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Adaptive thresholding based low complexity QRS detection algorithm

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Abstract

In this study, a QRS detection algorithm with a low processing load based on time-domain thresholding is proposed. The ECG signal is filtered only with a low pass filter to reduce the computational load. After the filtering, derivation and squaring are also performed. In the Thresholding stage, a linear decreasing threshold voltage method using addition operation instead of multiplication is proposed. Simulations on MIT-BIT Arrhythmia Database have yielded 99.2925% sensitivity (% Se) and 99.6759% positive predictivity (+ P). The proposed algorithm is compared with two similar algorithms in terms of both performance and processing load. It is shown that the proposed algorithm is better than its counterparts, especially in terms of processing load. However, it is observed that it gave worse results in terms of Sensitivity (% Se).

Keywords: *Ecg signal, qrs detection, time domain thresholding, computational load.*

Adaptif eşik temelli az karmaşık QRS algılama algoritması

Öz

Bu çalışmada düşük işlem yoğunluğa sahip, zaman domeninde, adaptif eşik gerilimi tabanlı bir QRS algılama algoritması önerilmiştir. İşlem yükünü azaltmak için EKG işareti sadece alçak geçiren bir filtre ile filtrelenmiştir. Filtrelemenin ardından türev ve kare alma işlemleri sırasıyla yapılmıştır. Adaptif Eşik geriliminin hesaplanmasında çarpma işlem sayısını azaltmak için doğrusal azalan bir eşik gerilimi yöntemi kullanılmış ve önerilmiştir. MIT-BIT Arrhythmia veri tabanından alınan işaretler kullanılarak yapılan simülasyon sonuçlarına göre Sensitivity (% Se) %99.2925 ve Positive Predictivity (+ P) %99.6759 olarak tespit edilmiştir. Önerilen algoritma hem

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işlem yükü hem de performans açısından benzer iki algoritma ile karşılaştırılmıştır. Önerilen algoritmanın özellikle işlem yükü bakımında benzerlerinden üstün olduğu ancak Sensitivity (% Se) açısından daha kötü sonuçlar verdiği görülmüştür

***Anahtar kelimeler**: Ekg sinyali, qrs algılama, zaman domeninde eşikleme, işlemsel yük.*

1. Introduction

ECG is the most widely used measurement method in the diagnosis of various heart-related diseases, they are non-invasive, cheap, easy to do, and contain a lot of information about the physiology of the heart [1]. The first ECG was recorded and described by the British physiologist Augustus D. Waller in 1887. In 1893, Einthoven measured ECG using a string galvanometer developed himself and consequently formulated the waves called P, Q, R, S, and T [2]. These signals are the electrophysiological results of the cardiac period such as atrial depolarization, ventricular depolarization, and repolarization. Of these waves, the QRS is the most important because it represents the depolarization of the ventricles and has the highest voltage peak in the ECG signal [1, 2]. QRS complexes are also important in detecting the HR (Heart Rate) on the ECG. The time period between two QRS complexes (RR interval) represents the period of a cardiac cycle and the heart rate information (HR (Heart Rate) or the BPM (Beat Per Minute) can be obtained from this information with a simple equation. In addition, the variability of the RR interval over time contains valuable information about the state of the nervous system and is called HRV (Heart Rate Variability) [3, 4].

In this respect, it is important to locate the QRS complexes in the time axis. However, some problems draw attention during the detection of the QRS complexes. For example, there can be many artifacts on the ECG signal taken by hardware. These can be exemplified as noises emitted by surrounding devices and skin-electrode contact alterations. Movements of the subject and muscle activities can also be the source of the noise. These artifacts are sometimes perceived by the measuring system as QRS complexes and cause erroneous measurements. Consequently, it is very important to have high SNR (Signal to Noise Ratio) signals [5].

