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R PEAK DETERMINATION USING A WDFR ALGORITHM AND ADAPTIVE THRESHOLD

Abstract

The determination of the R peak position in the ECG signal helps physicians not only to know the heart rate per minute, but also to monitor the patient's health related to heart disease. This paper proposes a system to accurately determine the R peak position in the ECG signal. The system consists of a pre-processing block for filtering out noise using a WDFR algorithm and highlighting the amplitude of the R peak and a threshold value is calculated for determining the R peak. In this research, the MIT-BIH ECG dataset with 48 records are used for evaluation of the system. The results of the SEN, +P, DER and ACC parameters related to the system quality are 99.70%, 99.59%, 0.70% and 99.31%, respectively. The obtained performance of the proposed R peak position determination system is very high and can be applied to determine the R peak of the ECG signal measuring devices in practice.

1. INTRODUCTION

Information of ECG signal is very important for monitoring and diagnosing patient heart diseases (Chen et al., 2021; Rahman & Jambek, 2019; Ribeiro et al., 2020). In particular, the R peak of the QRS complex in the ECG signal is an important information which can allow a physician to determine the beat-per-minute parameter of patient. Therefore, the R peak determination may be applied in heart disease classification systems to produce more accurate results (Darmawahyuni et al., 2021; Mohebbanaaz, Sai & Kumari, 2021; Olanrewaju et al., 2021; Wu et al., 2021). In which one can determine heartbeats in one ECG signal based on the position of the R peak in the QRS complex. With the determined heartbeats or heart rhythms, heart disease categories may be classified using deep learning networks (Alhussainy & Jasim, 2021; Aziz, Ahmed & Alouini, 2021; Dang et al., 2019; Meqdad, Abdali-Mohammadi & Kadry, 2022; Nguyen & Nguyen, 2021). For classifying the heart disease categories, each heartbeat based on the R peak needs to be labelled by heart disease imaging experts. Therefore, the accurate position of the R peak in the signal is determined plays an important role in classifying the heart diseases using the deep learning network. This paper proposes a method to accurately determinate the R peak position of the QRS complex in the ECG signal.

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Filtering the noise in the ECG signal for accurately determining the R peak positions is a necessary task. ECG signal often has many different noises such as baseline wander (BW), powerline interference (LPI), and artifact, in which noisy filtering in R peak determination systems is always applied (Chen et al., 2020; Lee et al., 2018; Lin et al., 2019; Nguyen, Nguyen & Ngo, 2020; Xiang, Lin & Meng, 2018; Zhang, Li & Li, 2020). Therefore, with best filtering out the noise components in the ECG signal, it is possible to more accurately determine the R peak position in the ECG signal. In (Qin et al., 2017), authors have proposed a wavelet-based multiresolution analysis (WMRA) method for filtering noise in the ECG signal and then the filtered ECG signal was inverted before determining the position of the R peak using an adaptive threshold. For evaluating the effectiveness of the proposed method, MIT-BIH database (MITDB) and the QT database (QTDB) were used in this research, particularly, the accuracies of the R peak determination with MITDB and QTBD databased are 98.89% and 99.73%, respectively.

The artificial neural network method has been applied to determine R-peaks in ECG signals in recent years (Cai & Hu, 2020; Laitala et al., 2020; Zahid et al., 2021). In this method, several data points around the R peak position are used to be input data for training and testing the neural network. Moreover, the R peaks position determination results are often evaluated using a confusion matrix method. In (Zhou et al., 2020), Peishan Zhou et al. proposed to employ an one-dimensional convolution network (1D CNN) with a long short-term memory (LSTM) network for detecting R peaks in ECG signals. In particular, in this paper, the proposed neural network structure includes 13 layers with 6 layers of the convolution, 3 layers of max-pooling, 1 layer of LSTM and 3 layers of full-connected. Three ECG signals including 112, 122, and 117 records were randomly selected from the MIT-BIH database for evaluating the proposed system and the accuracy of an R-peak position determination system is 90.61%.

