QRS COMPLEX DETECTION IN NOISY HOLTER ECG BASED ON WAVELET SINGULARITY ANALYSIS

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Abstract: In this paper, we propose a QRS complex detector based on the Mallat and Hwang singularity analysis algorithm which uses dyadic wavelet transform. We design a spline wavelet that is suitable for QRS detection. The scales of this decomposition are chosen based on the spectral characteristics of electrocardiogram records. By proceeding with the multiscale analysis we can find the location of a rapid change of a signal, and hence the location of the QRS complex. The performance of the algorithm was tested using the records of the MIT-BIH Arrhythmia Database. The method is less sensitive to time-varying QRS complex morphology, minimizes the problems associated with baseline drift, motion artifacts and muscular noise, and allows R waves to be differentiated from large T and P waves. We propose an original, new approach to adaptive threshold algorithm that exploits statistical properties of the observed signal and additional heuristic. The threshold is independent for each successive ECG signal window and the algorithm uses the properties of a series of distribution with a compartments class. The noise sensitivity of the new proposed adaptive thresholding QRS detector was also tested using clinical Holter ECG records from the Medical University of Bialystok. We illustrate the performance of the wavelet-based QRS detector by considering problematic ECG signals from a Holter device. We have compared this algorithm with the commercial Holter system - Del Mar's Reynolds Pathfinder on the special episodes selected by cardiologist.

Keywords: ECG, heartbeat detection, QRS complex, wavelet singularity analysis, modulus maxima, noisy ECG, Holter recordings, adaptive threshold, dyadic wavelet transform

1. Introduction

Very often, QRS detection is difficult, not only because of the morphological variability of the QRS complexes, but also because of the various types of artifacts that can be present in ECG signals. Artifact sources include muscle noise, artifacts due to electrode motion, power-line interference, baseline wander, and high-frequency P or T waves similar to QRS complexes.

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However, as a matter of fact, QRS detection is a first step to be used in automatic analysis. It is necessary to determine the heart rate, and as reference for heartbeat type recognition and arrhythmia classification. A wide variety of algorithms for QRS detection have been proposed in the literature [21], [9], [10], [14], [22], [3], [1], [4], [19], [6], [2]. An extensive review of the approaches can be found in [13], [8].

High detection accuracy is often difficult to achieve, since various sources of noise are frequently encountered. Furthermore, morphological differences in an ECG waveform increase the complexity of QRS detection, due to the high degree of heterogeneity in QRS waveform and the difficulty in differentiating the QRS complex from tall peaked P or T waves.

Analysis of the local signal properties is of great importance to the signal processing, because the so-called *singularity* very often carries information important for further processing. According to the power spectra of the ECG signal, the frequency width of singularity overlaps the frequency width of normal QRS complex. A great deal of work's related to the QRS detection based on wavelet transform uses an analysis of the singularities proposed by Mallat and Hwang [16]. The most interesting works are Strang et al. [25], Burrus et al. [5], Bahoura et al. [3], Kadambe et al. [12], Li et al. [14], Martinez et al. [19], Sahambi et al. [23], Szilagyi et al. [26].

The algorithm we presented for the QRS detection in the ECG signal uses the Mallat and Hwang [16] wavelet singularity analysis. Using both, theory presented by Mallat and Hwang and our own experiments, a QRS detector has been built. Our solution contains additional original elements presented in this paper. One of them is a new approach to compute an adaptive threshold for QRS detection. The second, that is a set of rules connected with multiscale analysis. The heuristics allow to detect duplicate overlooked the QRS and determine the final set of QRS complexes from a wider set of candidates.

2. Wavelet transform and singularity analysis

The fundamentals of singularity detection in signal using the wavelet transform have been shown by Stéphane Mallat in [15], [16], [17].

Signal $f(t)$ smoothed by the function $\theta(t)$ can be represented as the result of the convolution

$$f(t) = f \star \overline{\theta}(u), \tag{1}$$

where

$$\overline{\theta}(t) = \theta(-t). \tag{2}$$

The derivative of the smoothed signal is equal to the convolution of the signal $f(t)$ with the derivative of smoothing function $\overline{\theta}'(t)$

$$\frac{d}{du}(f \star \overline{\theta})(u) = (f \star \overline{\theta}')(u) \tag{3}$$

where

$$\overline{\theta}'(t) = \frac{d\overline{\theta}(t)}{dt}. \tag{4}$$

The smoothing function and its argument can be scaled

$$\theta_s(t) = \frac{1}{\sqrt{s}}\,\theta\left(\frac{t}{s}\right), \tag{5}$$

where s is the factor of the scale. For $s > 1$ the function $\theta(t)$ is dilated and average of $f(t)$ is performed on a wider range of the independent variable t.

