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R Wave Detection and Advanced Arrhythmia Classification Method through QRS Pattern Considering Complexity in Smart Healthcare Environments*

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스마트 헬스케어 환경에서 복잡도를 고려한 R파 검출 및 QRS 패턴을 통한 향상된 부정맥 분류 방법

조 익 성

<Abstract>

With the increased attention about healthcare and management of heart diseases, smart healthcare services and related devices have been actively developed recently.

R wave is the largest representative signal among ECG signals. R wave detection is very important because it detects QRS pattern and classifies arrhythmia. Several R wave detection algorithms have been proposed with different features, but the remaining problem is their implementation in low-cost portable platforms for real-time applications. In this paper, we propose R wave detection based on optimal threshold and arrhythmia classification through QRS pattern considering complexity in smart healthcare environments. For this purpose, we detected R wave from noise-free ECG signal through the preprocessing method. Also, we classify premature ventricular contraction arrhythmia in realtime through QRS pattern. The performance of R wave detection and premature ventricular contraction arrhythmia classification is evaluated by using 9 record of MIT-BIH arrhythmia database that included over 30 premature ventricular contraction. The achieved scores indicate the average of 98.72% in R wave detection and the rate of 94.28% in PVC classification.

Key Words : R wave, QRS, Arrhythmia, Premature Ventricular Contraction, MIT-BIH Database, Complexity, Smart Healthcare

Ⅰ. Introduction

Smart healthcare technology has brought health management, which was only possible under spatially restricted settings of hospitals in the past, into our day-to-day activities, and in recent years, the active utilization and spread of smart devices accelerate the development and dissemination of smart healthcare.

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In particular, devices and related contents that can help to prevent chronic diseases such as obesity, diabetes, and cardiovascular diseases as well as the function of exercise management have been actively developed.

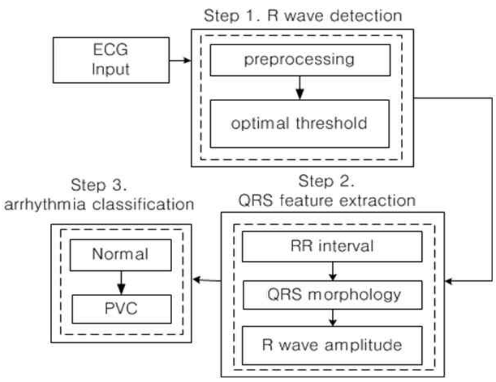
Among the various characteristic waveforms of the ECG signals, QRS is an important waveform that indicates ventricular depolarization. Arrythmia refers to an abnormal heart rate or irregular cardiac rhythms and can range from mild dysrhythmia in an otherwise healthy patient to a lethal condition. PVC(Premature Ventricular Contraction) is the most common types of arrythmia and can induce lethal heart diseases such as ventricular tachycardia in patients with an underlying heart disease; for this reason, early detection of PVC is critical[1-4].

The conventional method for R wave detection is a method of R peak extraction based on a threshold according to the size, and in this method, ECG signals are acquired and characteristic parameters, such as time intervals between minimum or maximum values are extracted from the ECG waveforms. However, with these methods, different characteristics such as the shape and size of signals and periodic variations according to the ECG database are obtained, resulting in misdiagnosis. This is because when multiple ECG databases are applied to different environments, due to signal differences according to the sample frequency, the performance shows much variation and it is difficult to ensure the reliability of the algorithm. In addition, the processing and computation of data are complicated, which causes difficulties in real-time application [5-8].

In this study, we propose an R wave detection method taking into account the complexity in smart healthcare environment and arrhythmia classification method through QRS pattern. To this end, using the moving average and square function based on the differential, preprocessing was performed and the optimal thresholds were set according to the sample frequency. Then, arrhythmia was classified using RR interval, QRS morphology, and amplitude of R wave. In order to demonstrate the excellence of the proposed method, R wave detection and arrhythmia classification rate were determined for the MIT-BIH standard database. The structure of this paper is as follows. Section 2 discusses the proposed method, Section 3 describes the experimental results, and Section 4 summarizes the findings with a conclusion.