In order to evaluate the performance of the R-peak position determination system in ECG signals, some parameters such as values of TP, FP and FN are often used. The peak R position determination results from the recognition system are compared with the actual R-peak position for calculating the values of SEN, $+P$, DER and ACC (Park, Lee & Park, 2017). From these values, if the obtained SEN, $+P$, and ACC are large, while DER has a smaller value, the R peak position determination system will produce more accurately. Furthermore, the waveform of the ECG signal with the position of the identified R peak is presented to demonstrate the performance of the R peak position determination system. Another problem is that one ECG signal has a special R peak position with low amplitude, but the system is still determined the R peak position, called the well system.

With the improved noise filter on the ECG signal, a deep learning network or other classification network topologies for peak R position determination in QRS complex can be applied and the accuracy of the peak R position determination using one of these algorithms is high (Al et al., 2021; Jang et al., 2022; Suboh et al., 2020). However, for the ECG signals with huge noise effects, the problem of accurately determining the position of the R peaks in the QRS complex is a challenge (Nguyen et al., 2019). Therefore, the application of the deep learning network algorithm to locate the peak R in the QRS complex can obtain high accuracy. However, some R peak locating systems often have a large processing time, so it is difficult to apply for real-time R peak locators.

In this paper, a method of the R peak position determination system is proposed. In practice, one ECG signal is preprocessed using filters to eliminate noises using a Wavelet Decomposition Filter-Reconstruction (WDFR) algorithm. Hence, the filtered ECG signal is used to calculate the threshold for determining the R peak position. Therefore, the rest of this paper is organized as follows: Section-2 presents related fundamental knowledge and proposed method. The experimental results and discussion are described in Section-3. The conclusion of the article is shown in the final section.

2. METHODOLOGY

This paper proposes a system to determine the R peak position in the QRS complex of one ECG signal. In particular, noise of the ECG signal is eliminated using the WDFR algorithm, in which a wavelet decomposition and filter reconstruction are combined to perform filtering the noise. Therefore, the ECG signal with the filtered noise will be passed through the differential, squared, and convolution blocks to enhance the amplitude of the R peaks. Finally, the threshold value will be calculated to determine the R peak position. The results of determining the R peak position will be combined with the standard R peak position for evaluating the performance of the system.

2.1. Proposed R peak determination

To determine the R peak position in the ECG signal, a system is built as shown in Figure 1. Therefore, a set of ECG signals is used to combine with the input to the system for determining the R peaks. In addition, the ECG signal is preprocessed to remove noise in the ECG signal and then the system can transform the ECG signal for easily detecting the R peak. Thus, the ECG signal after preprocessing will be used to calculate the threshold for determining the R peak position. The result of the R peak position will be evaluated based on the standard R peak position.

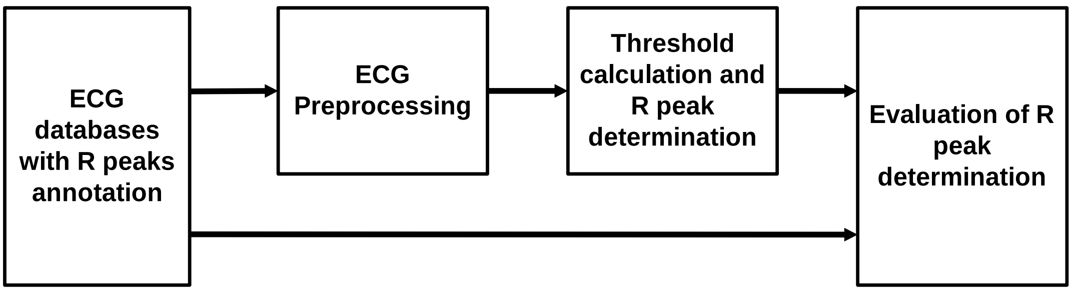

Fig. 1. Block diagram of the R peak determination system

In this paper, the set of ECG signals is obtained from the MIT-BIH database (Moody & Mark, 2001). The set consists of 48 records from 47 patients with R peak positions marked by physicians. Each ECG signal record was acquired with a duration of 30 minutes and has a total of 65,000 points. Moreover, the set of the ECG signals has been used in many research projects and has high reliability.

2.2. ECG signal preprocessing

The ECG signal was filtered using the WDFR algorithm as described in Figure 2 (Nguyen, Nguyen & Ngo, 2020), particularly the ECG signal is decomposed into detailed and approximate components with different frequencies using a wavelet transform at Level-8. Therefore, the approximation and detail components will be used to create threshold for noise filtering. Finally, the signal components after noise filtering based on the threshold will be reconstructed to produce the ECG signal with the least noise.