The derivative of the smoothed signal is given by the convolution of the signal with the scaled derivative of the smoothing function

$$\frac{d}{du}(f \star \overline{\theta}_s)(u) = f \star \overline{\theta}'_s(u), \tag{6}$$

where

$$\overline{\theta}'_s(u) = \frac{d\overline{\theta}_s(u)}{du}. \tag{7}$$

In order to show the connection between the *Continuous Wavelet Transform* (CWT) and the derivative of the smoothed signal, we define wavelet $\psi(t)$ in the form of the derivative smoothing function with the changed sign

$$\psi(t) = -\frac{d\theta(t)}{dt}. \tag{8}$$

The result is

$$\overline{\psi}(t) = \frac{d\overline{\theta}(t)}{dt} \tag{9}$$

and

$$\overline{\psi}\left(\frac{t}{s}\right) = s\,\frac{d}{dt}\left[\overline{\theta}\left(\frac{t}{s}\right)\right],$$

which means that

$$\overline{\psi}_s(t) = s\,\overline{\theta}'_s(t). \tag{10}$$

The CWT is determined and defined as follows [18]

$$Wf(u,s) = f \star \overline{\psi}_s(u). \tag{11}$$

By substituting in (11) with $\overline{\psi}_s(t)$ the right side of (10), we get

$$Wf(u,s) = s\ (f \star \overline{\theta}'_s)(u). \tag{12}$$

Based on the above equations and (6), we get

$$Wf(u,s) = s\ \frac{d}{du}\left(f \star \overline{\theta}_s\right)(u). \tag{13}$$

To differentiate the signal smoothing by the function $\theta(t)$, it is enough to calculate the CWT of the signal with the wavelet defined by the equation (8).

The domain of CWT is plane $0us$. For calculation purposes, it is necessary to discretize variables u and s. In the following, it is assumed that the signal $f(t)$ is analyzed in the range $[0,\ N-1]$.

2.1 Dyadic wavelet representation of a signal

For the purpose of singularity analysis, a *dyadic wavelet transform* of the signal $f(t)$ can be used for with the scale s takes dyadic values, i.e. $s = 2^k,\ \ k \in Z$.

The digital signal

$$a_0 = (a_0[n])_{n\in Z}, \tag{14}$$

should be calculated by the formula

$$a_0[n] = \int_{-\infty}^{+\infty} f(t)\ \phi(t-n)\ dt, \quad n \in Z. \tag{15}$$

where $\phi(t)$ is the scaling function of the wavelet analysis.
Scaling ϕ by dyadic step we can get a series of digital representation

$$(a_k)_{k\in Z}, \tag{16}$$

where

$$a_k[n] = \int_{-\infty}^{+\infty} f(t)\ \frac{1}{\sqrt{2^k}}\ \phi\left(\frac{t-n}{2^k}\right) dt, \quad n \in Z. \tag{17}$$

Averaging of the signal is performed at a distance proportional to the scale 2^k.

Detailed signals d_k are calculated by analogous to the signals a_k.

$$(d_k)_{k\in Z}, \tag{18}$$

where

$$d_k[n] = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{2^k}}\ \psi\left(\frac{t-n}{2^k}\right) dt, \quad n \in Z. \tag{19}$$

Starting from the digital signal a_0 given by (15), we calculate the *dyadic discrete wavelet transform* of a signal as:

$$\{(d_k)_{1\leq k\leq K}, a_K\}, \tag{20}$$

where a_K is a coarse representation of the signal at scale 2^K, and d_k is a detail signal at scale 2^k, wherein $1 \leq k \leq K$. Most of the details are in the signal d_1, least in d_K.

For the purposes of the singular points detection in a signal, it is sufficient to perform only signal analysis, i.e. to find the dyadic discrete wavelet transform. If the coefficients $a_0[n]$ are zero for $n < 0$ and $n \geq N$ then the dyadic discrete wavelet transform corresponds to the grid points of K rows, $K \leq log_2 N$ for N points in each row. Detection of singular points is associated with searching modulus maxima of wavelet coefficients *centered* around the vertical lines of the grid corresponding to fixed values of u.

