Classification of Premature Ventricular Contraction using Error Back-Propagation

Eunkwang Jeon[*], Bong-Keun Jung[**], Yunyoung Nam[***], HwaMin Lee[****]

[*]Department of Computer Science & Engineering, Soonchunhyang University
Asan, South Korea
[**]Department of Occupational Therapy, Soonchunhyang University
Asan, South Korea
[***]Department of Computer Engineering, Soonchunhyang University
Asan, South Korea
[****]Department of Computer Software Engineering, Soonchunhyang University
Asan, South Korea
[e-mail: imdae11@gmail.com, {jungb, ynam, leehm}@sch.ac.kr]
*Corresponding author: HwaMin Lee

Received October 19, 2017; accepted December 28, 2017; published February 28, 2018

Abstract

Arrhythmia has recently emerged as one of the major causes of death in Koreans. Premature Ventricular Contraction (PVC) is the most common arrhythmia that can be found in clinical practice, and it may be a precursor to dangerous arrhythmias, such as paroxysmal insomnia, ventricular fibrillation, and coronary artery disease. Therefore, we need for a method that can detect an abnormal heart beat and diagnose arrhythmia early. We extracted the features corresponding to the QRS pattern from the subject's ECG signal and classify the premature ventricular contraction waveform using the features. We modified the weighting and bias values based on the error back-propagation algorithm through learning data. We classify the normal signal and the premature ventricular contraction signal through the modified weights and deflection values. MIT-BIH arrhythmia data sets were used for performance tests. We used RR interval, QS interval, QR amplitude and RS amplitude features. And the hidden layer with two nodes is composed of two layers to form a total three layers (input layer 0, output layer 3).

***Keywords*:** ARRHYTHMIA, BACK-PROPAGATION, PREMATURE VENTRICULAR CONTRACTION

A preliminary version of this paper was presented at APIC-IST 2017, and was selected as an outstanding paper.
This research was financially supported by the "ICT Convergence Smart Rehabilitation Industrial Education Program" through the Ministry of Trade, Industry & Energy (MOTIE) and Korea Institute for Advancement of Technology (KIAT) and by the Soonchunhyang University Research Fund.

http://doi.org/10.3837/tiis.2018.02.028 **ISSN : 1976-7277**

1. Introduction

As domestic economic growth and living environment have been westernized recently, heart disease has become one of the major causes of death in Korea, along with cancer and cerebrovascular disease. Typical types of heart disease include coronary artery disease (CAD), arrhythmia, and heart failure. The most important signal for the prognosis and prognosis of these heart diseases is ECG signal from cardiac activity, especially for the diagnosis of arrhythmia which is caused by electrical stimulation of the heart and conduction disturbance [1]. Particularly, heart disease such as premature ventricular contraction (PVC) and premature atrial contraction (PAC) may require precautions because they can be a precursor to dangerous arrhythmias such as paroxysmal tachycardia, ventricular fibrillation, and coronary artery disease.

The Electrocardiogram (ECG) is an easy to measure device that attaches an electrode to a human body surface, which is an important measure for diagnosing the presence or absence of a heart disease [2,3]. The Electrocardiogram is a low cost and non-invasive test which effectively presents valuable clinical information regarding the morphology, rate, and regularity of the heart. It is of utmost importance to accurately detect ECG beats so that the timely diagnosis of worrying heart conditions can lead to immediate medical attention. Especially, the timely detection of premature ventricular contractions (PVCs) is of utmost importance as this may lead to cardiac arrhythmias that may turn out to be fatal. A premature ventricular contraction is a relatively common event where the heartbeat is initiated by the heart ventricles that are independent of the pace set by the sinoatrial node[4].

The ECG signal has a time periodicity allowing to define an elementary beat composed by specific waveforms, appearing periodically in time. **Fig. 1** shows a heartbeat and its respective waveform labels. The study of the waveform amplitudes and patterns constitutes the basis of the ECG signal analysis. For instance, one can easily show that the heart rate is estimated after detecting the QRS-complex from a beat sequence. In the same way, the time-distance between two consecutive QRS-complexes, known as RR-interval, is used to detect premature beats. We can extend this analysis to other conditions like the ST-segment deviation from a long period, necessary to early diagnosis of ischemia. As a result, reliable ECG analysis depends directly on the ECG beat segmentation results[5, 6, 7].