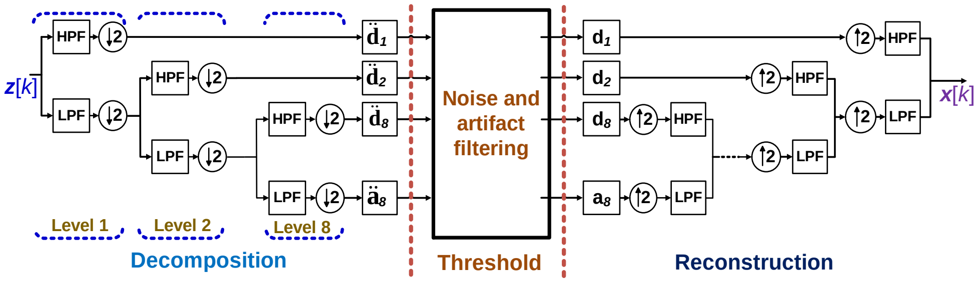

Fig. 2. The representation of the WDFR algorithm for eliminating noise of ECG signal

The approximation and detail components obtained after applying the wavelet transform are presented as follows:

$$\ddot{d}_m = \sum_{k=-\infty}^{\infty} z[k]h[2n-k] \tag{1}$$

$$\ddot{a}_m = \sum_{k=-\infty}^{\infty} z[k]g[2n-k] \tag{2}$$

where: $h[2n-k]$ – the high pass filter,
$g[2n-k]$ – presents the low pass filter,
$\ddot{d}_m$ – the detail component,
$\ddot{a}_m$ – the approximation component,
$z[k]$ – the ECG signal.

The approximation and detail components obtained after applying the threshold to eliminate noise and artifacts are expressed as follows:

$$a_m = \begin{cases} 0 & \text{if } f_{\ddot{a}_m} < f_a \\ \ddot{a}_m & otherwise \end{cases} \tag{3}$$

$$d_m = \begin{cases} 0 & \text{if } f_{\ddot{a}_m} < f_a \\ \ddot{a}_m & otherwise \end{cases} \tag{4}$$

where: f_a – the maximum frequency of the BW noise,
$f_{\ddot{a}_m}$ – the frequency of $\ddot{a}_m$,
f_d – a maximum frequency of ECG information,
$f_{\ddot{d}_m}$ – the frequency of $\ddot{d}_m$.

The filtered ECG signal $x[k]$ obtained from a_m and d_m is determined as follows (Kumar, Kumar & Pandey, 2012):

$$x[k] = a_m + \sum_{i=0}^{m} d_i \tag{5}$$

Therefore, the filtered ECG signal will be passed through the differential block to find the slope peak of the QRS complex. The signal is further fed through the square block to enhance the amplitude of the slope crest. Finally, the signal will be passed through the integration block to merge the adjacent peaks for accurately identifying one R peak. Furthermore, a moving window with 24 data points is used for tradeoff between false and missed detections. The process of differentiation, squaring, and integration is summarized and described as follows (Lu, Pan & Yu, 2018):

$$p(nT) = \frac{1}{8}[-x(nT-2T) - 2x(nT-T) + 2x(nT+T) + x(nT+2T) \tag{6}$$

$$k(nT) = [p(nT)]^2 \tag{7}$$

$$r(nT) = \frac{1}{N}[p(nT-(N-1)T) - p(nT-(N-2)T) + \cdots + p(nT)] \tag{8}$$

where: $y(nT)$ – the outputs of the differentiation stages,
$k(nT)$ – the outputs of the squaring stages,
$r(nT)$ – the outputs of the integration stages,
N – the number of samples in the moving window.

From the ECG signal after preprocessing, the threshold method is applied to determine the position of the peak R. The formula for determining the threshold is presented as follows:

$$\begin{gathered} \mathrm{M_{VAL}} = \max\left(\mathrm{ECG}_{pre}\,(1:300)\right) \\ \mathrm{SPK} = 0.13 * \mathrm{M_{VAL}} \\ \mathrm{NPK} = 0.1 * \mathrm{SPK} \end{gathered} \tag{9}$$

$$\mathrm{THRE} = 0.25 * \mathrm{SPK} + 0.75 * \mathrm{NPK} \tag{10}$$

where: $\mathrm{M_{VAL}}$ – the maximum 300 data points of the ECG signal,
ECG_{pre} – the ECG signal after pre-processing,
SPK – the R peak,
NPK – the noise peak,
THRE – the threshold.