2.2 The à trous algorithm of dyadic wavelet decomposition

Coefficients defined by (17) and (19) can be calculated iteratively using the so-called *à trous algorithm* proposed by Holschneidera, Kronland-Martineta, Morleta and Tchamitchiana [11] [24].

After selecting the scaling function ϕ and wavelet ψ based on the wavelet equations there calculated two digital filters: the low pass filter h and high pass filter g. Let, h_k is filter obtained by inserting $2^k - 1$ zeros between each pair of impulse response filter coefficients h. The extension of the filter by inserting zeros creates *holes* (franc. trous) that are mentioned in the name of algorithm. By definition

$$\overline{h}_k[n] = h_k[-n]. \tag{21}$$

The same designations apply to the filters g and g_k.

Coefficients of the dyadic discrete wavelet transform of a signal a_0 can be calculated using the following iterative calculation scheme [18]

$$d_{k+1}[n] = a_k \star \overline{g}_k[n], \tag{22}$$

$$a_{k+1}[n] = a_k \star \overline{h}_k[n] \tag{23}$$

for $k = 0, 1, 2, \ldots$.
If the input signal $(a_0[n])_{n\in Z}$ has a finite length of N samples, then the operations (22) and (23) can be achieved by using circular convolution (recurring).

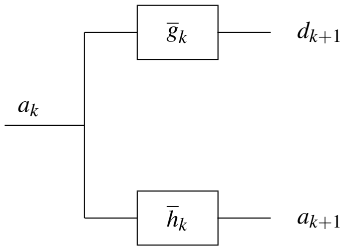

Fig. 1. Filter bank implementing one step of à trous algorithm

3. QRS detection based on singularity analysis approach

All of the wavelet-based peak detection methods mentioned in this paper [25], [5], [3], [12], [14], [19], [23], [26] are based on Mallat and Hwang's approach for singularity detection [16].

Therein, the correspondence between singularities of a function $f(t)$ and local maxima in its wavelet transform $Wf(u,s)$ is investigated. The authors of these works have used the dyadic wavelet transform (DyWT) for detecting singular points. Analysis of the value that characterize the QRS complex based on the local modulus maxima of wavelet transform. The QRS complex and other singularities in the signal are represented by local maxima at successive levels of decomposition.

It is shown that singularities correspond to pairs of modulus maxima across several scales (Fig. 2). The figure clarifies the correspondence between a signal with singularities and its wavelet coefficients. Characteristic points are detected by comparing the coefficients of the discrete DyWT of selected scales against fixed thresholds. R-peaks are detected when the locations of modulus maxima of adjacent scales exceed a threshold that is calculated for every segment. For most R waves, their energies are concentrated at scales $|d_3[n]|$ and $|d_4[n]|$.

The developed QRS detector based on wavelet singularity analysis of a signal consists of three main blocks:

- filtering ECG signal by a filter bank of dyadic wavelet transform (DyWT) using a quadratic spline wavelet and a quadratic box spline scaling function,
- detection of candidates for QRS complexes using locations of modulus maxima on selected scales with adaptive thresholds,
- determining the final list of QRS complexes using heuristic methods which use additional decision rules for reducing the number of false-positive detections.