In the literature, there is a large number of methods suggested for QRS detection. These algorithms are generally divided into two parts as preprocessing and R wave detection. In the preprocessing sequence, the ECG signal is cleaned from noises and processed so that the R waves become clear and ready for the R wave detection stage. Operations such as filtering the signal with digital filters, taking differentiation, squaring sample by sample or moving average can be performed at this stage. In this way, the signal becomes free from most of the noise [6]. In the R wave detection sequence, the location of the R waves on the time axis is detected. Numerous methods have been proposed in the literature for both of the stages [4, 6]. Some of these methods are time-domain thresholding [7-9], digital filters [10, 11], Wavelet Transforms [12-14], and Hilbert Transform [15]. Most of the work suggested use time-domain thresholding in the R wave detection sequence [6].

Time-domain thresholding is suitable for systems with microprocessors and microcontrollers due to its low computational load and its ability to work in real-time.

Unlike computers, embedded systems (systems with microprocessors and microcontrollers) should run low complex algorithms because of their limited resources [9]. They work as operation centers in mobile ECG and similar systems such as wearable devices.

In this work Low Pass Filtering (LPF), derivation, and squaring are applied to the raw ECG data respectively in the preprocessing stage. A novel real-time QRS complex detection algorithm based on a linear and dynamic threshold to detect the R peaks is proposed. A linearly decreasing threshold voltage is proposed to reduce the operational load. The adaptive thresholding signal and the squared dECG (differentiated ECG) signal are compared and the points where the dECG exceeds the threshold voltage are detected as QRS. Due to its low computational cost, the proposed algorithm is very suitable for being implemented in devices with reduced computational resources. The ECG signals and the QRS points of these signals are taken from the MIT-BIH arrhythmia database [16]. This database provides a standardized means of comparing the basic performance of one algorithm to another.
In this article, the suggested algorithm is explained in the second section. Simulation results are given and are compared with other algorithms in the third section. The article is completed with a conclusion section.

2. Materials and methods

Pan and Tompkins proposed a real-time QRS detector in 1985 and it has influenced many studies and applications in this area [7]. In the preprocessing sequence of the Pan Tompkins algorithm, real-time low-pass filter, real-time high pass filter (HPF), five-points derivative, and squaring are the applied operations to be performed respectively [7]. In this way, the QRS complexes in the ECG signal are located in the positive voltage region and the noise is suppressed to a great extent. After the preprocessing stage, the positions of the QRS complexes of the ECG signal are determined in the time axis. The preprocessing sequence of Gutiérrez-Rivas et al. consists of derivative, moving average, and squaring steps, respectively [9]. They also proposed an exponentially decreasing threshold voltage following each QRS complex in the R wave detection sequence.

The algorithm suggested in this study can be divided into two parts: The preprocessing stage and the thresholding Stage. As shown in Figure 1, the ECG sample sequence is first passed through a real-time low-pass digital filter. In most studies, both an LPF and an HPF are used in the filtering stage [6,7]. In this study, it is recommended to apply only an LPF to reduce the computational load. Another reason for this is that, after filtering, derivatives are taken. The derivative process inherently exhibits a high pass filter-like behavior. For this reason, it is possible to apply only an LPF in this algorithm, especially to reduce the processing load. Pan and Tompkins suggested a five-point derivative scheme in the derivation stage. A backward difference scheme due to its less operational load was used in this study [9,21]. After being filtered and derivated, the signal is squared. In this way, it is ensured that the signal is only at the positive voltage level and the low magnitude voltage harmonics are suppressed.

In the R wave detection stage, which is proposed by Gutiérrez-Rivas et al., the adaptive threshold voltage decreases exponentially [9]. Their threshold voltage calculation is computationally complex. The threshold voltage proposed in this study is linearly decreasing and is operationally much simpler. By using operationally simpler methods in both Preprocessing and Thresholding stages, a much more suitable algorithm for embedded systems has been proposed.

