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ALGORITHMS FOR SEPARATING THE QRS COMPLEX FROM ECG

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Abstract
ECG is a diagnostic signal recorded in a patient's body at standard electrode positions, and it reflects the electrical activity of the heart muscle. One of the main features of the ECG is the form of an impulse wave, also called the QRS complex. This coincides with the time of depolarization of the complex ventricles and has an important diagnostic value.

Keywords: QRS complex, Differentialization, Pan-Tompkins algorithm, High Frequency Filter, Veyvlet substitution.

Introduction

The QRS complex (which usually lasts no more than 0.1 s) is a key point for ECG signal processing algorithms. This complex:

- analysis of heart rate variations,
- arrhythmia monitoring,
- Implantable heart stimulants,
- It is used in a variety of applications such as ECG signal compression methods.

The more accurate and reliable the detection of QRS, the higher the quality of ECG analyzers. However, due to the variability of ECG signals and various interferences (transmission line noises, radio frequency noises, muscle artifacts), the determination of the QRS complex is considered a complex task. Therefore, the research that is currently being conducted in the field of computer-assisted ECG analysis is aimed at solving this problem.

Digital signal processing algorithms are used in ECG analysis. In any ECG, the main distinguishing components are the R wave and the QRS complex.

Methods for analyzing ECG signals. The classical approach in electrocardiology is to use methods for analyzing the time domain of the signal. This approach is used in a variety of applications, such as standard ECG measurement, heart rate measurement, repolarization dispersion detection, etc.

However, analyzing the amplitude and duration of ECG components in the time domain alone is not sufficient to reveal all the characteristics of the signal. For example, late potentials located in the QRS complex are difficult to determine using time domain methods.

However, the time-domain analysis of heart rate provides a complete picture of the behavioral and parasympathetic effects of RR intervals. However, the activity of the sympathetic system cannot be judged through the domain of time.

Thus, the combination of time and frequency domains allows for more complete results in ECG analysis. The Veyvlet substitution technique is one of the promising methods for analyzing the time-frequency properties of ECG components.

The problem of defining the QRS complex is considered as a problem of detection and discrimination within the framework of the theory of radio engineering statistics. Over the past decade, many new approaches have been proposed to detect QRS, such as artificial neural networks, genetic algorithms, and wavelet substitutions.

Let us consider modern and widely used ECG analysis algorithms, as well as classical approaches for determining the QRS complex.

Algorithms for the QRS complex detection of ECG signal based on difference. Let us now consider the main types of algorithms presented in the source [1] **in terms of** differentiation.

1. Algorithm based on the first derivative and amplitude limit

The first derivation **at each point of the ECG signal** $Y'(n)$ is calculated by the following formula:

$$Y'(n) = X\,n + 1 - X(n-1) \quad (1)$$

After that, points of excess over the constant limit are found:

$$Y'(n) > 0.15$$

Then all three consecutive derivatives must exceed this limit:

$$Y'(n+1), Y'(n+2)\ va\ Y'(n+3)$$

If the above conditions are met, n points are classified as belonging to the QRS complex, provided that the following conditions are also met:

$$Y'(n+1)X(n+1)\ va\ Y'(n+2)X(n+2) > 0$$

2. First Derivative Based Algorithm

This algorithm computes the **first derivative** $Y'(n)$ using the formula:

$$Y'(n) = [X\,n+2 - 2(n-2) + X(n+1) - X(n-1)] \quad (2)$$

The overhang limit (L) is determined by the following formula:

$$L = 0.7 * (Y'(n))$$

The first point exceeding the slope boundary is taken as the starting point of the QRS complex:

$$Y'(i) > L$$

3. Algorithm based on first and second derivatives

This algorithm calculates the first and $Y'(n)$second derivatives of the ECG signal $Y''(n)$ and compares their absolute values.

$$Y'(n) = X(n+1) - X(n-1)$$

$$Y''(n) = X(n+2) - 2X(n) + X(n-2) \quad (3)$$

Next, these two massives are scaled up and aggregated:

$$Y(n) = 1{,}3Y'(n) + 1{,}1Y''(n) \quad (4)$$

Then, the threshold is compared to the value:

$$Y(n) > 1 \quad (5)$$

Once this condition is met , the next eight points will also be checked against the boundary.

If at least six of the eight points are equal to or greater than the threshold value, they are considered to belong to the QRS complex.

Detection of the QRS wave of an ECG using the Pan-Tompkins algorithm. The Pan-Tompkins algorithm is described in detail in the article [2] and operates on the basis of an analysis of the amplitude, width, and oblique of the QRS complex.