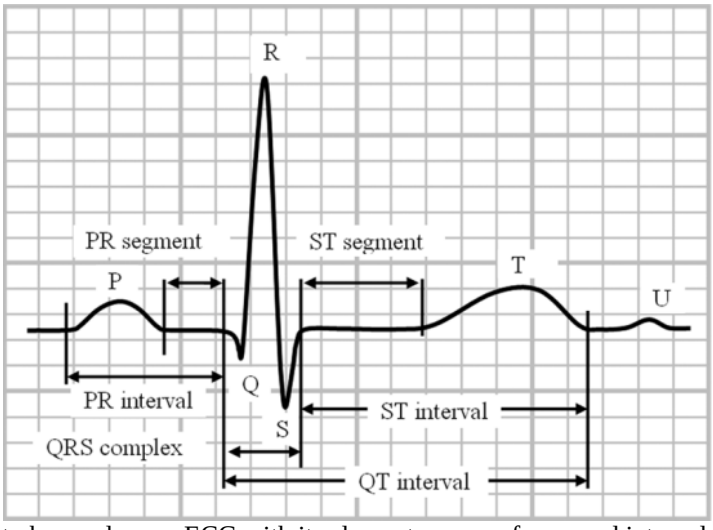

Fig. 1. Heartbeat observed on an ECG with its elementary waveforms and intervals identified.

Many PVC detections and classification algorithms have been developed so far. The PVC detection algorithms include Discrete Cosine Transform (DCT) and autoregressive modeling[8], symbolic dynamics[9], correlation coefficient in ECG signal[10], while the PVC classification algorithms are developed mainly using Artificial Neural Networks[11] considering timing information between the detected peaks as a feature set for classification.

ECG signal analysis is the most common way to study and diagnose cardiac dysfunctions. The normal signal is characterized by recurrent or periodic waveforms with each beat. Beat-to-beat detection and classification of the QRS complexes allow the heart rhythm evolution to be followed and arrhythmias such as premature ventricular contractions (PVC) to be detected. Detection and classification of ventricular beat changes is of considerable importance in real-time critical care or operating room patient monitoring. It is also important for older patients with underlying heart disease. The clinical significance is dependent on PVC frequency, complexity, and hemodynamic response. In these applications, it is important to develop signal-processing techniques that allow real-time feature extraction for the classification of the QRS complexes and other ventricular beat patterns [12].

Premature ventricular contraction is the most common arrhythmia that can be found in clinical practice. The occurrence of premature ventricular contraction in patients with past heart disease is likely to cause a dangerous heart disease such as ventricular tachycardia. Therefore, the detection of this is very important as a basis for further investigation [13,14]. PVC can occur in a healthy person of any age but becomes more frequent in the elderly people and is more commonly found in men. The immediate detection and subsequent treatment of PVCs are essential for patients with cardiovascular disease because studies have shown that PVCs when associated with heart attack, can be linked to mortality. Computer-aided automatic diagnosis of cardiac events assists doctors to ascertain the exigency and nature of the medical intervention required. The automatic detection and classification of ECG beats using biomedical signal processing techniques have evolved as an active area of research [15-24].

Several methods for automatic detection and classification of cardiac arrhythmias have been reported in the literature, including algorithms based on self-organizing maps [15], filter banks [16], hidden Markov models [17] and neural networks [18–20]. In [21], Senhadji et al. used discrete a wavelet transform (DWT) aided linear discriminant classifier for ECG beat classification to achieve 98% classification accuracy. But their classifier used only 25 beats in training and 28 beats for testing. Shyu et al. could also achieve a high classification accuracy of 97.04% for PVC beat classification, utilizing wavelet transform based feature extraction in tandem with fuzzy neural network based classifier. However, their classification results were based on only seven files of the MIT/BIH arrhythmia database, out of which two files were used in the training dataset of the neural network [15]. In [16], Hosseini et al. achieved a classification accuracy of 88.3% using multilayer perceptron neural network (MLPNN) classifier using 10 files of the MIT/BIH arrhythmia database. Similar classifiers were also developed in [19–21] which were tested over small datasets. In the literature [18,22,23], classification results were reported on the basis of comparatively larger testing datasets. In [22] a linear discriminant based classification scheme was reported that could achieve a classification accuracy of 89% over 44 files of the MIT/BIH arrhythmia database.

This study was conducted to detect the abnormal heartbeat and to detect the arrhythmia early. After extracting the features for the ECG signal from the premature ventricular contraction classification, a method of classifying the normal waveform and the early contraction waveform by using the error back-propagation algorithm was studied.

2. Related Work

2.1 Analysis and Classification of Existing ECG Signal

Diagnosis of heart disease using electrocardiogram signal requires the sequential processing of preprocessing, waveform detection and segmentation, feature extraction, and classification as shown in **Fig. 2**. Here, the compression of the signal for each step is an essential element for effectively storing and transmitting an enormous amount of electrocardiogram data and reproduces higher compression performance as the processing progresses.