Ⅱ. Proposed methods

The overall flow chart of the proposed algorithm is divided into steps as shown in <Fig. 1>. First of all, noise is removed from the ECG signals through a preprocessing process, and the R wave is detected through the differential section according to the sample frequency, the moving average interval and the optimal threshold, and the characteristic features such as RR interval, QRS morphology, and R wave amplitude are detected, and then arrhythmia classification is performed according to the QRS pattern.



<Fig. 1> System Flowchart

2.1 Preprocessing

For noise-resistant R wave detection, a preprocessing technique based on differential, moving average, and square function was used. The preprocessing process for R wave detection is shown in <Fig. 1>.

First of all, low-frequency noise such as the baseline signals were removed to attenuate the P and T waves, and for emphasis on the gradient of R wave, a differential function was used as shown in Equation (1). For signals processed through the differential function, multiple signals form one section, and in order to remove this high-frequency noise, an integral using a moving average is used as shown in Equation (2). Finally, the signals with the low-frequency and high-frequency noise removed are amplified through the square function as shown in Equation (3), so that the signals can be clearly differentiated from other noise.

$$Y_{diff}[n] = X[n] - X[n - N_{diff}] \tag{1}$$

$$Y_{mov}[n] = \frac{1}{N}\sum_{k=1}^{N} Y_{diff}[n-k] \tag{2}$$

$$Y_{squ}[n] = (Y_{mov}[n])^2 \tag{3}$$

2.2 Threshold setting

The change according to the amplitude of the preprocessed signals was used as the threshold, and the minimum RR interval and the minimum QRS interval were considered to determine the initial threshold. According to clinical definition, the minimum RR interval cannot exceed 300bpm (bit per minute) and it was set to 200ms and the minimum QRS interval were set to 60ms [9-11].

After receiving the preprocessed signal, the number of detections of the R wave, the time value of the R wave, and the amplitude of the R wave are initialized, and the maximum amplitude value is detected in the range of the minimum RR interval and the sum of minimum RR interval. At this time, the detected value is determined as R wave, and the number of detections and thresholds are updated.

2.3 Optimal value setting

The preprocessing process and threshold proposed above are techniques to improve detection accuracy and computational efficiency. In this study, the sample frequency(), the differential section(), and the optimal window size() were set for improved preprocessing. The threshold for R wave detection becomes an important setting value for performance improvement according to preprocessing and sample frequency. This is the optimal value selected through cross-validation of the MIT-BIH arrhythmia database. The parameters for the optimum performance of R wave detection were acquired through the following process.

The reference sampling rate was 360 samples/s, the range was 256Hz interval, the moving average had intervals of 2 in 1-20 , and the differential value range was increased with the interval of 2 in the range of 1-20. In the case of the MIT-BIH arrhythmia database, the reference sampling frequency was 360Hz, and it was confirmed that the sampling frequency was 360Hz, the moving average range was 8, and the differential parameter range was 8.

2.4 QRS Pattern Extraction

In this study, QRS features were used for arrhythmia classification. This is to increase the accuracy of classification according to the different types of arrhythmia depending on the individual.

(1) RR interval

The RR interval is very useful as information for determining arrhythmia. In the case of normal, the rate of change is constant, whereas in the case of arrhythmia, the rate of change is very large in general. In particular, in the case of premature ventricular contraction arrhythmia, the RR interval is sharply narrowed compared to normal and the rate of change is constantly increased. Therefore, it is possible to classify premature ventricular contraction by using the mean of the RR interval and the amount of change.

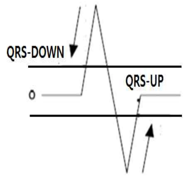
(2) QRS morphology

Most of the normal waveforms show the same morphology, but the QRS morphology of arrhythmia can be categorized in several ways. In this study, four QRS patterns were defined.

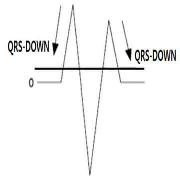
As a result of analyzing the MIT-BIH arrhythmia database, a case of Normal as shown in <Fig. 2> and three different morphologies of premature ventricular contraction arrhythmia as shown in <Fig. 2>(b), <Fig. 2>(c), and <Fig. 2>(d) are confirmed. By experiments, it can be seen that most of the differential values of QRS morphology have two positive peaks (+) and one negative peak (-). That is, when a specific threshold is set, the QRS morphology can be determined according to whether the values of the left peak and the right peak satisfy the threshold range.