In this system, if no data point is detected after using 400 data points, the SPK value will be updated again using the formula of $\mathrm{SPK} = 0.5 * \mathrm{SPK}$ for adaptive threshold.

2.3. Evaluation of R peak detection

To evaluate the R peak detection performance, the parameters of true positive (TP), false positive (FP), and false negative (FN) are applied. In particular, TP is called the R peak, when it is correctly identified; FP is the R peak, but the system can not detect it; and FN is not the R peak, while the system identifies it as the R peak. In addition, the parameters of accuracy (ACC), sensitivity (SEN), positive predictability ($+P$), detection error rate (DER), are calculated from TP, FN and FP as follows (Park, Lee & Park, 2017; Sharma & Sunkaria, 2016; Zalabarria et al., 2020):

$$ACC = \frac{TP}{TP+FN+FP} \times 100\% \tag{11}$$

$$SEN = \frac{TP}{TP+FN} \times 100\% \tag{12}$$

$$+P = \frac{TP}{TP+FP} \times 100\% \tag{13}$$

$$DER = \frac{FN+FP}{TP} \times 100\% \tag{14}$$

3. RESULTS AND DISCUSSION

To evaluate the performance of the proposed R peak determination system, the MIT-BIH ECG dataset is used in this research. The original ECG signal and the signals after preprocessing are shown in Figure 3, in which the original ECG signal with 2000 data points taken from the record 117 of the MIT-BIH dataset is presented.

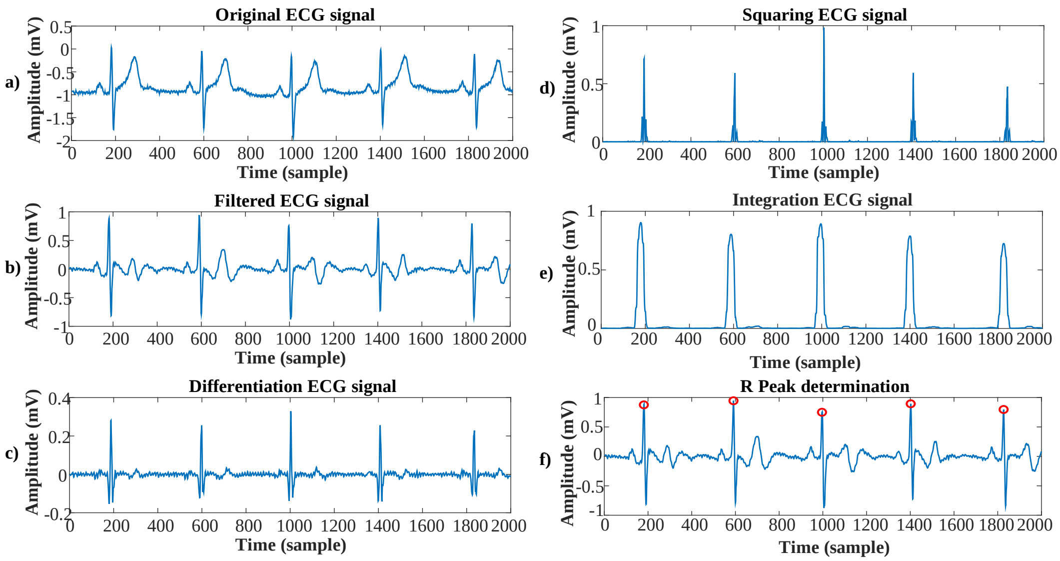

Fig. 3. Results of preprocessing the ECG signal using the MIT-BIH database

Therefore, this signal is filtered to eliminate noise using the WDFR algorithm with the wavelet function “dmey”. In this WDFR algorithm, the detail components d_1, d_2, d_3 and the approximation component a_8 are filtered out of the ECG signal. It is obvious that Figure 3b shows that the ECG signal has been filtered the noise of the BW components and high frequency components compared to the original signal in Figure 3a. Moreover, the R peaks of the QRS complex in the filtered signal are more obviously seen and are easy to determine their R peak positions.