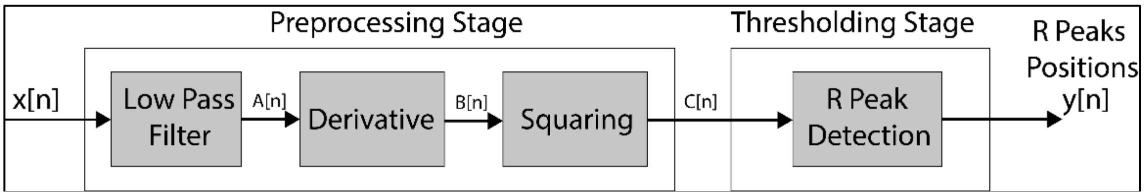

Figure 1. Block scheme of the proposed algorithm

Almost all of the studies on QRS detection use the Massachusetts Institute of Technology's Beth Israel Hospital (MIT-BIH) Arrhythmia Database [16]. This database is open access and RR detection studies can be performed comparatively. The database includes 48 records 30 minutes long each. While creating the database, the sampling frequency is taken as 360 Hz and ADC (Analog Digital Converter) resolution as 11 bits. In addition, the RR intervals of the data sets can also be obtained in the database. Massachusetts Institute of Technology's Beth Israel Hospital (MIT-BIH) Arrhythmia Database is used to evaluate the performance of this study.

2.1. Preprocessing stage

In this study, the proposed Preprocessing stage includes LPF, derivative and squaring operations. The filter used in this stage is a low pass filter and its transfer function in z-domain is given as,

$$H(z) = \frac{A(z)}{x(z)} = \frac{\left(1-z^{-6}\right)^2}{(1-z^{-1})^2} \quad (1)$$

where A is the filtered data set, and x denotes the unfiltered data set in z-domain. The difference equation of the filter in discrete time is,

$$A[n] = 2A[n-1] - A[n-2] + x[n] - 2x[n-6] + x[n-12] \quad (2)$$

This filtering algorithm causes a phase delay of 6 samples and the filter gain is 36 [7]. After this process, the derivative process comes. Due to the derivative process, low-frequency components such as baseline wandering are reduced significantly. Numerous derivation methods have been proposed in the literature [17-21]. A backward difference scheme [9,21] is proposed by Okada et.al. and this method is used in this study due to its low computational load. The backward difference scheme can be applied as,

$$B[n] = A[n] - A[n-1] \quad (3)$$

Differentiated ECG signal is squared as the last step of the preprocessing stage. The benefit of this application is that it suppresses the small-amplitude high-frequency signal components and transfers the negative components of the signal to the positive voltage region. However, both the processing load and variation in the peak voltages of the signal are its negative aspects. Squaring dECG, the output of the preprocessing stage is obtained as,

$$C[n] = B^2[n] \quad (4)$$

Figure 2 shows the ECG of Record 101 from the MIT-BIH database [16] and the preprocessing steps applied to this signal. The red circles seen in Figure 2 (a) are the QRS points of the ECG signal and they are also taken from the database. The filtered and dECG signals can be seen in Figure 2 (b). In Figure 2 (b), after the filter and derivative, the QRS pulses become more apparent. In Figure 2 (c), it can be seen that after each sample is squared, the signal is moved to the positive voltage region, the small amplitude components are suppressed, and the variations in the amplitudes of the QRS peaks increase.