(3) Amplitude of R wave

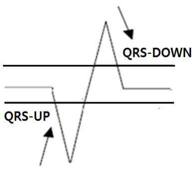
In addition to the QRS morphology, the amplitude of the R wave was used to classify the arrhythmia of a specific record. The amplitude of premature ventricular contraction arrhythmia is about twice as that of normal, while premature ventricular contraction arrhythmia is similar to that of normal or shows about 1.5 times of the amplitude change. Therefore, the R wave amplitude of premature ventricular contraction arrhythmia, which is more than twice the value of normal, can detect bits not classified by the QRS morphology. The condition for the R peak amplitude are formed into 15 groups of 15 before and 9 after based on the current R peak as shown in Equation (4). This is a method for determining the rate of change in the current R peak by defining the waveforms of the signals before and after as a representative signal of the group.



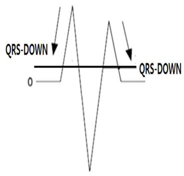
(a) Normal



(b) A morphology



(c) B morphology



(d) C morphology

<Fig. 2> QRS morphology

$$R_G = \frac{1}{N}\sum_{k=11}^{n}\left[R_{k-15}, R_{k-14}, \cdots R_k, \cdots R_{k+8}, R_{k+9}\right] \quad (4)$$
$$R_G = Representative\ signal,$$
$$R_k = Amplitude\ f\ Rwave$$

Ⅲ. Results and Discussion

3.1 R wave detection

Performance evaluation of R wave detection was conducted through the MIT-BIH arrhythmia database.

The detection rate is obtained through Equation (5). In the equation below, FP is a case where the proposed method detected R wave, but it does not exist in the MIT-BIH database, and FN is the case that it is in the MIT-BIH standard database, but not detected by the proposed method. The total number of bits is the total number of R waves in MIT-BIH. As shown in Table 1, the average R wave detection rate for a total of 9 records showed excellent performance of 98.72%.

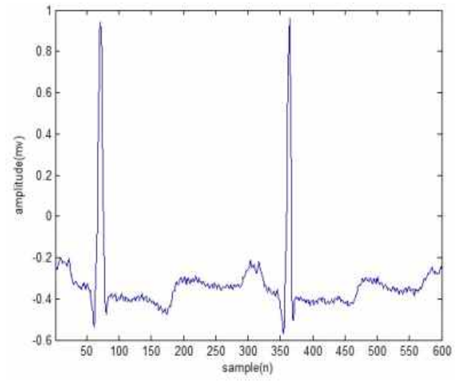
$$Detection\ Rate(\%)\ = \quad (5)$$

3.2 Arrhythmia classification

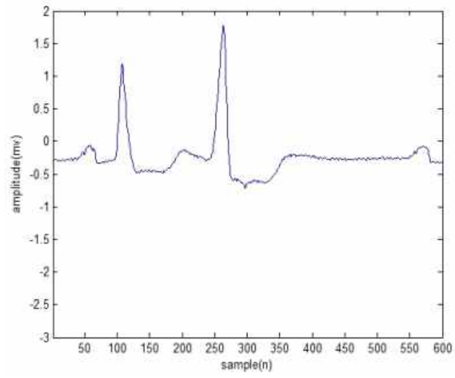
The R wave detection method based on optimal threshold and arrhythmia classification method using QRS features perform arrhythmia classification using RR interval, QRS pattern, and amplitude of R wave.

<Fig. 3> is an analysis of 9 records containing normal and premature ventricular contraction, a type of arrhythmia with high risk, to determine the threshold of each feature point. As shown in <Fig. 3>(a), in the case of record No. 100, it indicates normal and regular form of QRS morphology is observed. On the other hand, as shown in <Fig. 3>(b), records No. 105, 106, 114, 116, and 223 show A morphology arrhythmia, and it can be seen that the change in RR interval is large. In this case, a classification method using the RR interval was applied.