The ECG signal after filtering noise will be differentially calculated to determine the amplitude of the R peaks in the QRS complex as shown in Figure 3c. Thus, this signal is squared to enhance the amplitude of the R peak positions as described in Figure 3d. Finally, the signal is passed through the integration block to arrange all the R peaks together to avoid the wrong detection of 2 R peak positions too close together as shown in Figure 3e. The adaptive threshold value will be calculated and updated to determine the position of the R peak and also we can see that the R peak positions are accurately determined correctly in Figure 3f.

In this paper, the parameters of TP, FN and FP are used for evaluating the performance of the R peak position determination system in the QRS complex as described as shown in Figure 4. In particular, Figure 4a shows the actual R peak position and Figure 4b shows the R peak position determined from the system, in which TP, FN and FP are defined based on the R peak positions. Therefore, FN is the number of the undetected R peaks; FP is the number of the R peaks mistakenly detected by the system; TP is the number of the correctly detected R peaks.

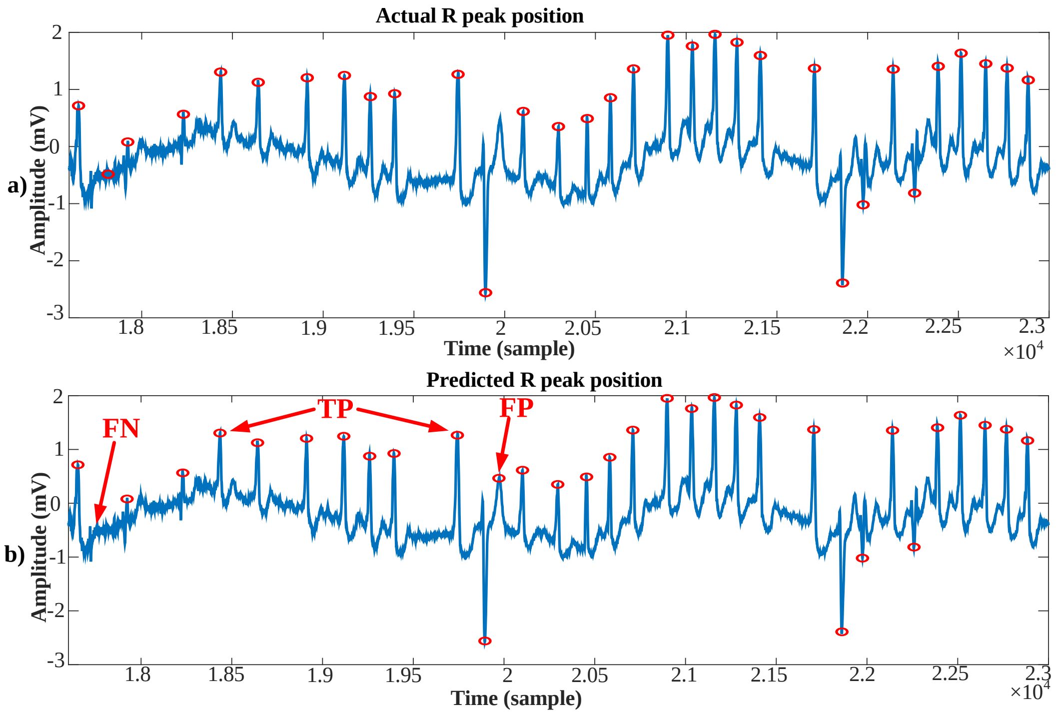

Fig. 4. Representation of TP, FN and FP in the R peak determination result

From the TP, FN and FP parameters, the values of ACC, SEN, $+P$, and DER will be calculated for evaluating the performance of the proposed R peak determination system. In particular, if the obtained ACC, SEN, and $+P$, values are large and the obtained DER value is small, then the proposed system is very good. Table 1 presents the evaluation results about the performance of the R peak position determination system using the MIT-BIH ECG dataset, in which the dataset consists of 48 records and the parameters are calculated for each record. From Table 1, it can be seen that the results of determining the R peak positions using the proposed system are effective, in which the mean values of ACC, SEN, $+P$, and DER are 99.31%, 99.70%, 0.70%, and 99.60%, respectively.

From Table 1, it is obvious that the performance of the proposed R peak position determination system is effective, particularly, most of the ECG signals in the MIT-BIH dataset have the accuracy of over 98%. However, with record 207, the obtained accuracy is only 85.53%. The reason is that record 207 has some signal segments with too much noise as shown in Figure 5.