1. Digital filter and noise suppression

Digital filter is a low frequency filter and it is used to reduce the noise. It is performed by using two series infinity impulse digital filters with integer number coefficients and a transmitting function

$$K(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2} = \frac{(1-z^{-6})}{(1-z^{-1})} \times \frac{(1-z^{-6})}{(1-z^{-1})} = \frac{1-2z^{-6}+z^{-12}}{1-2z^{-1}+z^{-2}} \quad (6)$$

Filter difference equation:

$$y(n) = 2y(n-1) - y(n-2) + x(n) - 2x(n-6) + x(n-12), \quad (7)$$

where x(n) is the input signal. At a sample rate of 200 Hz, and an off frequency of 11 Hz, the filter generates a 5 sample delay (25 ms).

2. High-frequency filter

An infinite impulse digital filter is accomplished by separating a first-order finite impulse digital filter from a fully conductive filter.

High Pass Filter Transfer Function:

$$K(z) = z^{-16} - \frac{K}{32} = z^{-16} - \frac{1}{32} \times \left(\frac{1-z^{-32}}{1-z^{-1}}\right) \quad (8)$$

Difference Equation:

$$y(n) = 32x(n-16) - y(n-1) + x(n) - x(n-32), \quad (9)$$

Here x(n) and y(n) are the input and output values of the high-conductive wire.

3. Operation of differentiation

This operation is used to determine the slope of the QRS complex.It amplifies the high-frequency components associated with the QRS complex while suppressing the P and T waves.

$$K(z) = \frac{2z+z^{-1}-z^{-3}-2z^{-4}}{8} \quad (10)$$

Difference Equation:

$$y(n) = 0.125[2x(n) + x(n-1) - x(n-3) - 2x(n-4)] \quad (2.30)$$

4. Operation Squared

At this phase, all points of the signal will have a positive value. This operation serves to highlight the high frequencies of the QRS complex.

$$y(n) = x(n)^2 \quad (11)$$

5. Integrated sliding window-type filter

This is used to align the signal. The equation is given as follows:

$$y(n) = \frac{x(n-N-1) + x(n-N-2) + \cdots + x(n)}{N}, \quad (12)$$

Where N is the width of the window. The window width should not be too large, otherwise other ECG parts may also be incorrectly identified as QRS complexes. Also be too small, otherwise several tops will form for one complex.

6. Searching for R-Tops

This is done by searching for the adaptive boundary function and local maximums. The initial value of the boundary function is defined as follows:

$$L_0 = \frac{1}{3} \times (ecgw) \quad (13)$$

Here are the $ecgw$first 150 samples of the processed signal.

Next, the local maximums are searched and compared with the boundary. If the peak height exceeds the current limit, it is classified as R wave.

The new threshold value is calculated as follows:

$$\begin{cases} Speak = 0.125 * pks + 0.875 * Speak \\ Npeak = 0.125 * pks + 0.875 * Npeak \\ L = Npeak + 0.25 * Speak - Npeak \end{cases} \quad (14)$$

In this case, the current value of the local maximum.pks

Algorithm for determining the QRS complex using a digital filter. This algorithm consists of five steps, as described in the source [3].

1. Pre-alignment

Aligns the initial **ECG signal using** a three-point **moving average filter**:

$$Y_0(n) = \frac{X(n-1) + 2X(n) + X(n+1)}{4} \quad (15)$$

2. Low conductivity filter

The signal from the moving average filter output is transmitted through a low pass filter by:

$$Y_1(n) = \frac{1}{2m+1} \sum_{k=n-m}^{n+m} Y_0(k) \text{ , bunda } m < n \quad (16)$$

3. Calculate the square difference

The low conductivity filter is the difference squared of the input and output signal:

$$Y_2(n) = [Y_0(n) - Y_1(n)]^2 \quad (17)$$

Square difference filtered:

$$Y_3(n) = Y_2(n) \times \sum_{k=n-m}^{n+m} Y_2(k) \text{ , bunda } m < n \quad (18)$$

4. Fulfillment of the QRS condition

A mass is formed if the following condition is met:

$$Y_4(n) = \{Y_3(n), \ agar \ [Y_0(n) - Y_0(n-m)] \times [Y_0(n) - Y_0(n+m)] > 0 \quad (19)$$

The maximum value of the mass is used to determine and measure the boundary:

$$lev = 0{,}125 \, max(Y_4(n)) \quad (20)$$

If its value $Y_4(n)$exceeds the limit, it is considered to belong to the QRS complex.

5. Selection of optimal parameters

When m > 4 , computing productivity starts to decrease, but computing resources increase. To ensure optimal performance, m=6 is selected.

