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Research Article

A NEW ROBUST QRS DETECTION ALGORITHM IN ARRHYTHMIC ECG SIGNALS

Süleyman BILGIN [*1], Zahide Elif AKIN[2]

[1] Akdeniz University, Engineering Faculty, Dept. of Electrical & Electronics Engineering, Antalya, Turkey
[2] Akdeniz University, Institute of Natural Sciences, Dept. of Electrical & Electronics Engineering, Antalya, Turkey

Keywords

Electrocardiogram,
QRS Detection,
Discrete Wavelet Transform,
Digital Filters,

Abstract

The QRS detection in electrocardiogram (ECG) signals provides significant information to help automatic diagnosis of some cardiovascular disorders. There are many studies about QRS detection in the literature. All these studies have focused on the development of QRS detection including noise, baseline wander, artifacts, small and wide QRS complexes. However, some QRS complexes cannot be detected due to their morphological and arrhythmic disorders. These types of beats are misevaluated during observation. Therefore, increasing the success and accuracy of such algorithms is of great importance for the development of wearable cardiac diagnostic devices. Arrhythmic ECG signals include different morphologic features, such as sudden, narrow, small, and negative QRS complexes, which are very difficult to automatically detect. In this study, we propose a new algorithm with higher accuracy than other studies in the literature for the detection these types of QRS complexes. The proposed method based on digital filtering and Discrete Wavelet Transform (DWT) is evaluated and tested using the two-channel ECG records obtained from 48 patients in the MIT/BIH arrhythmia database. The overall performance results of this algorithm are calculated as 99.79% of the sensitivity, 99.95% of the predictivity rate, the detection error rate of 0.26 and 99.74% of accuracy score.

ARİTMİK EKG SİNYALLERİNDE DAYANIKLI YENİ BİR QRS YAKALAMA ALGORİTMASI

Anahtar Kelimeler

Elektrokardiyogram,
QRS Yakalama,
Ayrık Dalgacık Dönüşümü,
Sayısal Süzgeçler,

Öz

Elektrokardiyogram (EKG) sinyallerindeki QRS algılama, bazı kardiyovasküler bozuklukların otomatik teşhisine yardımcı olmak için önemli bilgiler sağlamaktadır. Literatürde QRS tespiti ile ilgili birçok çalışma bulunmaktadır. Tüm bu çalışmalar, elektriksel gürültü, taban hattı kayması, kas gürültüleri, küçük ve geniş QRS kompleksleri dahil olmak üzere QRS algılamanın geliştirilmesine odaklanmıştır. Bununla birlikte, bazı QRS kompleksleri morfolojik ve aritmik bozuklukları nedeniyle tespit edilemez. Bu vuruş türleri gözlem sırasında yanlış değerlendirilir. Bu nedenle, bu tür algoritmaların başarısını ve doğruluğunu arttırmak, giyilebilir kalp tanı cihazlarının geliştirilmesi için büyük önem taşımaktadır. Aritmik EKG sinyalleri, otomatik olarak algılanması çok zor olan ani, dar, küçük ve negatif QRS kompleksleri gibi farklı morfolojik özellikleri içerir. Bu çalışmada, bu tür QRS komplekslerinin saptanması için literatürdeki diğer çalışmalardan daha yüksek doğrulukta yeni bir algoritma önermekteyiz. Dijital filtrelemeye ve Ayrık Dalgacık Dönüşümüne (ADD) dayanan bu yöntem MIT / BIH aritmi veri tabanındaki 48 hastadan elde edilen iki kanallı EKG kayıtlarını kullanarak değerlendirildi ve test edildi. Bu algoritmanın genel performans sonuçlarında, duyarlılık %99,79, öngörme oranı %99,95, algılama hata oranı 0,26 ve doğruluk skoru %99,74 olarak hesaplanmaktadır.