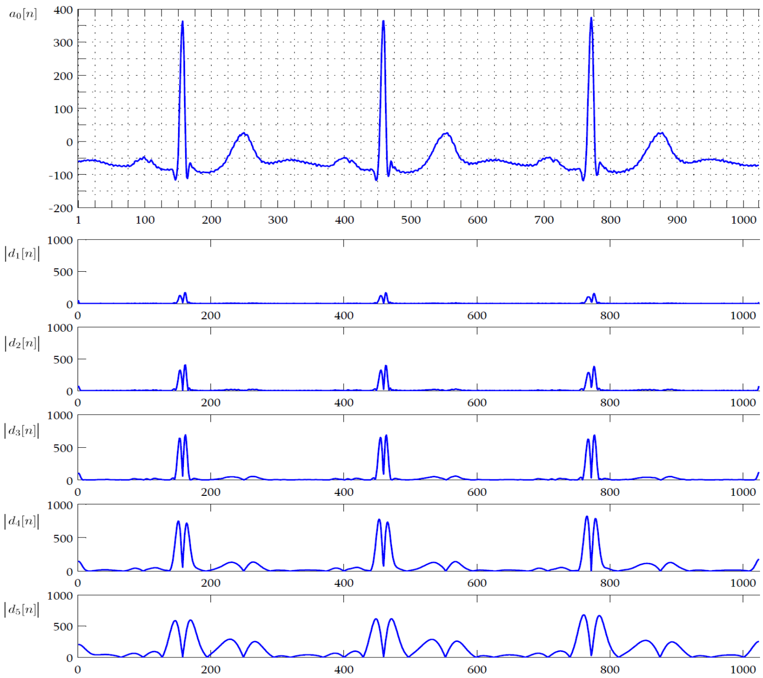

Fig. 2. The singularities in the ECG signal and its dyadic WT calculated by the *à trous* algorithm; $a_0[n]$ - ECG signal, $|d_1[n]| - |d_5[n]|$ - the modulus maxima of details coefficients in different scales.

The main part of the detection stage of the QRS complex is an original adaptive algorithm for the calculation of a QRS detection threshold.

4. An adaptive threshold for QRS complex detection

Problems in detection of the QRS complex have already been studied. The main problem is due to the presence of various types of noise (slow baseline drift, high frequency noise, impulsive noise). The great variability of patterns depends on the specific characteristics of the patient and change over time. The idea of a threshold for the detection algorithm presented in the paper uses the distribution of class intervals as one of several properties. The length of the analyzed window encloses the time interval of 16 cycles of ECG, which statistically should contain the average number of normal QRS.

Methods of determining the threshold presented in many other publications are based of empirical research on ECG signal. Therefore, complicated algorithms for the QRS detection threshold [4], [6], [2] was built on experiments, in which linear combinations of the factors is result of fine tuning on particular set of data, such as the MIT-BIH database [1], [14], [19]. Empirically selected thresholds for the MIT-BIH database do not provide the same high accuracy, for other ECG databases, e.g. in clinical practice.

The adaptive method of threshold detection of the QRS complex that we present in this paper is independent for each successive ECG signal window. The threshold algorithm uses the properties of distribution with a compartments class.

Let the modulus maxima DyWT values of the processed ECG window

$$x_{k,1},\dots,x_{k,n_k} \tag{24}$$

will be n_k-element samples which contain the absolute modulus maxima values at each level k dyadic wavelet transform.

The *distance* of the *feature X* is the difference

$$R_k = x_{k,max} - x_{k,min}, \tag{25}$$

where $x_{k,max}$ and $x_{k,min}$ denotes the highest and lowest value in a sample.

The distance is thus the length of the shortest interval in which all values are within a sample. With a larger sample size (over 30), in which facilitates analysis, aggregated in *classes*. For simplicity, we assume that intervals is equal length. Let suppose that all values in a given class are identical to the measure class. There are several rules for determining the number of classes c_k depending on the cardinality n_k of the sample. In our research here, they are:

$$c_k \approx \sqrt{n_k} \quad or \quad c_k \approx 1 + 3.322 \log n_k, \tag{26}$$

If R_k is the range of the sample, the number of classes c_k, then b_k denotes the *length of class*, and we assume that $b_k \approx R_k/c_k$. The number of samples with values contained in the i-class is called cardinality (the size) i of the class, and we denote $n_{k,i}$ and take into account the k levels of dyadic wavelet decomposition $n_{k,i}$. The symbol $\bar{x}_{k,i}$ means the center of a subsequent class, whose values are mean values lower and upper limit for each interval i class. The result is a series of pairs of numbers: center of the class $\bar{x}_{k,i}$ and the cardinality $n_{k,i}$, called distribution with a compartments class.

Each windows are contain modulus maxima values of DyWT to be analyzed. The value of the threshold for every DyWT scale is calculated as follows:

1. Two classes are calculated that contains the local maxima with the largest values - $x_{k,c_{k-1}} = x_{k,max} - 3/2 \cdot R_k/c_k$ and $x_{k,c_k} = x_{k,max} - 1/2 \cdot R_k/c_k$, for the distribution $\bar{x}_{k,i}$ values of modulus maxima for all scales of decomposition k.

2. Thresholds for QRS detection are established at each level k as central values in the interval $[x_{k,c_{k-1}}, x_{k,c_k}]$ for all decomposition scales k.