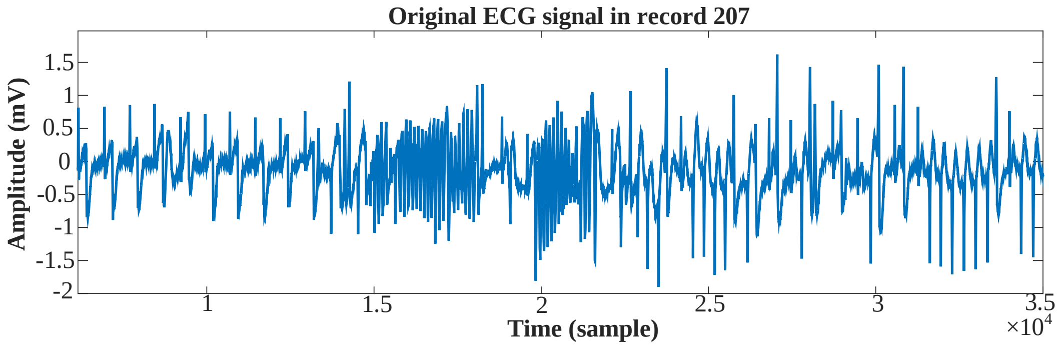

Fig. 5. Representation of original ECG signal in record 207 with huge noise

Tab. 1. The performance of the R peak determination system using the MIT-BIH database

No.	Records	R peaks	TP	FN	FP	SEN	$+P$	DER	ACC
1	100	2273	2273	0	0	100.00	100.00	0.00	100.00
2	101	1865	1865	1	0	99.95	100.00	0.05	99.95
3	102	2187	2187	0	0	100.00	100.00	0.00	100.00
4	103	2084	2084	0	0	100.00	100.00	0.00	100.00
5	104	2229	2220	8	9	99.64	99.60	0.77	99.24
6	105	2572	2545	12	27	99.53	98.95	1.53	98.49
7	106	2027	2017	7	10	99.65	99.51	0.84	99.16
8	107	2137	2136	4	1	99.81	99.95	0.23	99.77
9	108	1763	1761	0	2	100.00	99.89	0.11	99.89
10	109	2532	2528	2	4	99.92	99.84	0.24	99.76
11	111	2124	2124	1	0	99.95	100.00	0.05	99.95
12	112	2539	2539	0	0	100.00	100.00	0.00	100.00
13	113	1795	1795	0	0	100.00	100.00	0.00	100.00
14	114	1879	1841	23	38	98.77	97.98	3.31	96.79
15	115	1953	1953	0	0	100.00	100.00	0.00	100.00
16	116	2412	2405	4	7	99.83	99.71	0.46	99.54
17	117	1535	1519	14	16	99.09	98.96	1.97	98.06
18	118	2278	2278	0	0	100.00	100.00	0.00	100.00
19	119	1987	1987	1	0	99.95	100.00	0.05	99.95
20	121	1863	1863	0	0	100.00	100.00	0.00	100.00
21	122	2476	2475	0	1	100.00	99.96	0.04	99.96
22	123	1518	1518	0	0	100.00	100.00	0.00	100.00
23	124	1619	1619	0	0	100.00	100.00	0.00	100.00
24	200	2601	2601	2	0	99.92	100.00	0.08	99.92
25	201	1963	1936	8	27	99.59	98.62	1.81	98.22
26	202	2136	2130	10	6	99.53	99.72	0.75	99.25
27	203	2980	2955	37	25	98.76	99.16	2.10	97.94
28	205	2656	2651	17	5	99.36	99.81	0.83	99.18
29	207	2332	2116	142	216	93.71	90.74	16.92	85.53
30	208	2955	2954	4	1	99.86	99.97	0.17	99.83
31	209	3005	3005	0	0	100.00	100.00	0.00	100.00
32	210	2650	2650	0	0	100.00	100.00	0.00	100.00
33	212	2748	2748	3	0	99.89	100.00	0.11	99.89
34	213	3251	3251	1	0	99.97	100.00	0.03	99.97
35	214	2262	2262	0	0	100.00	100.00	0.00	100.00
36	215	3363	3363	0	0	100.00	100.00	0.00	100.00
37	217	2208	2200	5	8	99.77	99.64	0.59	99.41
38	219	2154	2154	0	0	100.00	100.00	0.00	100.00
39	220	2048	2048	0	0	100.00	100.00	0.00	100.00
40	221	2427	2426	3	1	99.88	99.96	0.16	99.84
41	222	2483	2483	0	0	100.00	100.00	0.00	100.00
42	223	2605	2605	4	0	99.85	100.00	0.15	99.85
43	228	2053	2024	13	29	99.36	98.59	2.08	97.97
44	230	2256	2256	0	0	100.00	100.00	0.00	100.00
45	231	1571	1571	0	0	100.00	100.00	0.00	100.00
46	232	1780	1777	0	3	100.00	99.83	0.17	99.83
47	233	3079	3079	2	0	99.94	100.00	0.06	99.94
48	243	2753	2753	0	0	100.00	100.00	0.00	100.00
Total/Average		**109966**	**109530**	**328**	**436**	**99.70**	**99.60**	**0.70**	**99.31**