[*] Corresponding author: suleymanbilgin@akdeniz.edu.tr, +90-242-310-6388

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Yazar Kimliği / Author ID (ORCID Number)

S. BILGIN / 0000-0003-0496-8943
Z.E. AKIN / 0000-0001-5358-225X

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1. Introduction

Cardiac disturbances and cardiovascular disorders are one of the most important sudden death causes in the world. Considerable research in many fields has been performed for diagnosis and detection of such disorders related to the circulatory system. Various imaging techniques and laboratory tests are available for diagnosis and monitoring of cardiovascular disorders. One of the most common ones is undoubtedly ECG devices. They contain important information about the electrical conduction of the heart and also allow diagnosis of arrhythmias. They can be obtained with recording devices available in hospitals and outpatient clinics and can also be obtained in 24-hour and 48-hour records via Holter ECG devices that can be carried on the patients. It can even exist as a wearable device on the market by means of developing technologies. Scientific studies on the possibility of automatic disease detection, during recording or after being transferred to the computer environment, on such devices are continuing rapidly.

It is very difficult and time consuming for physicians to examine 24-hour or 48-hour ECG recordings. Automatic detection of arrhythmias is an important tool for physicians due to developing technology and new signal processing methods. The capture of the critical points on the ECG has also great importance for these automatic determinations to be performed. These critical points on the ECG signals are P, Q, R, S, T and U, seriatim. Many arrhythmias are provided with automatic capture of these points and features that will be derived from them. One of the first procedures performed in this type of study is to determine automatically R points. In this way, a lot of information that allows facilities for diagnosis and monitoring related to the heart is obtained from the ECG signal. In the literature, there are a lot of studies about automatic detection of QRS complex. The advantages and disadvantages of these studies vary among each other, but in general high accuracy has been achieved in them.

2. Scientific Literature Survey

According to the literature, the Pan and Tompkins algorithm, which inspired many studies based on filtering and differentiation, detects the QRS complex with an error rate of 0% to 12.54% (Pan and Tompkins, 1985). Paoletti et al. have obtained the achievement with 0.85% error using threshold-based algorithm in their study (Paoletti et al., 2006). Xue et al. have caught the QRS complex with error rates of 0.50% to 12.54% by virtue of neural network-based algorithm (Xue et al., 1992). Zidelmal and colleagues detect R points with 0.54% error using their algorithm based on DWT (Discrete Wavelet Transform) (Zidelmal et al., 2012). Chen et al. have achieved about 99.5% of the detection rate by using their algorithm based on moving-averaging incorporating with wavelet denoising (Chen et al., 2006). Rufas et al. have proposed algorithm the MaMeMi filter that is a non-linear HPF useful in order to remove ECG baseline wander and achieved 99.22% accuracy rate, 99.43% sensitivity and 99.67% positive prediction (Rufas et al., 2015). Yeh and his team performed detection with 0.19% error rate using different operation method (Yeh and Wang, 2008). Moraes et al. achieved a sensitivity of 99.73% using the capture algorithm implemented by the dual detection model (Moraes et al., 2002). Manikandan and colleagues achieved R-point detection success with 99.79% accuracy with a Moving Average Filtering (MAF) and Hilbert Transform (HT) based algorithm (Manikandan and Soman, 2012). Farashi has developed a Multi-Resolution Entropy based QRS capture algorithm and achieved 99.60% accuracy (Farashi, 2016). Sharma and colleagues used Savitzky Golay Filtering (SGF) and quadratic averaging methods to detect R points and obtained an accuracy of 99.08% (Sharma and Sunkaria, 2016). Arzeno and his team have achieved a QRS detection with 99% accuracy using the five-stage algorithm which they have developed (Arzeno et al., 2008). Chouhan et al. have achieved an accuracy of 98.56% in the QRS algorithms based on threshold values and square method (Chouhan and Mehta, 2008). Tan and colleagues found R points with a sensitivity of 95.60% and 88.96% in the study performed on the basis of Chan and Pan-Tompkins methods (Tan et al., 2000). Slimane et al. obtained 99% accuracy from their algorithm based on Mode Decomposition method (Slimane and Naït-Ali, 2010). Zhang and his team have developed an important system for QRS detection using the Multi-Scale Mathematical Morphology Filtering method. At the end of this algorithm, QRS detection has been performed with a sensitivity of 99.81% (Zhang and