In the field of signal processing and pattern recognition, researches on the analysis and classification of electrocardiogram signals have been continuously carried out. In recent years, the design of early diagnosis algorithms for heart diseases for practical use with the advent of U- Various approaches have been attempted to implement the system. Previous studies have proposed a corresponding approach to each purpose, such as pre-processing to correspond to baseline fluctuation noise, external noise, ECG feature point extraction as a diagnostic element, and classifier optimization based on extracted feature points [25]. For the design of the proposed method, the background and purpose of the research, and the performance index should be carefully examined.

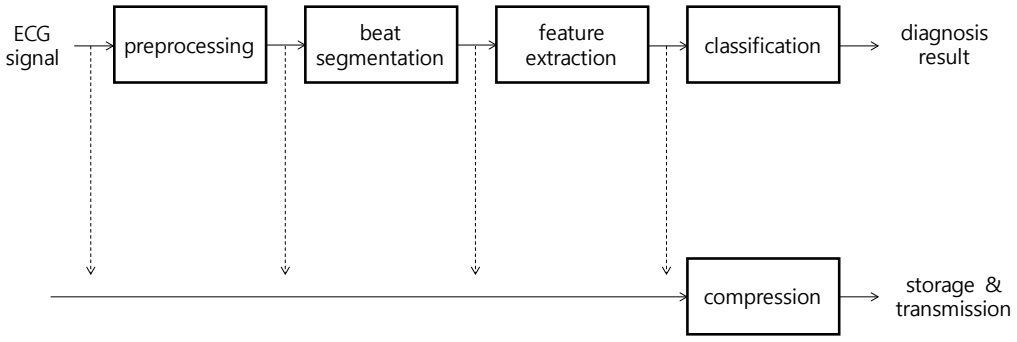

Fig. 2. Typical process flowchart of ECG based diagnosis

2.2 Premature Ventricular Contraction Arrhythmia

Premature ventricular premature contraction is an arrhythmia signal generated by premature depolarization of the ventricle by ectopic stimulation occurring in the ventricle as shown in **Fig. 3**, and excited cells in the ventricle before direct contraction of the ventricular node (SA node) And arrhythmia is most commonly observed and can be seen in healthy people.Myocardial infarction is the most common cause of myocardial infarction, and other causes include such as taking drugs such as Digitalis, intake of cardiac stimulants such as caffeine, nicotine and drugs and electrolyte imbalance, tachycardia, Bradycardia.

The cardiac heart rate keeps 60 ~ 100 times per minute. The P wave appears reversed when the stimulation started from the ventricle is reversed and shrinks the atrium, but most of the stimulation is not transmitted to the atrium. In the case of the QRS complex, it lasts for more than 0.12 seconds and is wider than the normal QRS complex and it has deformed shape. Also, contraction stimulation initiated from the ventricle reverses and is transmitted to the atrioventricular node and the atrium, but most of the atrium does not reach the atrium, thus maintaining the original rhythm. As a result, after ventricular premature contraction, we have a compensatory period, so the time required for early ventricular contraction and subsequent normal pacing does not differ from the time required for two normal beats. Ventricular premature contraction does not cause cardiac abnormality in itself, but it is judged to be a sign

of ventricular tachycardia or ventricular fibrillation if ventricular premature contraction arrhythmia occurs more than six times per minute, so detection of ventricular premature contraction arrhythmia is very important.

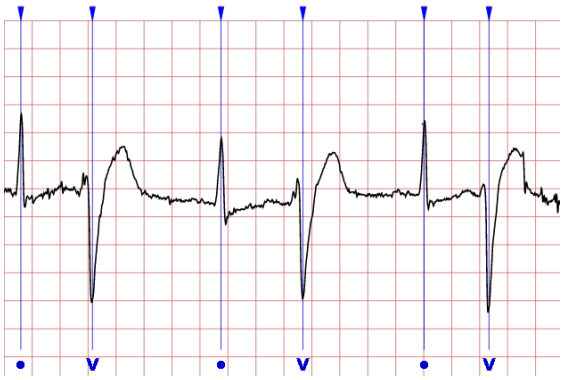

Fig. 3. Premature Ventricular Contraction Arrhythmia

2.3 QRS Peak Detection

Pan & Tompkins QRS Peak Detection algorithm is typical QRS peak detection algorithm. After the Pan & Tompkins algorithm was published in 1985, many ECG related studies have used this detection method. The algorithm detection process is shown in **Fig. 4**.