Determine the QRS complex using filter banks. A bank of filters consists of a set of analyzers that divide the input signal into smaller ranges with the same conductivity [4]. The sampling rate of these small ranges may decrease because their bandwidth is smaller than the width of the ECG input signal.

The lower ranges provide information about different frequency ranges, so that the input signal can be processed over time and frequency. To receive sub-band signals Ui(z), the original signal X(z) passes through filters with the transmission function K $_i$(z):

$$U_i(z) = K_i(z) \times X(z),\ bunda\ \text{i} = 0, 1, \dots, -1 \quad (21)$$

The effective bandwidth is π/M for Ui(z). The process of reducing the sampling frequency of the lower range signals is then performed by sample cutting:

$$W_i(z) = \frac{1}{M}\sum_{k=1}^{M} U_i(z^{1/M} \times e^{-2\pi \text{i}/\text{M}}) \quad (22).$$

It is possible to distinguish it through various features that reflect the QRS complex. For example, the sum of the absolute values of a function can be calculated using sub-ranges from i = 1 to i = 4. Of these sub-ranges, six properties (p1,p2,...,p6) are defined as follows:$W_i(z)$

$$\{p_2(n) = \sum_{i=1}^{4} |W_i(z)|\,,\ p_3(n) = \sum_{i=2}^{4} |W_i(z)|,\ p_4(n) = \sum_{i=1}^{3} \big(W_i(z)\big)^2$$

$$p_5(n) = \sum_{i=1}^{4} \big(W_i(z)\big)^2,\ p_6(n) = \sum_{i=2}^{4} \big(W_i(z)\big)^2 \quad (23)$$

An algorithm for isolating the QRS wave of an ECG signal based on the Gilbert transform and adaptive boundary function.

This algorithm is shown in [5]. The Gilbert transform for the x(t) function is defined as:

$$x_h(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \quad (24)$$

Using the original signal and its Gilbert transform, the analytic waveform is written as follows:

$$y(t) = x(t) + jx_h(t) \quad (25)$$

The analytical signal envelope is defined as:

$$B(t) = \sqrt{x(t)^2 + x_h(t)^2} \quad (26)$$

The proposed detection algorithm consists of five steps:

1. Band-filtering of the initial ECG signal in range 8 to 20 Hz. For this purpose, the second type uses the Chebyshev filter.
2. Applying the Gilbert transform to the signal at the output of a bandwidth filter to generate an analytical signal.
3. Compute the modulus of the analytical signal and subtract its envelope.
4. To further amplify the high amplitude components corresponding to the QRS complex of ECG signal, then square the envelope of the analytical signal.
5. Define a flexible boundary function.

The detector circuit consists of an adaptive floor block and a three-point hill detector. A flexible detection algorithm breaks down the input signal into small sequences using a moving window. Peaks are obtained for each subsequent sequence between signal samples that exceed the limit

value. The boundary value is determined for each moving window based on the following boundary function:

$$Lev\ (i)\ = \begin{cases} 0{,}4\text{Max(i)};\ \text{если}\ \Omega\text{(i)}\ \geq\ 0{,}2\text{Max(i)}\ ,\text{Max(i)}\ <\ 2\text{Max(i}\ -1); \\ 0{,}4\text{Max(i}\ -1);\ \text{если}\ \Omega\text{(i)}\ \geq\ 0{,}2\text{Max(i)}\ ,\text{Max(i)}\ \geq\ 2\text{Max(i}\ -1); \\ 1{,}6\Omega\text{(i)};\ \text{если}\ \Omega\text{(i)}\ <\ 0{,}2\text{Max(i)}\ . \end{cases} \quad (27)$$

In this case, Ω(i) is the standard deviation of the signal in the current i-slide window, and Max(i) is the maximum signal value within this window. If the following conditions are met:

$$A\ (n)\ >\ lev\&A(n)\ >\ A(n-1)\&A\ (n)\ >\ A(n+1) \quad (28)$$

Then A(n) belongs to the QRS complex.

Correlation algorithm for QRS complex detection. In the absence of slow varying ECG signal and pathological ECG deviations, correlation algorithm is used.

Determination of the QRS complex. The correlation algorithm is based on calculating the correlation coefficients between the y(n) template samples and the studied x(n) ECG signal with a length of N, and comparing them with the margin [6]:

$$r\ = \frac{\sum_{n=1}^{N}(x\ (n)-\underline{x})(y(n)-\underline{y})}{\sum_{n=1}^{N}(x\ (n)-\underline{x})^2\ \sum_{n=1}^{N}(y(n)-\underline{y})^2} \quad (29)$$

The value of the correlation coefficient ranges from −1 to 1 depending on the similarity of the ECG signal sample patterns and template. Once the template signal is chosen correctly, the value of the correlation coefficient approaches 1 only when it is correlated with the template QRS complex.