Tab. 2. Comparison of R peak determination with other methods

Authors	R peaks	TP	FN	FP	SEN	$+P$	DER	ACC
Unai Zalabarria *et al.* (Zalabarria et al., 2020)	106,581	106,096	485	431	99.54	99.60	0.86	99.14
Qin Qin *et al.* (Qin et al., 2017)	109,966	109,298	668	561	99.39	99.49	1.12	98.89
Lakhan Dev Sharma *et al.* (Sharma & Sunkaria, 2016)	109,488	108,979	509	428	99.50	99.56	0.93	99.08
Proposed method, 2022	109966	109530	328	436	99.70	99.59	0.70	99.31

The results of determining the R peak position are compared with previous works for evaluating the performance of the proposed system as shown in Table 2. In particular, Unai Zalabarria et al. (Zalabarria et al., 2020) proposed a system for determining the peak R position, including preprocessing, detecting the region containing the R peak and iterative smart processing to accurately determine the R peak. In the preprocessing block, the signal was filtered the BW noise applying moving median filtering and a cubic interpolation. The accuracy and DER obtained using the MIT-BIH dataset are 99.14% and 0.86%, respectively. Another research is that Qui Qui et al. (Qin et al., 2017) et al. proposed a Wavelet-based Multiresolution Analysis (WMRA) method for filtering the noise on the ECG signal for determining the R peak position. The obtained accuracy is 98.9% and DER is 1.12% using the MIT-BIH dataset.

In (Sharma & Sunkaria, 2016), Lakhan Dev Sharma et al. applied filters of two-stage median and Savitzky–Golay smoothing for pre-processing to remove noise on ECG signals. Moreover, the root-mean-square method was employed for determining the region containing the QRS complex for detecting of the R peak. The MIT-BIH dataset was used to evaluate the system quality based on the obtained results, in which the accuracy and DER are 99.08% and 0.93%, respectively. In this research, we proposed an ECG signal preprocessing system by applying the WDFR algorithm for filtering noise, in which differentiation, squaring, and integration methods were employed to highlight the QRS complex. Therefore, a threshold was applied for determining the R peak position and the obtained accuracy and DER using the MIT-BIH dataset are 99.31% and 0.70%, respectively.

4. CONCLUSIONS

This paper proposed a system for determining the R peak position in the QRS complex of the ECG signal based on the signal processing method. In particular, the ECG dataset was filtered to remove noise components using the WDFR algorithm. The ECG after filtering the noise was processed to enhance the amplitude of the R peak for determining the R peaks more accurately using the differentiation, squaring, and integration algorithm. Therefore, the threshold value was calculated based on the determined R peak positions. For evaluation of the systemquality, the MIT-BIH ECG dataset was employed and the obtained accuracy result of the proposed R peak position system is 99.31%. However, for ECG signals with a large amount of noise such as the signal 207, the accuracy of the R peak position determination still needs to be improved. With the R peak positions accurately determined, a deep learning network applied for classifying heart diseases may make a highly increasing performance. In future work, we will apply the proposed R peak position determination algorithm to locate R peak and then calculate the beat-per-minute ratio for the measured ECG wearable device.

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Conflicts of Interest

The authors declare that we don't have any conflict of interest regarding this article.

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