Lian, 2009). Köhler et al. captured the R-points using a zero-detection algorithm and obtained 99.70% accuracy (Köhler et al., 2003). Yochuma et al. detected R points with 98.64% accuracy using Continuous Wavelet Transform (CWT) (Yochuma et al., 2016). Bahoura and his colleagues achieved 99.8% accuracy with the Algorithm based on Wavelet Transform (WT) (Bahoura et al., 1997). Phukpattaranont captured the QRS complex with a success rate of 99.62% in his quadratic filtering-based studies (Phukpattaranont, 2015). Hongyan et al. have developed an algorithm based on empirical mode decomposition and obtained 99.33% accuracy score (Hongyan and Minsong, 2008). Choi, Karimipour and Bouaziz have achieved 99.45%, 99.57% and 99.66% accuracy scores using their method based on Wavelet Transform, respectively (Choi et al., 2010; Karimipour and Homaeinezhad, 2014; Bouaziz et al., 2014). Martinez et al. have acquired 98.66% accuracy with method including quadratic spline wavelet (Martinez et al., 2004). Arbateni and Bennia have obtained 99.70% in the study based on artificial neural networks (Arbateni and Bennia, 2014). Zhu and Dong achieved 99.83% accuracy using an algorithm based on Shannon energy envelope (Zhu and Dong, 2013). Finally, we proposed a method based on HT and DWT and achieved 98.11% accuracy value in our last study (Guzeler and Bilgin, 2016). However, the Hilbert Transform used in this study is not as successful as the digital filtering methods used in this algorithm.

From a literature perspective, it is clear that accuracy values in most of the studies done are reached to about 99% scores. Since each QRS complex must be assessed in detail in determining cardiac disease, it is of great importance that success rates reach high levels even on long-term registrations. The purpose of this study is to improve the accuracy of automatic recognition of QRS complexes in long-term ECG recordings. Thus, diagnosis and treatment of the physician will be more accurate with the results obtained in automatic detection.

3. Material and Methods

The basic operation steps of the algorithm are shown in Figure 1. As seen from the algorithm, in the first step, the signals obtained from the database are passed through the SGF (Savitzky-Golay Filtering) to suppress the high frequency components on them. Then, BPF (Band Pass Filter) is applied to signal in order to suppress the P and T waves and make the QRS regions more distinct. After the BPF processing, the DWT method is used to make the QRS regions even more prominent. The rest of the study focuses on the regulation of the morphology of QRS regions and the identification of zones by means of adaptive threshold levels. The function of High Pass Filter (HPF) on the algorithm is to remove the signal baseline wander that occurs after the applied operations. Thus, the base level of the signal becomes flat. The last of the study, the QRS zones are detected by means of adaptive threshold determination depending on the STD (Standard Deviation) and mean values of the signals.

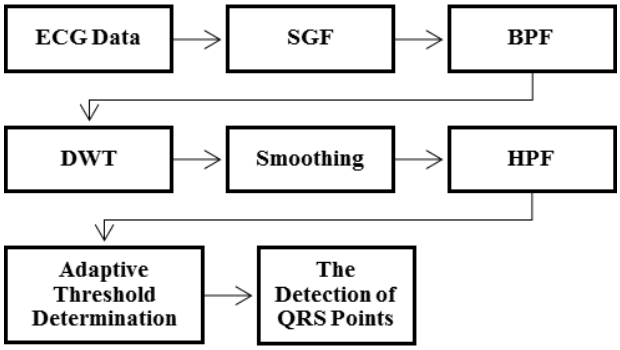

Figure 1. The Overview of Algorithm

3.1. Database

The MIT / BIH Arrhythmia database, which was used as the database for many of the similar studies, is also used in this study and easily compared with other studies in the literature. The MIT / BIH Arrhythmia database contains 2-channel ECG recordings from 48 arrhythmia patients aged between 23 and 89 years (Moody and Mark, 2001). There are some noise and disturbances in the signals which are digital values sampled at 360 Hz in the database. When the signals are examined; noise and artifacts are observed on the records 104, 105, 108, 200, 203, 210 and 228 while instantaneous changes and axial deviations are found in the records 108, 111, 112, 116, 201, 203, 205, 208, 210, 217, 219, 222 and 228. In addition, records 201, 202, 203, 219 and 222 show various irregular arrhythmias, 200, 203, and 233 records have the abrupt fluctuations on QRS morphology and negative QRS polarities, Records 201, 219 and 232 have long waiting durations, Records 108 and 222 have long and sharp P waves, Records 116 and 208 have smaller QRS complexes than them in other records, Record 113 has long and sharp T waves, 208 record has Premature Ventricular Contractions (PVCs) and record 223 contains abrupt fluctuated QRS complexes. In this study, the original ECG signals obtained from database are amplified by 30 times gain at first.