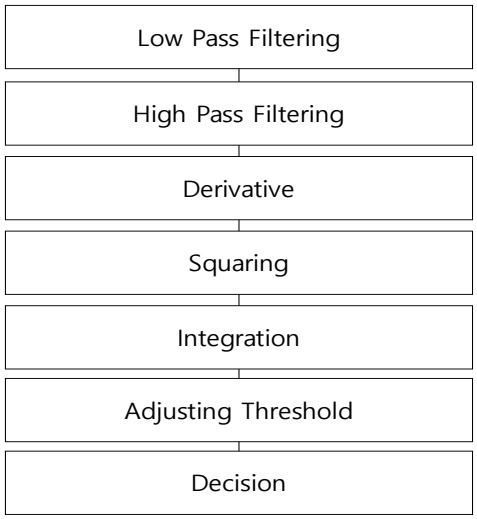

Fig. 4. QRS Detection Process

Low Pass Filtering and High Pass Filtering are processed to remove the noise contained in the ECG signal. Noise such as muscle noise, power supply noise, and baseline shaking included in the ECG signal is reduced using a 5 to 11 Hz bandpass filter. This process results in a delay of 16 samples. After performing the derivative and squaring it, the negative value of the signal is removed and the location of R peak is highlighted. Next, the preprocessing process ends when the moving average is passed. After all the preprocessing steps are performed, Q, R and S peaks are detected by applying the threshold [26].

2.4 Error Back-Propagation Algorithm

The error back-propagation is a supervised learning algorithm that uses a gradient descent method to minimize the cost function, which is the mean square error between the ideal output and the actual output [27]. In this case, the connection strength between the nodes is initialized to a small value, and the learning data is repeatedly provided to the input and output layers to learn. The error value, which is the difference between the value in the output layer calculated by the input data and the expected value, is propagated to the lower layer, so that the connection strength with the lower layer is readjusted, and the total strength of the neural network converges, and the total error becomes very small we will study it repeatedly.

2.4.1 Error Back-Propagation Algorithm Learning

The error back-propagation algorithm required data and desired output data (o) to be learned. The learning process of error propagation propagates the output of the input (Tag_o) by repeating the process of multiplying and adding the input with the weight of the neural network several times. At this time, the output (Tag_o) differs from the expected output (Pre_o) given in the learning data. In the neural network, an error of (Tag_o - Pre_o) occurs, and the weight of the output layer is updated in proportion to the error, and the weight of the hidden layer is updated. Since the direction of updating the weights is opposite to the processing direction of the neural network, it is called back-propagation algorithm.

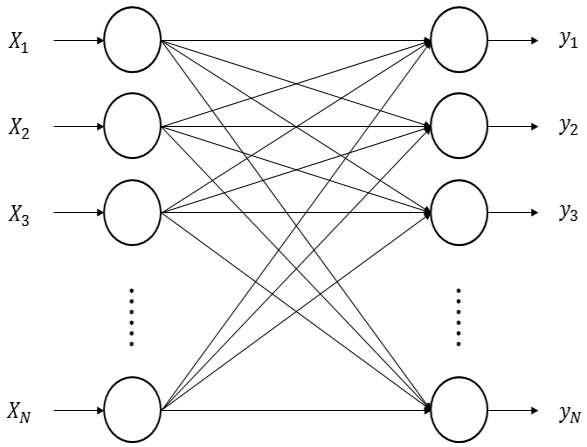

Fig. 5. Architecture of Single-layer Perceptron

3. Methods

In this paper, the whole structure of the premature ventricular contraction classification based on the error back-propagation is composed as shown in the **Fig. 6**. First, the noise is removed from the ECG signal by a preprocessing process, and then an R wave is detected, and a QS-wave is detected based on the detected R wave. QRS-waves are set as one pattern and features of R-R interval, Q-S interval, Q-R amplitude, and R-S amplitude are extracted from each pattern. Using the extracted feature values as training data, the weight value and the bias value are updated using the error back-propagation technique to obtain the final weight value and the bias value. Normal and PVC are classified through the features and operations that are input using the final weight value and a bias value.