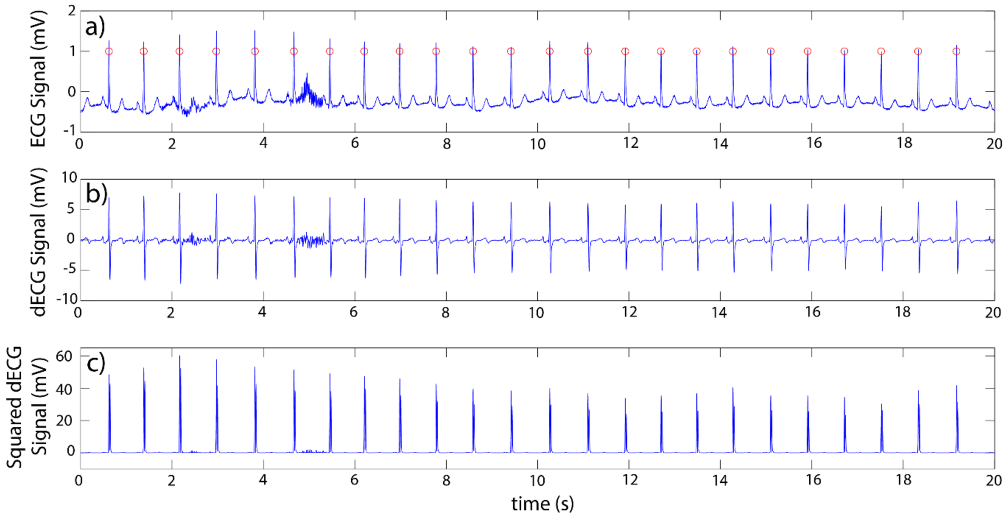

Figure 2. a) MIT-BIH record 101 and QRS points taken from the database (red circles), b) dECG of record 101, and c) The squared dECG trace.

2.2. Thresholding stage

Although many methods are suggested for QRS detection, it is seen that the most studied method is time-domain thresholding [7-9]. The thresholding stage is divided into two phases: the initialization phase and the detection phase. In the initialization phase, the algorithm does not detect qrs for 2 seconds and detects the peak level of this period [6]. At the end of this period, 20% of the peak level is set as the threshold. The detection phase begins with the first incoming qrs.

In the detection phase, the signal obtained at the end of preprocessing is compared with the threshold voltage. Points, where the squared dECG signal exceeds the threshold voltage value, are accepted as QRS complexes. In some studies, the threshold voltage is obtained by multiplying the last received QRS peak voltage with a coefficient [22, 23]. Thus, the value of the threshold (A_{th}) voltage is revised after each detected QRS complex:

$$A_{th} = \propto . \max \{A[n]\} \tag{5}$$

where $\propto$ is the threshold coefficient and it must be chosen as,

$$0 < \propto < 1 \tag{6}$$

In many thresholding methods, the threshold voltage value exhibits a variable behavior during every single cardiac period [6]. Gutierrez-Rivas et al. proposed a parameter that reduces the threshold voltage exponentially after the QRS peak [9]. However, in their algorithm the preprocessing stage consists of differentiation, moving average, and squaring. The adaptive threshold voltage proposed by Gutierrez-Rivas et al. is,

$$th[n] = th[n-1].e^{-\frac{P_{Th}}{fs}} \quad (7)$$

where *th* threshold voltage, P_{Th} is a parameter obtained from the sampling frequency, *fs* sample number [9]. After QRS detection, the threshold voltage decreases from high values to low values. Thus, the detection of high amplitude signals and noises as QRS is prevented. One of the main problems of this method is the computational load. Threshold value obtained as a result of a large number of multiplications and calculation of the exponential term can consume the resources of systems with limited resources such as microcontrollers.

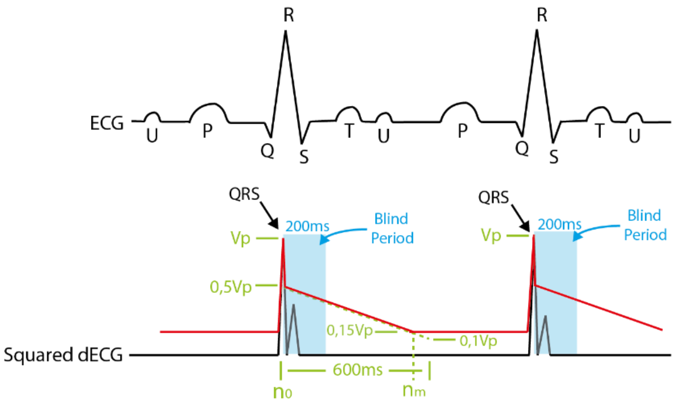

Figure 3. The proposed QRS detection scheme

The scheme of the QRS detection method recommended in this article can be seen in Figure 3. In this scheme, the threshold voltage is expressed in red, and the blind areas where detection is suspended are highlighted in blue. In Figure 3, the threshold voltage drawn in green decreases linearly. After a QRS detection, a certain time must pass before another QRS can occur due to the electrophysiology of the heart. In this scheme, the blind period is chosen as 200ms. For a QRS to occur within this 200ms, the patient's pulse rate would have to be 500 BPM (Beat Per Minute). It is not possible because of the electrophysiology of the heart. In addition, the squared dECG signal may have a double voltage peak as shown in Figure 3. As a result of the blind period application, the possibility of detecting the second voltage peak as another QRS is also eliminated.