3.2. Savitzky-Golay Filtering

SGF is used for smoothing out of a noisy signal in the ECG in this study. This type of filters performs much better than standard averaging FIR filters, which tend to filter out an important portion of the signal having high frequency component with the noise

(Chakraborty and Shreya, 2012). If the order and window size of SGF increase, the noise becomes even less. However, in this case the QRS regions begin to disappear. On the other hand, if these values decrease, the noise is still available on the signal. Thus, optimally, the data frame is selected as 25 in the second-order SGF that is applied to the signal in this study. The output of SGF for record 104 is shown in Figure 2.

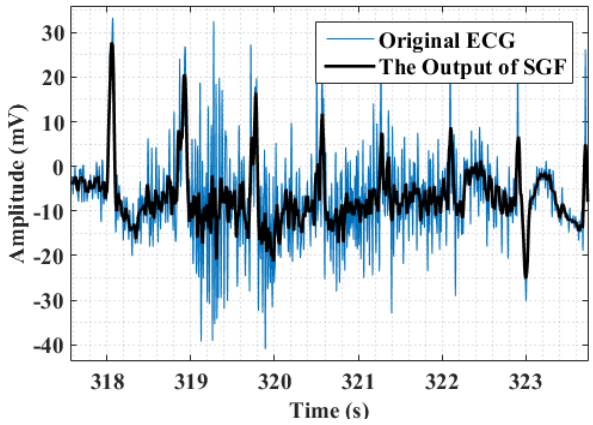

Figure 2. The SGF output of record 104.

3.3. Band Pass Filtering

In this part of the study, A Band Pass FIR filter based on Parks-McClellan algorithm is used to suppress the P and T waves and reveal the QRS regions. The Parks–McClellan algorithm proposes a solution to a minimax or Chebyshev approximation problem using Remez Exchange Method and develops optimal equiripple filters (Manolakis and Ingle, 2012). The order of the filter whose cut-off frequencies are 7 Hz and 28 Hz respectively is selected experimentally as 100. After BPF processing, the absolute value of obtained output signal for record 114 is shown in Figure 3.

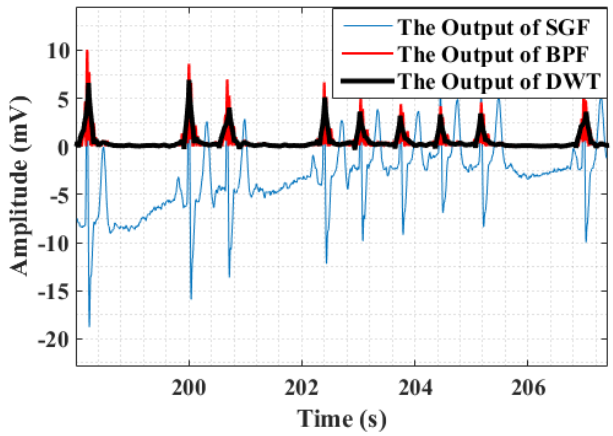

Figure 3. The SGF output and DWT output of record 232.

3.4. Discrete Wavelet Transform and Smoothing

DWT is especially efficient tool for the analysis of low-frequency signals. In this study, the purpose of the DWT and smoothing stage is to help the QRS regions that are on the signal obtained after the BPF processing to be smoother and sharper by suppressing high frequency components. The selection of wavelet function and level of decomposition are very significant in DWT for detection of QRS regions. During the analysis, it is observed that the 'coif1', which is denoted as 'coifflet1' wavelet function, selected by considering both the observations and the errors resulting from the capture algorithm gives both flatness and sharpness for the QRS morphologies. The level of DWT is selected depending on the effect of smoothness and sharpness. At higher levels of the decomposition in DWT, while the flatness of QRS morphology increases, conversely, the amplitude decreases. At lower levels of the decomposition, while the amplitude of QRS regions increases the flatness inversely decreases. This comparison is shown in Figure 4. The optimum morphology is provided at 4-level decomposition. It is noticed that the 'A4', which is denoted as approximation component at 4th decomposition level, provides a smoother and sharper morphology than the others. 'A4' component is ranged between 0 Hz and 11.25 Hz depending on 360 Hz sampling frequency in this study. The decomposition level is adjusted automatically to desired sampling frequency in algorithm so that the bandwidth is ranged between 0 Hz and 11.25 Hz.