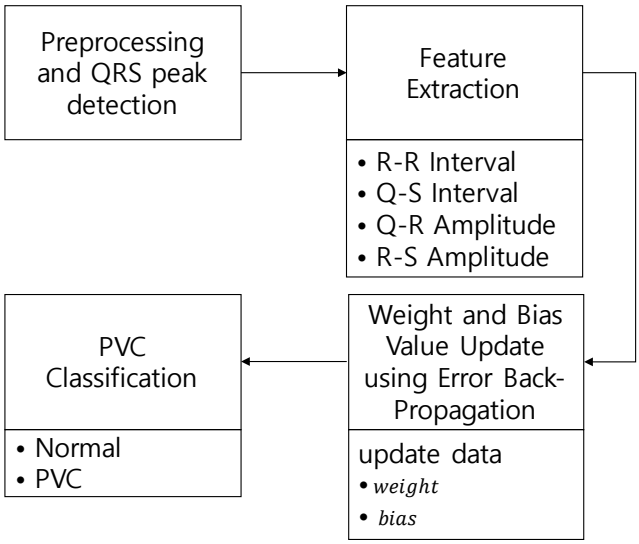

Fig. 6. PVC Classification Structure

3.1 Pre-Processing and QRS Detection

To detect an accurate QRS wave, the QRS wave must be detected after removing the noise included in the ECG signal. In this paper, we use Pan & Tompkins QRS Detection Algorithm for preprocessing and QRS detection.

3.2 Feature Extraction

Premature ventricular contraction is one of the arrhythmia diseases, and because the pattern is different for each arrhythmia disease, relevant features should be used for accurate classification. The accuracy was confirmed by selecting the correct features rather than the features and using them for classification. In this paper, we used R-R interval, Q-S interval, Q-R amplitude, and R-S amplitude for early ventricular contraction classification.

In the **Fig. 7**, when the normal signal and the premature ventricular contraction signal are compared, it can be seen that the R-R distance is shorter and the Q-R amplitude is larger and the R-S amplitude is smaller than that of premature ventricular contraction signal.

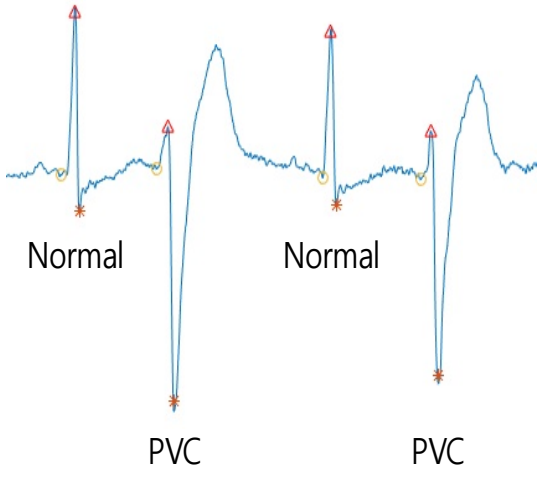

Fig. 7. Normal and Premature Venticular Contraction Signals

After feature extraction, label data was added for each feature. The label data was based on data provided by Physionet [28]. Additionally, for each label, the normal signal was added to the 1 and premature ventricular contraction signal was added to the 0 label.

3.3 Update Weight Value and Bias Value

The initial weight value and the bias value are set to 0.1 and the learning rate is set to 0.1. The final value is determined by updating the weight value and the bias value through the training process. The input layer neurons consist of three as the number of features. Hidden neurons consisted of three, including bias neurons. And the hidden layer has built up two layers. The output layer consists of one neuron outputting the result through a sigmoid function.

3.4 Premature Ventricular Contraction Classification

The result value is calculated through the operation with the feature values input using the finally determined weight value and the bias value. If the result is greater than 0.5, it is classified as a normal signal. If it is less than or equal to 0.5, it is classified as a premature ventricular contraction signal.

4. Experiments

4.1 Data

The data used in the experiments were the MIT-BIH Arrhythmia 106, 119, 200, 223, 233 Record provided by Physionet. The sample rate of the data was recorded at 360 Hz. The data length is 30 minutes.

4.2 Pre-Processing and QRS Detection

We used the Pan & Tompkins QRS Detection Algorithm to detect the Q, R and S peaks of the MIT-BIH Arrhythmia Record. Perform the high-pass filtering step, the low-pass filtering step, derivative step, squaring step, integration step, adjusting threshold step and decision step as shown in **Fig. 2** to detect Q, R and S peaks. Q, R, and S peaks were detected, and the incorrectly detected parts were processed. FP (False Positive) that detected R peak had a negative value with R peak value less than 0. Therefore, R peak value smaller than 0 and corresponding Q and S peak values are removed from the detected data. The location value and the time value of the data are detected for each peak.