The occurrence of a QRS complex is detected by comparing the QRS candidates for selected level of all scales of DyWT. If the locations of the local maxima exceed the threshold correlated across two consecutive scales $2^3, 2^4$ (Fig. 2), we assume that the locations of these maxima correspond to the location of QRS complexes.

Almost all algorithms use additional decision rules for reducing the number of false-positive detections e.g. search-back or eyeclosing strategy [1]. Besides this condition, the algorithm applies heuristic decision rules such as conditions on the timing of the peak occurrence within the different scales. For example, we chose one representative of the QRS when for a short time was detected a few candidates for the QRS complex, and then we remove the remaining values as a potential duplicate QRS. Due to the intrinsic refractory period of cardiac muscle, a valid QRS complex cannot occur within 200 *ms* of the previous QRS complex.

5. Results of QRS detection for the MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database provided by MIT and Boston's Beth Israel Hospital was used for evaluating the proposed QRS detection algorithm. To evaluate the performance of the detection algorithm we use rates including false negative (FN), which means failing to detect a true beat (actual QRS), and false positive (FP), which represents a false beat detection. By using FN and FP the Sensitivity (SE), Positive Prediction $P+$ and Detection Error D_{err} can be calculated using the following equations respectively: $SE = TP/(TP+FN)$, $P+ = TP/(TP+FP)$ and $D_{err} = (FP+FN/totalQRS)$ where true positive (TP) is the total number of QRS correctly detected by the algorithm.

Obtained results of QRS detection for all MIT-BIH records gives sensitivity of 98.72% and a positive prediction of 99.12%. The quadratic spline wavelet with compact support and quadratic box spline scaling function were used [16].

In order to give an impression about difficulties in ECG analysis and QRS detection, the presented algorithms have been applied to selected signals from MIT-BIH database. They are shown in Table 1. These signals are the records 105, 108, 201, 208, 222. Generally, detection problems may occur for: record 105 (very high level of noise); record 108 (high P wave amplitude, often wrongly interpreted as R wave); record 201 (junctional escape beat occurs immediately after episodes of premature beat); record 208 (complexes which include among others premature ventricular contractions are grouped in 2- or 3-element blocks); and record 222 (noise and interference at higher frequencies is very similar to the QRS complex).

These signals are often part of a separate analysis of the publications: record 105 [14], [22], [3], [4]; record 108 [14], [22], [3], [1]; record 207 [22], [19], [6]; record 222 [21], [14], [3]. Their specificity means that they cause the most problems in automatic analysis. Our QRS detector performed well even in the presence of noise.

Table 1. Results QRS detection selected signals from MIT-BIH Arrhythmia Database.

	[record in MIT-BIH database] / [number of QRS complexes in record]														
	105 / 2572			108 / 1763			201 / 1963			208 / 2956			222 / 2484		
Publication	FP	FN	D_{err}	FP	FN	D_{err}	FP	FN	D_{err}	FP	FN	D_{err}	FP	FN	D_{err}
Pan & Tompkins et al., 1985 [21]	67	22	3.46	199	22	12.54	0	10	0.51	4	14	0.60	101	81	7.33
Hamilton & Tompkins, 1986 [9]	53	22	2.95	50	47	5.67	3	19	1.14	9	19	0.95	40	37	3.14
Li et al., 1995 [14]	15	13	1.09	13	15	1.59	1	12	0.66	0	4	0.14	1	9	0.40
Poli et al., 1995 [22]	86	5	3.53	143	25	9.52	0	45	2.29	15	18	1.12	4	10	0.56
Bahoura et al., 1997 [3]	27	15	0.63	20	29	2.78	7	24	1.07	2	6	0.27	12	27	1.57
Afonso et al., 1999 [1]	53	16	3.22	121	55	9.98	4	7	0.56	8	43	1.73	4	4	0.32
Chiarugi et al., 2007 [6]	37	17	2.10	34	5	2.21	0	65	3.31	11	19	1.02	1	3	0.16
this work	19	8	1.07	83	13	5.45	82	22	5.30	1	17	0.61	18	11	1.17

The processed signal window contains 2048 samples of MIT-BIH ECG recording with a sampling rate of 360 Hz. There should be about 6-10 potential candidates for QRS complexes. The set of DyWT modulus maxima values was divided into 15 ranges on each decomposition level. Detection threshold was as the central of the two average values of greatest ranges. Heuristic applied on the decision stage says that the QRS candidate must occur at least on two levels of the wavelet decomposition.