During the QRS detection, a threshold line is drawn between 50% and 10% of the squared dECG peak value for 600ms. This time is about 220 samples length for signals taken at 360Hz. When QRS is detected, threshold step value to be calculated. This calculation will be done just once and, after that, the step value will be decreased from the existing threshold. The slope of the linearly decreasing threshold voltage equation can be given as,

$$m = \frac{0{,}1V_p - 0{,}5V_p}{0{,}6} \quad (8)$$

where V_p is the last detected squared dECG voltage peak value, m is the slope of the threshold line. In addition, the threshold voltage will be prevented from falling below 15% of the peak voltage value. Threshold value can be calculated as follows,

$$V_{TH}[n] = \begin{cases} 0{,}15V_p & , \quad n_m \leq n \\ m(n - n_0) + 0{,}5V_{p,} & n_0 \leq n \leq n_m \end{cases} \tag{9}$$

where V_{TH} is the threshold value, k is the sample number which starts with every detected QRS complex, n_0 is the sample number of the last detected QRS complex, and n_m is the sample number of the point where the threshold last decreased. By this means, the threshold voltage is prevented from approaching the 0 Volt level too much in the processing of ECG signals of patients with low HR. If the Threshold gets too close to the baseline, the noises could be detected as QRS.

Although the threshold voltage is expressed with a line equation in Equation 9, the line equation is not calculated every time for the determination of each threshold point. At the time of QRS detection, the value that needs to be subtracted from the current threshold value at each cycle is calculated and is subtracted from the threshold at each cycle. Thus, the processing load of the algorithm is reduced.

3. Results and discussion

According to the method described in the second section, the simulations are run on the data set taken from the MIT-BIH Arrythmia database. Simulations regarding the performance of the algorithm are carried out on Matlab^{TM}. Figure 4 (a) shows the MIT-BIH Arrhythmia Database Record 101 and the QRS complexes (Red Points) determined by the proposed algorithm. Figure 4 (b) shows the squared dECG signal and the adaptive threshold (Red Line) on the signal. It can be seen that the adaptive threshold starts at a 50% voltage level of the last detected QRS complex. The threshold does not fall below 15% of the last detected QRS peak. The slope of the threshold line after higher QRS peaks becomes much higher. In this way, it is prevented that the noises originating from *T* and *U* waves following the QRS are detected as QRS erroneously.