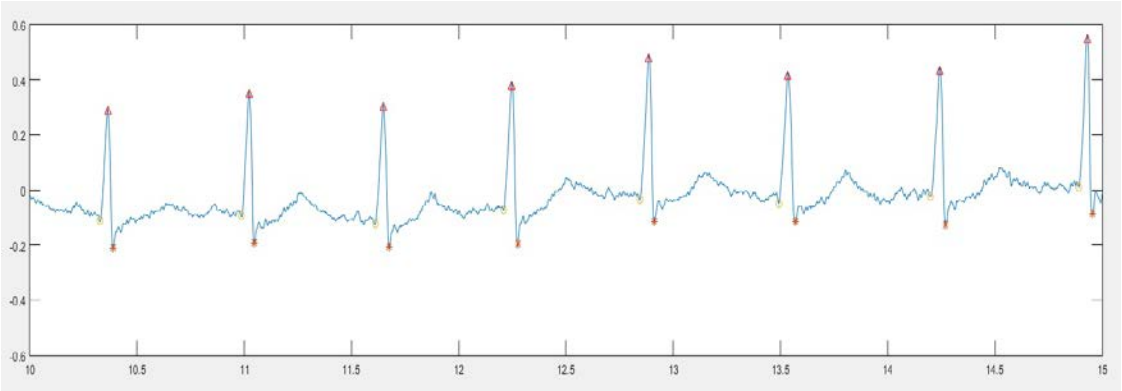

Fig. 8. MIT-BIH Record 200 QRS Wave Detection Example

Fig. 8 shows an example of QRS detection of MIT-BIH Arrhythmia 200 Record data. We used the Pan & Tompkins QRS Peak detection algorithm in MATLAB.

4.3 Feature Extraction

In this paper, four characteristics of R-R distance, Q-S distance, QR amplitude, and RS amplitude are used for PVC classification. The R-R distance was calculated using the R-peak location data. And Q-S distance was calculated using Q-peak location data and S-peak location data. The used data was sampled at 360 Hz and the location value was divided by 360 to obtain the unit in seconds.

QR amplitude and RS amplitude were calculated using the signal values of each peak. The formula is as follows. And **Fig. 9** shows the features used for classification.

$$RR_{interval(x)} = \left(\frac{R_{location(x+1)}}{360}\right) - \left(\frac{R_{location(x)}}{360}\right)$$
$$QS_{interval(x)} = \left(\frac{S_{location(x+1)}}{360}\right) - \left(\frac{Q_{location(x)}}{360}\right)$$
$$QR_{amplitude(x)} = R_{value(x)} - Q_{value(x)}$$
$$RS_{amplitude(x)} = R_{value(x)} - S_{value(x)}$$

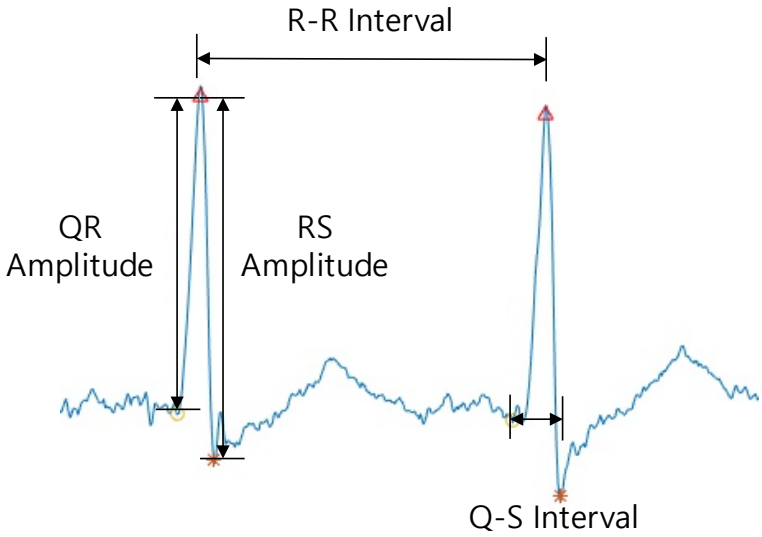

Fig. 9. Features Used for Classification

We then added annotations for each feature using data from RR distance and annotation provided by Physionet. For annotations, except for normal signal N and PVC signal V for the entire feature, it was added while removing and syncing features and annotations via Physionet's LiveWAVE. The other signals except for the normal signal and the PVC signal were removed from the data. To derive the result through learning, we changed the normal signal N value to 1 and the PVC signal V value to 0 value.

The results obtained through the procedure are the location and time values and output value of 1 or 0 for four features for weight and bias learning.

4.4 Final Weight and Bias Value Determination

70% of the data of each record was used as learning data in the weight and bias value determination process. We set the initial weight value, the bias value, and the learning rate to 0.1, and update the weight value and the bias value based on the error back-propagation. In the step of updating the weight value and the bias value, the normal signal is set to a value of 1 and the PVC signal is set to a value of 0 to proceed with the result.

The finally determined weight value and the bias value are stored separately for each record. This process was performed in MATLAB.

4.5 Premature Ventricular Contraction Classification

The final weight value and the bias value were used to classify the normal signal and the PVC signal. 30% of the extracted features were used as test data.