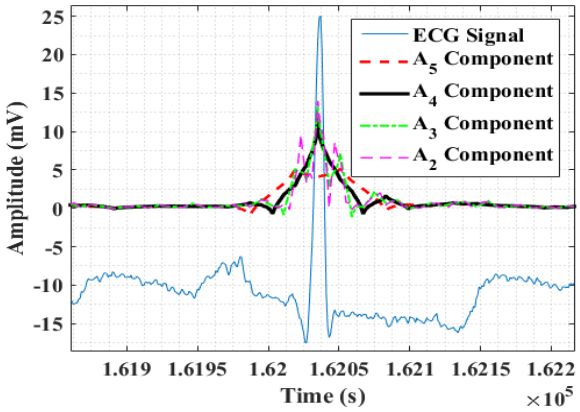

Figure 4. The selection of DWT level and Approximation component

The output signal is passed from smoothing process, which is a local regression using weighted linear least squares and a 1st degree polynomial model, after DWT operation. The smoothing is adjusted depending on a normal QRS formation time defined as 100 ms (milliseconds) in the literature. In this study, the span of smoothing is selected as 300 ms that equals about 3 times the duration of a normal QRS, which provides the optimum smoothing. The signal is squared after smoothing. The output of this stage is shown in Figure 5.

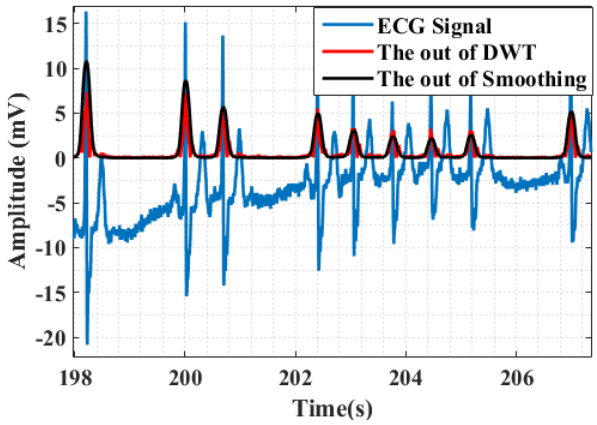

Figure 5. The DWT output and the smoothing of record 232.

3.5. High Pass Filtering

The valleys between some QRS regions very close to each other on the ECG make a shifting upward. Since these valleys are usually above the threshold level, two consecutive QRS regions close to each other are captured as a single QRS region. Therefore, it is considered as an error. This problem is solved by suppressing these valleys in virtue of high pass filter. This situation is shown for record 203 in Figure 6.

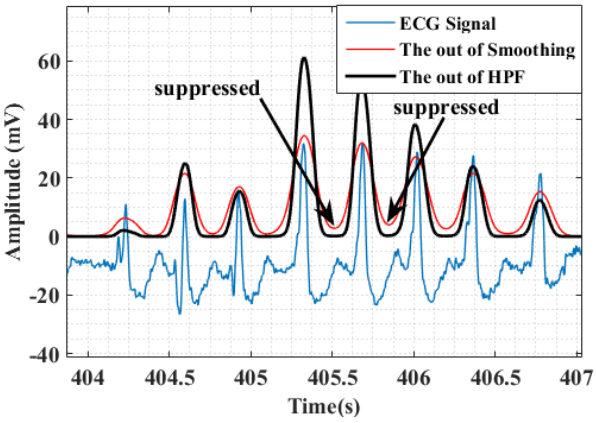

Figure 6. The HPF output of record 203.

The cut-off frequency of 40-order HPF are selected as 4.9 Hz in the study. The type of HPF is selected as FIR filter, optimally. The signal is squared after HPF processing, so that the signal has enough amplitude in adaptive threshold stage of the algorithm.