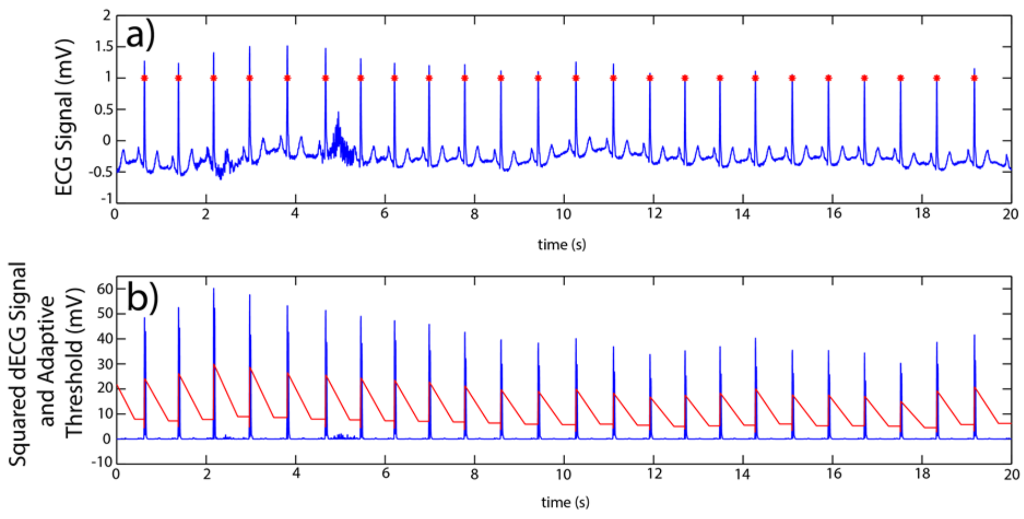

Figure 4. Simulation results of the proposed algorithm on MIT-BIH arrhythmia database record 101 a) The ECG signal and the detected QRS points (red points) by the proposed algorithm, b) The squared dECG signal and the proposed adaptive threshold voltage

Commonly used performance parameters for QRS detectors are Sensitivity (Se) and Positive Predictivity (+ P). The Sensitivity (*Se*) parameter is important since it gives the percentage values of the *R* waves that the QRS detector algorithm detects, and the Positive Prediction (+*P*) parameter of the *R* waves that it detects correctly. These two parameters are obtained as percentages from *TP* (True Positive), *FP* (False Positive), and *FN* (False Negative) parameters [6]. The equation for Sensitivity and Positive prediction (+P) equation are given respectively as,

$$\%Se = \frac{TP}{TP+FN}.100 \tag{8}$$

and

$$+P = \frac{TP}{TP+FP}.100 \tag{9}$$

where *TP* is the number of true QRS complexes, *FN* is the number of undetected QRS complexes, and *FP* is the number of false detected QRS complexes [4]. The proposed algorithm is evaluated on all 48 records in the MIT-BIH Arrhythmia Database. The results are given in Table 1. Each record is taken for two ECG leads in the MIT-BIH Arrhythmia database, except for two records (Records 102 and 105) one of the ECG leads in all records is *Einthoven II* (*MLII*). In this study, if one of the derivations is *MLII*, it is used during the simulations. In the absence of the *MLII* derivation (Records 102 and 105), *V5* derivation is preferred and this information is given next to the record name in Table 1.

Table 1. Simulation results

Record	Total Peaks	TP	FN	FP	%Se	+P
100	2273	2273	0	0	100	100
101	1865	1865	0	3	100	99,8394
102 (v5)	2187	2187	0	0	100	100
103	2084	2084	0	0	100	100
104 (v5)	2229	2181	48	67	97,8466	97,0196
105	2572	2557	15	38	99,4168	98,5356
106	2027	2022	5	1	99,7533	99,9506
107	2137	2134	3	1	99,8596	99,9532
108	1763	1725	38	62	97,8446	96,5305
109	2532	2532	0	0	100	100
111	2124	2123	1	2	99,9529	99,9059
112	2539	2539	0	0	100	100
113	1795	1795	0	0	100	100
114	1879	1878	1	0	99,9468	100
115	1953	1953	0	0	100	100
116	2412	2398	14	9	99,4196	99,6261
117	1535	1535	0	0	100	100
118	2278	2278	0	0	100	100
119	1987	1987	0	0	100	100

Table 1. (Continued.)

121	1863	1861	2	6	99,8926	99,6786
122	2476	2476	0	0	100	100
123	1518	1517	1	0	99,9341	100
124	1619	1619	0	1	100	99,9383
200	2601	2552	49	42	98,1161	98,3809
201	1963	1921	42	0	97,8604	100
202	2136	2130	6	2	99,7191	99,9062
203	2980	2922	58	19	98,0537	99,3540
205	2656	2656	0	0	100	100
207	2332	2145	187	12	91,9811	99,4437
208	2955	2938	17	3	99,4247	99,8980
209	3005	3005	0	0	100	100
210	2650	2628	22	5	99,1698	99,8101
212	2748	2748	0	0	100	100
213	3251	3247	4	0	99,877	100
214	2262	2260	2	2	99,9116	99,9116
215	3363	3362	1	0	99,9703	100
217	2208	2203	5	2	99,7736	99,9093
219	2154	2153	1	0	99,9536	100
220	2048	2048	0	0	100	100
221	2427	2421	6	0	99,7528	100
222	2483	2483	0	1	100	99,9597
223	2605	2500	105	1	95,9693	99,96
228	2053	1919	134	37	93,473	98,1084
230	2256	2256	0	0	100	100
231	1571	1571	0	0	100	100
232	1780	1774	6	37	99,6629	97,9569
233	3079	3076	3	2	99,9026	99,9350
234	2753	2751	2	0	99,9274	100
Total	**109966**	**109188**	**778**	**355**	**99,2925**	**99,6759**