A sigmoid function was used as an activation function in the hidden layer and the output layer. If the value calculated in the output layer is greater than 0.5, it is classified as a normal signal. If the value is less than or equal to 0.5, it is classified as a PVC signal.

The Precision, recall, and accuracy are as follows.

Table 1. PVC Classification Result using Test Dataset

106 Record		Actual Value	
		Positive	Negative
Classification Value	Positive	453	15
	Negative	1	137
119 Record		Actual Value	
		Positive	Negative
Classification Value	Positive	462	0
	Negative	0	119
200 Record		Actual Value	
		Positive	Negative
Classification Value	Positive	508	9
	Negative	0	183
223 Record		Actual Value	
		Positive	Negative
Classification Value	Positive	487	54
	Negative	14	195
233 Record		Actual Value	
		Positive	Negative
Classification Value	Positive	530	3
	Negative	0	372

Table 2. PVC Classification Result using Test Dataset

	Precision	Recall	Accuracy
106	96.7948	99.7797	97.3597
119	1	1	1
200	98.2591	1	98.7142
223	90.0184	97.2055	90.9333
233	99.4371	1	99.6685

5. Conclusions

In this paper, we use three features to find the final weight value and bias value through learning based on the error back-propagation algorithm and then classify the normal signal and the PVC signal for the input feature values. For this, we removed the noise of the signal through preprocessing and detected the Q, R and S peaks through the peak detection process. We then extracted the RR interval, QS interval, QR amplitude, and RS amplitude based on the Q, R, and S peaks. The extracted features are the input layer of the configured neural network, and the final weights were determined by updating the weights and bias values through an error back-propagation algorithm. We tested the final weight and bias value for each record. 30% of record data was used as test data. Test results are displayed with precision, recall, and accuracy to verify PVC classification performance through error back-propagation algorithm.

Future research will enable learning through ECG signals without feature extraction. By using the deep learning algorithm, learning ECG signals rather than learning by features, it is possible to omit preprocessing and feature extraction. This will lead to more accurate and less time spent on learning. Also, since the algorithm proposed in this paper determines the weight and bias value for each record, we cannot apply the weight value and bias value determined in A record to B record. The goal is to develop algorithms that can determine weight and bias values from one algorithm and classify premature ventricular contractions and other arrhythmia diseases by ECG signals from multiple people through further studies.

References

[1] Schijvenaars, Bob JA, Gerard van Herpen, and Jan A. Kors, "Intraindividual variability in electrocardiograms," *Journal of Electrocardiology*, vol. 41, no. 3, 190-196, 2008. Article (Ref Link).

[2] Chan, Adrian DC, et al. "Wavelet distance measure for person identification using electrocardiograms," *IEEE transactions on instrumentation and measurement*, vol. 57, no. 2, 248-253, 2008. Article (Ref Link).

[3] Chauhan, Sushil, A. S. Arora, and Amit Kaul, "A survey of emerging biometric modalities," *Procedia Computer Science*, vol. 2, 213-218, 2010. Article (Ref Link).

[4] Dutta, Saibal, Amitava Chatterjee, and Sugata Munshi, "Correlation technique and least square support vector machine combine for frequency domain based ECG beat classification," *Medical engineering & physics*, vol. 32, no. 10, 1161-1169, 2010. Article (Ref Link).

[5] Andreao, Rodrigo Varejao, Bernadette Dorizzi, and Jérôme Boudy, "ECG signal analysis through hidden Markov models," *IEEE Transactions on Biomedical engineering*, vol. 53, no. 8, 1541-1549, 2006. Article (Ref Link).