Use of mathematical morphology operators to define QRS complexes. Mathematical morphology uses the basic operations of erosion (⊖) and dilatation (⊕) in image and signal processing. These operations are used to study the interaction between an image or signal and a selected structural element.

The erosion of function f over template (function) k is determined as:

$$(f\ \ominus\ k)\ [m]f[m+n]\ -k[n]) \quad (30)$$

The extension (dilatation) of function f on k is expressed as:

$$f\ \oplus\ k)\ [m]\ =(f[n]-k[m-n] \quad (31)$$

By combining erosion and dilatation, additional operations are generated:

1. **Trench ()**○ — first erosion, then expansion operation is performed:

$$f\ \circ\ k\ =\ (f\ \ominus\ k)\ \oplus k \quad (32)$$

2. **Close (•)** — first expand, then erosion is performed:

$$f\ \bullet k\ =(\ f\ \oplus\ k)\ \ominus\ k \quad (33)$$

Both operators process signals based on comparison. By means of the structural element k, the opening operator extracts all the positive peaks in function f, and the closing operator extracts all the negative peaks.

Since QRS complexes consist of sequential positive and negative peaks, the combination of opening and closing operators can be used as an effective operator to define the QRS complex [7].

1. The filtering step. The filtering step to suppress improper peaks, which may be caused by noise, is performed through the following formula:

$$y = \frac{(x \circ k) \bullet k + (x \bullet k) \circ k}{2} \quad (34)$$

2. The stage of separation of peaks. This stage is characterized by the formula:

$$z = y - (y \circ k) \bullet k \quad (35)$$

After this stage, a new signal is formed, in which the QRS complexes are separated as sharp peaks, and the other main segments and waves of the ECG signal become almost zero.

After the morphological changes, the definition of the QRS complex becomes much easier. The adaptive boundary function is used in the recognition of QRS complexes. Once each QRS complex has been identified, the structure element is updated according to the shape of the final QRS complex.

An algorithm for detecting R ECG waves based on substitution. The Veyvlet substitution is defined as an integral expression for the function f(t) **(1).** This substitution generates a time-scale image, similar to a short-term frequency Furye substitution.

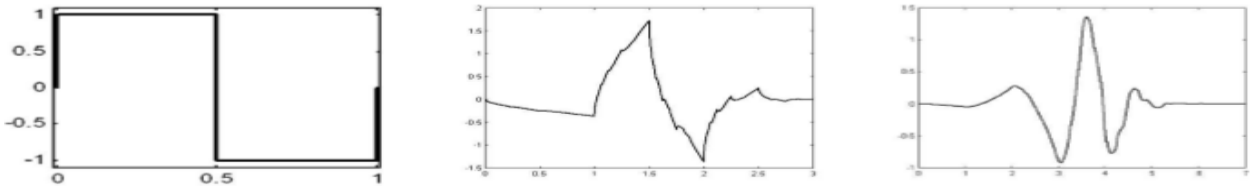

Figure 1. A sample of maternal wives for ECG analysis (Haar, Daubechies D4 and D6).

The normalized family of veyvlets is derived from the original (mother) veyvlet, where:$\psi(a,b)\psi(t)$

- **a** is the elongation (scaling) parameter,
- **B** — Siljish parameters.

In ECG analysis, short oscillations are used, the average value of which is zero, similar to the QRS complex. **Figure 1** provides an example of a wavelength function for ECG analysis.

In discrete substitution, the scaling and displacement parameters are defined by discrete values. Discreteness is defined by two-level expression:

$$a = 2m, b = n * 2m \quad (36)$$

Then the function **(1)** takes the following form:

$$\psi(m,n\,t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) = \frac{1}{\sqrt{2^m}}\psi\left(\frac{t-n\times 2^m}{2^m}\right) \quad (37)$$

In which n and m are integers.

Two important features of the Veyvlet replacement allow it to be used as a QRS integrated detector:

1. Separation of signal components into different frequency ranges
2. Option to select a mother violet similar to the signal being detected

As a result of Veyvlet analysis, the signal is divided into two components:

Approximate coefficients — represent a flattened signal.

Detail coefficients — describe noise.

In order to reduce noise, detail coefficients whose value is below the specified limit are removed.