In Table 1, the performance results of the algorithm are given per record. It is understood that the algorithm performs QRS detection with 100% success in records with low noise (e.g., 100, 102, and 103). On the other hand, in some records (207 and 228), it is understood that the algorithm made a lot of *FN* (*False Negative*) errors. It is also noteworthy that according to the table, total *FN* numbers are more than twice the total *FP* numbers. At the end of the squaring, the variation in the peak values of the QRS increases. In this case, a QRS with a lesser slope followed by a QRS with a high slope can be missed. For this reason, the number of *FN* errors is relatively high.

In Table 2, the algorithm proposed in this article is compared with the two algorithms, which have an important place in the literature in terms of both performance and computational load. The best values in each column are written in bold. Although the algorithm suggested in this article does not have the best values in the sensitivity (*Se*) and predictivity (*+P*) parameters, it has the best values in all computational load parameters except for add(s). The main reason for the lack of a big difference between the proposed algorithm and the Gutierrez-Rivas algorithm in terms of the number of multiplication operations is that Gutierrez-Rivas et al. used moving average instead of a LPF in the preprocessing stage.

Table 2. Comparison of the algorithms

Algorithm	**%Se(%)**	**+P(%)**	**Add(s)/sec**	**Comp.(s)/sec**	**Multi.(s)/sec**	**Total Op/sec**
Proposed	99,2925	99,6759	1721	**796**	**1084**	**3527**
Pan&Tompkins [6]	**99,7477**	99,5393	2817	1416	1201	5434
Gutierrez-Rivas [9]	99,5434	**99,7366**	**1205**	2163	1107	4475

While examining the processing loads in Table 2, it should be kept in mind that the multiplication consumes much more resources for microprocessors than add(s), sub(s) or comparison. Most processors with the RISC architecture used today do not have a logic circuit that performs the multiplication or a multiplication command within assembler command sets. The multiplication and division operations are done in the form of addition and subtraction sequences. The results in Table 2 should be evaluated in light of this information.

4. Conclusion

The processing load of algorithms, due to their limited processing capabilities, is very important, especially for microprocessor systems. In this study, a low-intensity algorithm is proposed to detect the positions of QRS complexes in the time axis. The algorithm consists of two stages, namely the preprocessing stage and the thresholding stage. In the preprocessing stage, LPF, derivative, and squaring processes ensure that the signal is partially de-noise and QRS impulses come to the fore. In the thresholding part, an algorithm based on adaptive time-domain thresholding is proposed. Again, in this section, an approach is suggested that limits multiplication operations in the calculation of the threshold voltage value doing often addition/subtraction operations instead. With this linearly varying threshold voltage, the multiplication and exponentially-weighted processing load are reduced and transformed into an addition and subtraction-weighted one. The results and comparative results of the study are discussed in the third section. Although the performance of the algorithm is not very high, it is seen that the low processing load emerges as the successful aspect of the proposed algorithm.

In the continuation of this study, the work can be improved with the changes that will reduce the processing load by changing the preprocessing stage. For instance, the squaring application significantly increases the processing load due to increasing the number of multiplication operations and, instead, it is possible to use fewer resources with merging the proposed method with an algorithm that applies the moving average method. The parameters of the linear threshold voltage given in this study were determined by various trials by working in narrow sections of the Ecgs taken from the MIT-BIH arrhythmia database. New algorithms can be obtained by changing the parameters of the threshold line.

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