The results of the comparison are shown in Table 1. The interpretation of the results provides a partial overview and gives a good impression on which algorithms are potentially useful for a real clinical analysis systems. However, from an objective point of view, reported in many publication results are not truly reliable, because an algorithms almost always was tuned to perform perfectly on such pathological signals from MIT-BIH, but not on a clinical ECG recordings.

Unfortunately, a QRS detector which performs well for a given training database often fails when presented with different ECG's data sets. Better results could be achieved by extreme fine tuning of its parameters. Such an inconsistency in performance is a major limitation that prevents highly reliable ECG processing systems to be widely used in clinical practice. Because of this, the threshold value was updated using the formula [13], [1], [14], [19], [21], [9] which corresponds to a linear combination of constant factor specific for particular ECG data sets, e.g. MIT-BIH Database. In such cases good reported results might be difficult to reproduce.

In our algorithm, the threshold level is automatically calculated independently for each signal window, using the algorithm described in section 4. No fixed threshold level can be used, and the value must adapt to varying signal levels in order to remain at the same relative level for different statistical properties of ECG signal.

In the next section we show that the implemented method is able to detect well, wider and unusually shaped QRS complexes even when it's performed in the presence of noise or artifacts.

6. Evaluation algorithm of QRS detection on clinical data

The currently achievable detection rates often determine only the overall performance of the detectors. These numbers hide the problems that are still present in case of noisy or pathological signals. A satisfying solution to these problems still does not exist. For example, the leading suppliers of solutions for analyzing Holter records, e.g. Mortara Instrument [20] or Del Mar Reynolds Medical [7] declare that the rate sensitivity of their methods is greater than 99% for the MIT-BIH Arrhythmia Database.

Collaboration with cardiology doctors of Medical University of Bialystok allowed us to evaluate the QRS detector algorithm developed in this work. In particular, it gave us the opportunity to compare our algorithm with the world-class commercial solution: Del Mar's Reynolds Pathfinder - Holter analysis system [7]. Three cases presented in Fig. 3, 4, 5 have been analyzed with doctor in order to compare the results of the our detection algorithm and the Pathfinder software. The examples are part of a wider range of material developed during the expertise. The medical doctor was decided to study the specially selected records of two patients, six episodes of ECG for each of them.

Examples shown on figures (Fig. 3, 4, 5) are the cases of the most common disorders of the ECG recording. There are several sources of distortion and Pathfinder consequently shows shortcomings of the QRS complex detection. They may be additional components of a signal, e.g. due to work the chest muscles or the presence of strong electromagnetic field. Noise sources include muscle noise, artifacts due to electrode motion, power-line interference, baseline wander, and T waves with high-frequency characteristics similar to QRS complexes.

As we can see, the algorithm for QRS detection in the Pathfinder system works poorly for the noisy ECG signal in real conditions. The world-class automatic analysis system is not always be able to properly analyze *difficult* ECG signals.

The experiments were performed using our QRS detector with the defaults settings of the thresholding algorithm and the same quadratic spline wavelet with