Within the ECG signals, the R wave has the greatest amplitude and can be distinguished from the other peaks. Determination of the QRS complex is carried out on the basis of the maximum modular rule of discrete surface substitution. According to this rule, the sharp peaks in the signal coincide with the maximum modulus.

Various methods for detecting QRS complexes using wavelet substitution are described in detail in the sources [8].

Accurate detection of heart rate is one of the main tasks of ECG processing. These results serve as the basis for further analysis and provide important information about heart rate. Since the energy of the heartbeat is mainly concentrated in the QRS complex , the accurate QRS detector is considered one of the most important parts of ECG analysis.

However, defining the QRS complex is a difficult task because:

1. Over time, the morphology of the heartbeat may change.
2. There is a possibility that there are different sources of noise.

Analysis of QRS detection algorithms shows that ECG signal processing consists of three main steps:

1. Pretreatment Stage
2. QRS complex separation step (using linear and nonlinear substitutions)
3. Decision-making stage

Pre-processing stage. At this stage, various filters and methods are applied to the signal:

- Linear Filters:
  - Filters with limited impulse characteristics (FIR)
  - Filters with Infinite Impulse Characteristics (IIR)
- Nonlinear Filters:
  - Flexible filters
  - Fast Furye Substitution (FFT)
  - Rapid Switch (FWT)

Grinding techniques are also used to deflect P- and T-waves and noise.

QRS complex separation stage. At this stage, with the help of mathematical means, the QRS complex is separated and other components are suppressed. For this, the "multiplication and addition" method is usually used, which is based on comparing the signal with a specific mirror (reference) function.

The decision-making stage. At this stage, defining boundaries is one of the most important tasks. In some cases, T-wave differential techniques are also used.

QRS detector algorithms still remain an important research topic. Today, many algorithms for detecting heart rate have been published, but most of them are:

- Does not provide source code
- Not confirmed in generic ECG databases

Often, these algorithms are explained in theory or only given short recommendations to implement. Therefore, it is important for users to be able to test their algorithms and compare their performance across different databases.

For initial digital filtering of ECGs (biosignals), filters with linear or continuous phase-in characteristics should be used. The frequency characteristic change during the filtering phase should not be more than 30%.

QRS complex detection algorithms are evaluated by the following key indicators:

1. Sezuvchanlik (Sensitivity, Sister)
2. O‘ziga xoslik (Specificity, Sp)

1. Sensitivity

Sensitivity — Measures the ratio of correctly defined actual positive outcomes and is expressed by the following formula:

$$S_e = \frac{TP}{TP+FN} \times 100\ \% \quad (38)$$

In this:

- **TP** — Correctly Identified Cases (True Positives)
- **FN** - Undetected Cases (False Negatives)

2. Originality

Specificity — measures the proportion of true-negative results correctly defined and is expressed by the formula:

$$S_p = \frac{TP}{TP+FP} \times 100\ \% \quad (39)$$

In this:

- **FP** — False Positives

Determination of the QRS complex is the most important part of ECG analysis, and the development of high-precision algorithms is still a pressing issue. Today, research is underway to improve the efficiency of heart rate detection using various filters, transformations, and mathematical methods.

Table 1. Test results for five common QRS detection algorithms.

Testing algorithms	ECG channel	HCMC	FN	FP	Herself	Sp
Derivative-based algorithm	I	10	0	0	100	100
	II	13	0	0	100	100
	III	34	0	1	100	97.14
	IV	11	0	0	100	100
Weighted derivative algorithm	I	10	0	0	100	100
	II	13	0	0	100	100
	III	34	0	0	100	100
	IV	11	0	0	100	100
Pana-Tompkins algorithm	I	10	0	0	100	100
	II	13	0	1	100	92.86
	III	34	3	0	91.18	100
	IV	11	0	0	100	100
Algorithm based on calculating the number of zero intersections	I	10	0	0	100	100
	II	13	0	0	100	100
	III	34	2	0	94.12	100
	IV	11	0	0	100	100
Correlation algorithm	I	10	0	0	100	100
	II	13	1	0	92.32	100
	III	34	0	6	100	85.00
	IV	11	0	0	100	100

Conclusion

A comparative analysis of the five most common algorithms for determining QRS complexes was conducted [9], the results of which are presented in Table 1. In this table, I is the ideal ECG type, II... IV – shows the actual ECG types taken from different directions. The researchers also conducted a comparative analysis of nine algorithms under the influence of different interferences [10]. The results showed that better results are achieved when filtering algorithms are combined with differentiation algorithms.

To evaluate the effectiveness of ECG analysis algorithms, there are open databases containing various ECG signals. These databases can be accessed via the following internet addresses:

- American Heart Association
- PhysioNet QT Database.

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