C., and Orglmeister, R., *QRS detection using zero crossing counts.* 2001.
110. Köhler, B.U., Hennig, C., and Orglmeister, R., *QRS detection using zero crossing counts.* Progress in Biomedical Research, 2003; **8**(3).
111. Yanli, Z. and Guangshu, H. *QRS complex detection by the combination of maxima and zero-crossing points of wavelet transform*. Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1998.
112. Mallat, S. and Hwang, W.L., *Singularity detection and processing with wavelets.* IEEE Transactions on Information Theory, 1992; **38**: 617-643.
113. Di Virgilio, V., Francaiancia, C., Lino, S., and Cerutti, S., *ECG fiducial points detection through wavelet transform*, in *the 17th Annual Conference IEEE Engineering in Medicine and Biology Society*, 1995: Montreal, Quebec, Canada.
114. Rao, K.D., *Dwt based detection of R-peaks and data compression of ECG signals.* IETE Jouranl of Research, 1997; **43**(5): 345-349.
115. Kadambe, S., Murray, R., and Boudreaux-Bartels, G.F., *Wavelet transform-based QRS complex detector.* IEEE Transactions on Biomedical Engineering, 1999; **46**: 838-848.
116. Chouhan, V. and Mehta, S., *Detection of QRS complexes in 12-lead ECG using adaptive quantized threshold.* International Journal of Computer Science and Network Security, 2008; **8**(1): 155-163.
117. Hamilton, P. *Open source ECG analysis*. Proceedings of Computers in Cardiology, 2002.
118. Lee, J., Jeong, K., Yoon, J., and Lee, M. *A simple real-time QRS detection algorithm*. Proceedings of the 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1996. Bridging Disciplines for Biomedicine, 1996.
119. Chen, S., Chen, H.C., and Chan, H.L., *A real-time QRS detection method based on moving-averaging incorporating with wavelet denoising.* Computer Methods and Programs in Biomedicine, 2006; **82**(3): 187-195.
120. Adnane, M., Jiang, Z., and Choi, S., *Development of QRS detection algorithm designed for wearable cardiorespiratory system.* Computer Methods and Programs in Biomedicine, 2009; **93**(1): 20-31.
121. Li, C., Zheng, C., and Tai, C., *Detection of ECG characteristic points using wavelet transforms.* IEEE Transactions on Biomedical Engineering, 1995; **42**(1): 21-28.
122. Martinez, J.P., Almeida, R., Olmos, S., Rocha, A.P., and Laguna, P., *A wavelet-based ECG delineator: evaluation on standard databases.* IEEE Transactions on Biomedical Engineering, 2004; **51**(4): 570-581.
123. Afonso, V.X., Tompkins, W.J., Nguyen, T.Q., and Luo, S. *Filter bank-based ECG beat detection*. Proceedings of the 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Bridging Disciplines for Biomedicine, 1996.
124. Ghaffari, A., H. Golbayani, and M. Ghasemi, *A new mathematical based QRS detector using continuous wavelet transform.* Computers and Electrical Engineering, 2008; **34**(2).
125. Huabin, Z. and Jiankang, W. *Real-time QRS detection method*. Proceedings of the 10th International Conference on e-health Networking, Applications and Services, 2008.
126. Fard, P., Moradi, M., and Tajvidi, M., *A novel approach in R peak detection using Hybrid Complex Wavelet (HCW).* International Journal of Cardiology, 2007; **124**: 250-253.
127. Ayat, M., Shamsollahi, M.B., Mozaffari, B., and Kharabian, S. *ECG denoising using modulus maxima of wavelet transform*. Proceedings of Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2009.
128. Moraes, J.C.T.B., Freitas, M.M., Vilani, F.N., and Costa, E.V. *A QRS complex detection algorithm using electrocardiogram leads*. Proceedings of Computers in Cardiology, 2002.

129. PhysioBank Archive Index. Boston, USA: Physionet, Massachusetts Institute of Technology; [updated: 2011 April 15; cited: 2011 May 15]. Available from: http://www.physionet.org/physiobank/database/.
130. Alvarado, C., Arregui, J., Ramos, J., and Pallas-Areny, R. *Automatic detection of ECG ventricular activity waves using continuous spline wavelet transform*. Proceedings of the 2nd International Conference on Electrical and Electronics Engineering, 2005.
131. Sufi, F., Fang, Q., and Cosic, I. *ECG R-R Peak Detection on Mobile Phones*. Proceedings of Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE, 2007.
132. Yan, L., Shipeng, L., and Huifeng, S., *Virtualized Screen: A Third Element for Cloud-Mobile Convergence.* IEEE Multimedia, 2011; **18**(2): 4-11.