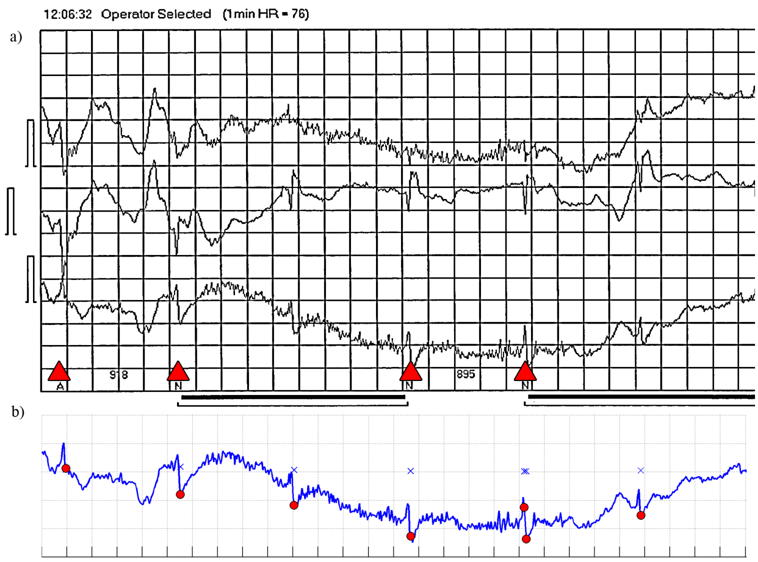

Fig. 3. The results of QRS detection for patient 1, episode 2: a) the Pathfinder has lost two QRS complexes, which are presented as dark sections of the timeline; QRS correctly detected are marked with triangle and letter "N", b) detector developed by the authors for that analyze the signal from 3th electrode has correctly detected all the QRS complexes, detected QRS are marked with dots.

compact support and a quadratic box spline scaling function. The results shows that our algorithm has detected the small number of QRS duplicates. This situation occurs because we intentionally deactivate heuristic rules for duplicates detector.

It should be noted that in the tests only one electrode was used to evaluating, although in some cases, see for example Fig. 5, where the signal from the other electrode was better quality in terms of detection.

7. Conclusions

In this paper, a QRS detection algorithm based on the Mallat and Hwang singularity analysis has been proposed. We have described the properties of the DyWT necessary for ECG signal processing. Our QRS detection algorithm results in a relatively low number of false-positives (FP) and false-negative (FN). Results obtained for full 48 recordings of MIT-BIH Arrhythmia Database are characterized by sensitivity of 98.72% and a positive prediction of 99.12%.

The conducted experiments show that the proposed algorithm may give very high efficiency in detection of QRS complex in the noisy ECG waveforms. Prelim-

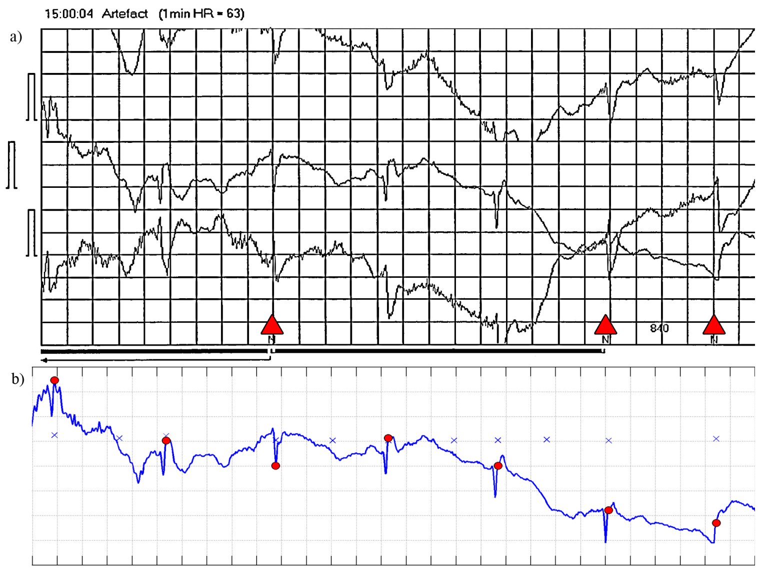

Fig. 4. The results of QRS detection for patient 1, episode 4: a) the Pathfinder has lost four QRS complexes, which are presented as dark sections of the timeline; QRS correctly detected are marked with triangle and letter "N", b) detector developed by the authors for that analyze the signal from 2nd electrode has correctly detected all the QRS complexes, detected QRS are marked with dots.

inary results obtained with clinical patient data, shows that the proposed algorithm correctly detects the QRS, even under the presence of noise, baseline drift, muscle noise and artifacts due to electrode motion. However, the large variation in the QRS complex waveforms as well as noise may still appear, so that further performance improvements are still an important goal of current research.

One of key advantages is that the QRS detection uses a reliable adaptive threshold algorithm. Calculation of the detection threshold was performed independently for each analyzed window of the signal. It makes a truly, highly adaptive algorithm. This means that the proposed solution has a great potential of clinical uses.

The algorithm has been also tested using ECG records from the Holter system at Medical University of Bialystok. In comparisons with the world-class commercial solution: Del Mar's Reynolds Pathfinder - Holter system. The proposed algorithm showed a better QRS detection results. This suggests that there is a real opportunity to create dedicated software for analyzing of Holter records that could be competitive for the currently available solutions system on the market.