3.6. Adaptive Threshold Determination and QRS Detection

Let X, which includes a finite data set $x_1, x_2, ..., x_N$, represents the signal at the HPF output. the standard deviation is;

$$\sigma_x = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu_x)^2} \quad (1)$$

Where, μ_x that is denoted as mean value of X is formulated as

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (2)$$

and y_i is calculated as;

$$y_i = \begin{cases} Thr1, & x_i \geq Thr1 \\ x_i, & x_i < Thr1 \end{cases} \quad (3)$$

The first and second threshold values are;

$$Thr1 = K_1\sigma \quad and \quad Thr2 = K_2\mu_y \quad (4)$$

Where K_1 and K_2 are coefficients for the adjustment of $Thr1$ and $Thr2$, respectively. Also, μ_y is denoted as mean value of Y, which includes a finite data set $y_1, y_2, ..., y_N$. Then, p_i values are calculated as $p_i = y_i - Thr2$. And finally, s_i logical values are determined as;

$$s_i = \begin{cases} 0, & p_i \leq Thr3 \\ 1, & p_i > Thr3 \end{cases} \quad where \quad Thr3 = K_3\mu_p \quad (5)$$

Here, K_3 is a coefficient for the adjustment of $Thr3$. K_1, K_2 and K_3 coefficients are determined experimentally as 0.56, 0.2 and 0.25, respectively in the study. Parameter μ_p is denoted as mean value of P, which consists of data set $p_1, p_2, ..., p_N$. The S data set including $s_1, s_2, ..., s_N$ refers to QRS regions to be detected in the study. These QRS regions are shown in Figure 7.

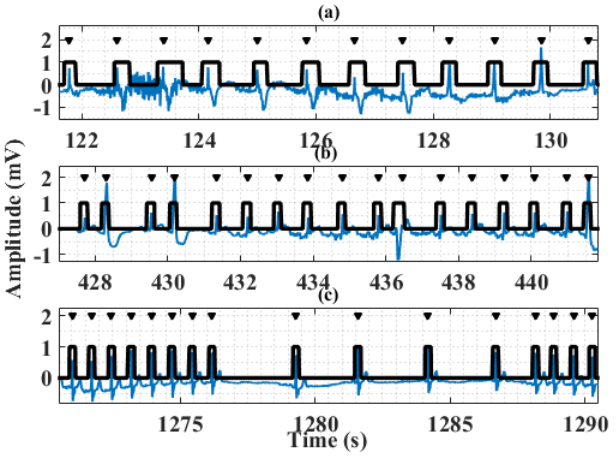

Figure 7. The QRS regions detected on (a) record 104 (b) record 228 (c) record 232.

4. Results & Discussions

The MIT / BIH Arrhythmia database used in the study contains two channel 30-minute ECG recordings, which is sampled at 360 Hz with 11-bit resolution over 10 mV range, obtained from 48 arrhythmia patients.

The ECG records in this database include signals having the fluctuations on QRS morphology, amplitude and directions, long pauses, random rhythms, muscle noise, long and sharp P and T waves, baseline drift and multiform premature ventricular contractions (PVCs). The algorithm is developed on a laptop consisting of i7-6500U CPU @ 2.5-GHz Intel core CPU and 8 GB RAM using MATLAB software, and is tested on the ECG signals obtained from the first (ch1) and second (ch2) channels of the MIT-BIH arrhythmia database depending on their channel performances. The average processing time during performing the algorithm for each 30-minute recordings in the database is approximately 400 ms. Four quantitative percentage scores for evaluation of results during the study include the sensitivity (Se), the positive predictivity rate (+P), the detection error rate (DER) and the detection accuracy (Acc) that is expressed as overall performance is calculated respectively;

$$Se = \frac{TP}{TP+FN} \times 100 \quad (6)$$

$$+P = \frac{TP}{TP+FP} \times 100 \quad (7)$$

$$DER = \frac{FP+FN}{TP} \times 100 \quad (8)$$

$$Acc = \frac{TP}{TP+FP+FN} \times 100 \quad (9)$$

Where, TP is denoted as True-positive that is number of accurately detected QRS regions, FN is defined as false-negative that is number of missed QRS regions, and FP that is defined as false-positive is falsely detected beats QRS regions.

The results after analysis show that the algorithm is quite successful. The evaluation of the study performed on the MIT / BIH Arrhythmia database is shown in Table 1. According to Table 1, the algorithm correctly recognizes 100% of the QRS regions in the records 100, 101, 102, 113, 115, 118, 122, 123, 213, 219, 220, 230, 231 and 234. The proposed algorithm reveals 256 FN regions and 55 FP regions. Detection accuracy scores belonging to each of 48 recordings show a fluctuation between 97.18% and 100% with respect to the specifications of normal and pathological QRS morphology. According to overall performance of the algorithm, the sensitivity is determined as 99.79%, the predictivity rate is calculated as 99.95%, detection error rate is obtained as 0.26 and accuracy score is determined as 99.74%. During the study, it is observed that ch2 provides better results on records 111, 113, 114, 116, 118, 119, 202, 203, 207, 222, 228, 230 while ch1 has better scores for other records in the database.