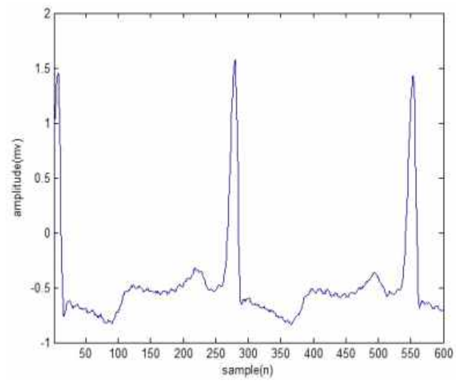
As shown in <Fig. 3>(c), in the case of record No. 223, it is premature ventricular contraction of B morphology, and it can be confirmed that the RR interval and QRS interval are large. In this case, a classification method that applied both the RR interval and the QRS interval was used. <Fig. 3>(d) is a case where both B and C morphology are represented, and it is difficult to classify using the RR interval and QRS interval. In this case, the classification method through the amplitude change



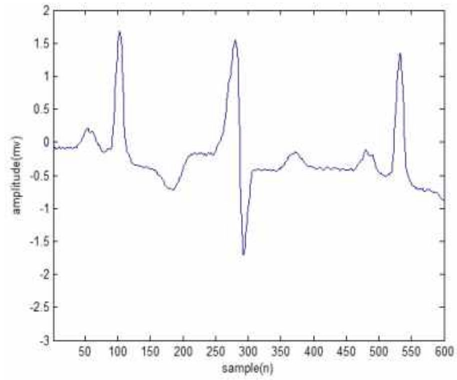
(a) Normal morphology



(b) A morphology(PVC)



(c) B morphology(PVC)



(d) C morphology(PVC)

<Fig. 3> Arrhythmia type

rate of the R wave was applied.

In order to evaluate the arrhythmia classification performance of the proposed method, we tested the performance with the MIT-BIH arrhythmia database. The calculation of the detection rate is as shown in Equation (5), and the records used in the performance evaluation were 9 records of No. 105, 106, 114, 116, 119, 200, 213, 223, and 233. Table 2 shows the results of premature ventricular contraction arrhythmia classification by the proposed method. As a result of performance evaluation, the average classification rate showed excellent performance of 94.28%. Therefore, it can be confirmed that the R wave detection based on the optimal threshold and the arrhythmia classification method based on the QRS feature points proposed in this study reduce the complexity and show an excellent classification rate. Furthermore, the proposed method resulted in a slightly lower detection rate than the Bayesian filtering method, but is much better in terms of classification simplicity, and obtained better results compared to the Gaussian method[12, 13].

<Table 1> R wave detection rate

MIT-BIH	R peak detection	
	Bit Count	rate(%)
105	2524	99.84
106	1988	96.2
114	1848	99.9
116	2366	98.45
119	1949	99.12
200	2550	98.82
213	3187	93.04
223	2558	98.14
233	3079	98.40
total	18,970	98.70

<Table 2> PVC classification rate

Record	MIT-BIH		rate(%)
	PVC Bit Count		
105	39		90.21
106	520		96.48
114	43		95.30
116	109		95.12
119	435		100
200	809		96.55
213	220		86.32
223	472		90.16
233	813		98.76
SUM	0	AVG	0.00

Ⅳ. Conclusion

In this study, in order to consider the complexity of the smart healthcare environment, for efficient and accurate arrhythmia classification through minimized computation, we proposed an arrhythmia classification based on R wave detection and QRS pattern.

To this end, preprocessing was performed using differential function-based moving average and square function, and the optimal threshold was set according to the sample frequency, enabling more accurate and efficient R wave detection. Then, arrhythmia classification was performed using the RR interval, QRS pattern, and amplitude of R wave. To demonstrate the excellence of the proposed method, the experimental results showed that the average detection rates of R wave and premature ventricular contraction arrhythmia for the MIT-BIH standard database were 98.72% and 94.28% respectively. Therefore, it is expected that the method proposed in this study can be applied to a smart healthcare system capable of accurate diagnosis of arrhythmia in real time while reducing computational complexity.

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