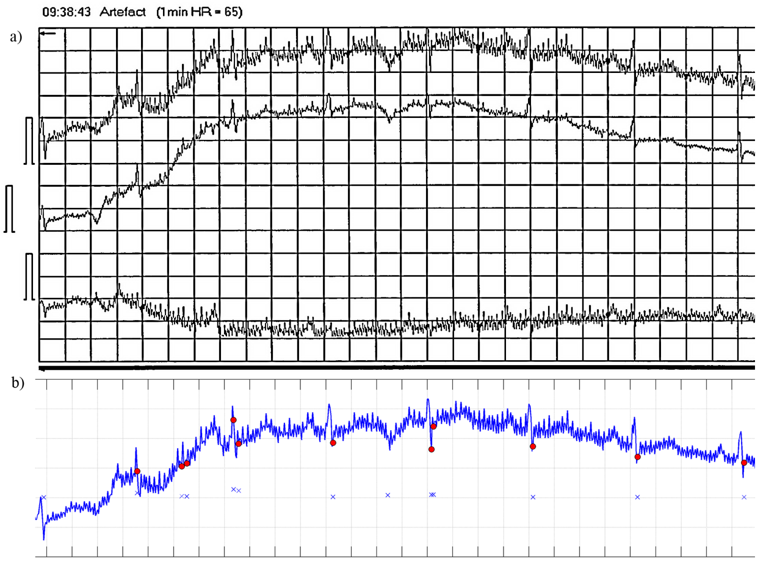

Fig. 5. The results of QRS detection for patient 2, episode 2: a) the Pathfinder has lost all QRS complexes, which are presented as dark sections of the timeline; QRS correctly detected are marked with triangle and letter "N", b) detector developed by the authors for that analyze the signal from 1st electrode has correctly detected all the QRS complexes, detected QRS are marked with dots. Three of the QRS complexes have been detected twice but the duplicate detection heuristic was inactive.

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DETEKCJA ZESPOŁU QRS OPARTA NA FALKOWEJ ANALIZIE OSOBLIWOŚCI SYGNAŁU W ZAKŁÓCONYCH ZAPISACH EKG POCHODZĄCYCH Z URZĄDZENIA HOLTERA

Streszczenie Praca przedstawia algorytm detekcji zespołu QRS oparty na falkowej analizie osobliwości sygnału Mallata i Hwanga, wykorzystujący diadyczną transformatę falkową. Filtry cyfrowe analizy falkowej odpowiadają falce i funkcji skalującej w postaci tzw. spline'ów bramkowych drugiego stopnia o zwartym i krótkim nośniku. Dzięki temu podczas analizy sygnału i detekcji osobliwości możemy dokładniej kontrolować parametry procesu separacji wybranych częstotliwości. Dzięki analizie wieloskalowej możliwe jest zlokalizowanie miejsca gwałtownej zmiany sygnału, a tym samym lokalizacji zespołu QRS. Metoda posiada mniejszą wrażliwość na zmiany morfologii kolejnych zespołów QRS, minimalizuje problemy związane z występowaniem składowej wolnozmiennej, artefaktów ruchu i napięcia mięśni oraz pozwala na łatwiejszą separację załamka R w stosunku do załamków P i T. W niniejszej pracy zaproponowano oryginalny, adaptacyjny sposób wyznaczania progu detekcji przy użyciu właściwości statystycznych obserwowanego sygnału oraz dodatkowych heurystyk. Metoda wyznaczania progu jest niezależna dla każdego kolejnego okna sygnału, składającego się z kilkunastu cykli EKG. Algorytm wyznacza wartość progu na podstawie analizy własności szeregu rozdzielczego z przedziałami klasowymi. Działanie algorytmu zostało przetestowane przy użyciu zapisów z bazy MIT-BIH Arytmia Database. Dodatkowo, wrażliwość na zakłócenia adaptacyjnego detektora QRS była przetestowana przy użyciu, specjalnie wyselekcjonowanych przez kardiologa, epizodów EKG z systemu Holtera z Uniwersytetu Medycznego w Białymstoku. Porównania wyników dokonano z komercyjnym systemem Pathfinder firmy Del Mar Reynolds.

Słowa kluczowe: EKG, detekcja uderzeń serca, zespół QRS, falkowa analiza osobliwości, modulus maxima, zakłócony EKG, zapisy Holtera, progowanie adaptacyjne, diadyczna transformata falkowa

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