Table 1. Performance evaluation of the proposed QRS detection algorithm.

Data	Channel	Total (Beats)	FN	FP	Se	+P	DER	Acc
100	ch1	2273	0	0	100	100	0.000	100
101	ch1	1866	0	0	100	100	0.000	100
102	ch1	2187	0	0	100	100	0.000	100
103	ch1	2084	1	0	99.95	100	0.048	99.95
104	ch1	2229	0	9	100	99.60	0.404	99.6
105	ch1	2579	11	11	99.57	99.57	0.853	99.15
106	ch1	2027	4	0	99.80	100	0.197	99.8
107	ch1	2135	5	0	99.77	100	0.234	99.77
108	ch1	1768	34	0	98.08	100	1.923	98.08
109	ch1	2531	4	0	99.84	100	0.158	99.84
111	ch2	2124	2	1	99.91	99.95	0.141	99.86
112	ch1	2539	0	3	100	99.88	0.118	99.88
113	ch2	1795	0	0	100	100	0.000	100
114	ch2	1879	1	0	99.95	100	0.053	99.95
115	ch1	1952	0	0	100	100	0.000	100
116	ch2	2412	3	0	99.88	100	0.124	99.88
117	ch1	1535	0	3	100	99.80	0.195	99.8
118	ch2	2278	0	0	100	100	0.000	100
119	ch2	1987	2	0	99.90	100	0.101	99.9
121	ch1	1863	2	0	99.89	100	0.107	99.89
122	ch1	2476	0	0	100	100	0.000	100
123	ch1	1519	0	0	100	100	0.000	100
124	ch1	1617	1	0	99.94	100	0.062	99.94
200	ch1	2599	1	0	99.96	100	0.038	99.96
201	ch1	1963	3	5	99.85	99.75	0.408	99.59
202	ch2	2136	1	6	99.95	99.72	0.328	99.67
203	ch2	2980	83	1	97.21	99.97	2.819	97.18
205	ch1	2656	12	0	99.55	100	0.452	99.55
207	ch2	1835	7	1	99.62	99.95	0.436	99.56

208	ch1	2955	27	0	99.09	100	0.914	99.09
209	ch1	3005	0	9	100	99.70	0.300	99.7
210	ch1	2650	16	1	99.40	99.96	0.642	99.36
212	ch1	2748	0	1	100	99.96	0.036	99.96
213	ch1	3250	0	0	100	100	0.000	100
214	ch1	2262	5	0	99.78	100	0.221	99.78
215	ch1	3363	10	0	99.70	100	0.297	99.7
217	ch1	2208	3	0	99.86	100	0.136	99.86
219	ch1	2154	0	0	100	100	0.000	100
220	ch1	2047	0	0	100	100	0.000	100
221	ch1	2427	3	0	99.88	100	0.124	99.88
222	ch2	2483	3	3	99.88	99.88	0.242	99.76
223	ch1	2602	8	0	99.69	100	0.307	99.69
228	ch2	2055	2	0	99.90	100	0.097	99.9
230	ch2	2256	0	0	100	100	0.000	100
231	ch1	1571	0	0	100	100	0.000	100
232	ch1	1780	0	1	100	99.94	0.056	99.94
233	ch1	3076	2	0	99.93	100	0.065	99.93
234	ch1	2752	0	0	100	100	0.000	100
Overall		109468	256	55	99.79	99.95	0.26	99.74

Table 2 shows the comparison of this study and previous studies. It is clear that this study is more successful than many studies (Pan and Tompkins, 1985; Zidelmal et al., 2012; Farashi, 2016; Arzeno et al., 2008; Zhang and Lian, 2009; Phukpattaranont, 2015; Hongyan and Minsong, 2008; Choi et al., 2010; Karimipour and Homaeinezhad, 2014; Bouaziz et al., 2014; Martinez et al., 2004; Arbateni and Bennia, 2014), but it has a lower success than the other two methods in Table 2 (Manikandan and Soman, 2012; Zhu and Dong, 2013).

Table 2. The QRS detection comparison performance with other methods.

Study	Method	FN (Beats)	FP (Beats)	Se (%)	+P (%)	Acc (%)
Arzeno et al. (2008)	Band pass filter, derivative and squarer	467	447	99.57	99.59	99.17
Hongyan and Minsong (2008)	Empirical mode decomposition and denoising	244	467	99.77	99.56	99.33
Choi et al. (2010)	Wavelet Transform	376	218	99.66	99.80	99.45
Pan and Tompkins (1985)	Band pass filter, derivative squarer and moving window integrator	340	248	99.69	99.77	99.46
Karimipour and Homaeinezhad (2014)	Wavelet Transform	192	308	99.83	99.74	99.57
Farashi (2016)	Multiresolution time-dependent entropy method	273	163	99.75	99.85	99.60
Zhang and Lian (2009)	Multiscale morphology filtering, differentiation and multi-frame accumulation	213	204	99.81	99.80	99.62
Phukpattaranont (2015)	Quadratic Filtering	202	210	99.82	99.81	99.62
Bouaziz et al. (2014)	Wavelet Transform	140	232	99.87	99.79	99.66

Martinez et al. (2004)	Quadratic spline wavelet	220	153	99.80	99.86	99.66
Arbateni and Bennia (2014)	Artificial Neural Networks	210	109	99.81	99.90	99.70
Zidelmal et al. (2012)	S-transform	171	97	99.84	99.91	99.74
The proposed Method	Digital Filtering and DWT	256	55	99.79	99.95	99.74
Manikandan and Soman (2012)	Band pass filter, derivative Shannon energy and Smoothing	79	140	99.93	99.88	99.80
Zhu and Dong (2013)	Linear Filtering	93	91	99.92	99.92	99.83

Compared to these two studies, Table 3 clearly states that 19 records are more advantageous than others. With the proposed algorithm, as the success rate increases, the QRS complex used to diagnose cardiovascular disease can be analyzed in more detail and the automatic diagnosis of the cardiovascular diseases will be more accurate.

Table 3. The Comparison of three methods for QRS detection

	FN			**FP**		
Record	**The Proposed Method**	**Zhu and Dong (2013)**	**Manikandan and Soman (2012)**	**The Proposed Method**	**Zhu and Dong (2013)**	**Manikandan and Soman (2012)**
100	0	1	0	0	0	0
101	0	1	2	0	4	4
104	0	1	0	9	6	14
105	11	7	8	11	25	18
113	0	1	0	0	0	3
114	1	2	0	0	2	0
115	0	0	1	0	0	3
116	3	18	16	0	2	8
118	0	0	0	0	1	3
119	2	0	0	0	2	0
124	1	0	0	0	2	0
200	1	1	0	0	3	6
212	0	0	9	1	0	0
219	0	0	0	0	0	2
228	2	1	6	0	12	7
230	0	0	0	0	1	2
231	0	0	2	0	0	9
232	0	0	0	1	1	18
234	0	0	0	0	0	1

5. Conclusions

A robust and novel algorithm consisting of six stages has been developed and tested for the detection of QRS regions on ECG recordings in MIT/BIH arrhythmia database in this study. The algorithm consists of SGF, BPF, DWT, smoothing, HPF and adaptive threshold processing. The study shows that the algorithm is so achieved for QRS detection in ECG signals including noise, baseline wander, arrhythmic beats, small and wide QRS complexes. Also, it provides faster detection

compared to other studies. Another advantage of the approach that it does not depend on the constant threshold value since it has adaptive threshold values calculated considering the mean and standard deviation of the signals obtained during processing. The achievement of the algorithm is tested on 30-minute ECG records obtained form 48 patients in MIT-BIH arrhythmia database owing to the evaluation FP, FN and TP values for each signal. The accuracy values of algorithm are evaluated and discussed considering other existing methods in the literature. The method provides a sensitivity of 99.79%, a positive predictivity rate of 99.95%, detection error rate of 0.26 and overall detection accuracy of 99.74%. Although the various noise, artifacts morphologies of the QRS complexes in ECG signals, the method achieves good detection rates.

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Conflict of Interest

No conflict of interest was declared by the authors.

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