[6] Kadish, Alan H., et al, "ACC/AHA clinical competence statement on electrocardiography and ambulatory electrocardiography: A report of the ACC/AHA/ACP–ASIM Task Force on Clinical Competence (ACC/AHA Committee to Develop a Clinical Competence Statement on Electrocardiography and Ambulatory Electrocardiography) Endorsed by the International Society for Holter and Noninvasive Electrocardiology," *Circulation*, vol. 104, no. 25, 3169-3178, 2001. Article (Ref Link).
[7] Corabian, Paula. "Accuracy and reliability of using computerized interpretation of electrocardiograms for routine examinations," *Alberta Heritage Foundation for Medical Research*, 2002. Article (Ref Link).
[8] Paul, Joseph S., M. R. S. Reddy, and V. Jagadeesh Kumar, "Automatic detection of pvcs using autoregressive models," in *Proc. of Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE.*, Vol. 1, 1997. Article (Ref Link).
[9] Zhao, Lichu, Matt Wiggins, and George Vachtsevanos. "Premature ventricular contraction beat detection based on symbolic dynamics analysis," *Proc. IASTED*, 2003. Article (Ref Link).
[10] Chiu, Chuang-Chien, Tong-Hong Lin, and Ben-Yi Liau, "Using correlation coefficient in ECG waveform for arrhythmia detection," *Biomedical Engineering: Applications, Basis and Communications*, vol. 17, no. 03, 147-152, 2005. Article (Ref Link).
[11] Inan, Omer T., Laurent Giovangrandi, and Gregory TA Kovacs, "Robust neural-network-based classification of premature ventricular contractions using wavelet transform and timing interval features," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 12, 2507-2515, 2006. Article (Ref Link).
[12] Christov, Ivalyo, and G. Bortolan, "Ranking of pattern recognition parameters for premature ventricular contractions classification by neural networks," *Physiological Measurement*, vol. 25, no. 5, 1281, 2004. Article (Ref Link).
[13] Wübbeler, Gerd, et al. "Verification of humans using the electrocardiogram," *Pattern Recognition Letters*, vol. 28, no. 10, 1172-1175, 2007. Article (Ref Link).
[14] Israel, Steven A., et al, "ECG to identify individuals," *Pattern recognition*, vol. 38, no. 1, 133-142, 2005. Article (Ref Link).
[15] Risk, Marcel0 R., Jamil F. Sobh, and J. Philip Saul, "Beat detection and classification of ECG using self organizing maps," in *Proc. of Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE*, vol. 1. IEEE, 1997. Article (Ref Link).
[16] Afonso, Valtino X., et al, "ECG beat detection using filter banks," *IEEE transactions on biomedical engineering*, vol. 46, no. 2, 192-202, 1999. Article (Ref Link).
[17] Cheng, W. T., and K. L. Chan, "Classification of electrocardiogram using hidden Markov models," in *Proc. of Engineering in Medicine and Biology Society, Proceedings of the 20th Annual International Conference of the IEEE*. IEEE, 1998. Article (Ref Link).
[18] Inan, Omer T., Laurent Giovangrandi, and Gregory TA Kovacs, "Robust neural-network-based classification of premature ventricular contractions using wavelet transform and timing interval features," *IEEE Transactions on Biomedical Engineering*, vol. 53, no. 12, 2507-2515, 2006. Article (Ref Link).
[19] Shyu, Liang-Yu, Ying-Hsuan Wu, and Weichih Hu, "Using wavelet transform and fuzzy neural network for VPC detection from the Holter ECG," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 7, 1269-1273, 2004. Article (Ref Link).
[20] Hosseini, H. Gholam, K. J. Reynolds, and D. Powers, "A multi-stage neural network classifier for ECG events," in *Proc. of Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE*, vol. 2. IEEE, 2001. Article (Ref Link).
[21] Senhadji, Lotfi, et al. "Comparing wavelet transforms for recognizing cardiac patterns." *IEEE Engineering in Medicine and Biology Magazine*, vol. 14, no. 2, 167-173, 1995. Article (Ref Link).
[22] Christov, Ivaylo, et al, "Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification," *Medical engineering & physics*, vol. 28, no. 9, 876-887, 2006. Article (Ref Link).

[23] de Chazal, Philip, and Richard B. Reilly, "Automatic classification of ECG beats using waveform shape and heart beat interval features," in *Proc. of Acoustics, Speech, and Signal Processing, 2003. Proceedings.(ICASSP'03). 2003 IEEE International Conference on*, vol. 2. IEEE, 2003. Article (Ref Link).
[24] Y.H. Hu, S. Palreddy, W.J. Tompkins, "Patient-adaptable ECG beat classifier using a mixture of experts approach," *IEEE Trans Biomed Eng*, vol. 44, no. 9, pp. 891-897, 1997, Article (Ref Link).
[25] Elham Dolatabadi and Serguei Primak, "Ubiquitous WBAN-based Electrocardiogram Monitoring System," in *Proc. of Proceedings of IEEE Conference on e-Health Networking, Applications and Services*, vol. 13, pp. 110-113, 2011, Article (Ref Link).
[26] Pan, Jiapu, and Willis J. Tompkins, "A real-time QRS detection algorithm," *IEEE transactions on biomedical engineering*, vol. 3, 230-236, 1985. Article (Ref Link).
[27] Le Cun, Yann, et al, "A theoretical framework for back-propagation," *Proceedings of the 1988 Connectionist Models Summer School*. CMU, Pittsburgh, Pa: Morgan Kaufmann, 1988. Article (Ref Link).
[28] Goldberger, Ary L., et al, "Physiobank, physiotoolkit, and physionet," *Circulation*, vol. 101, no. 23, e215-e220, 2000. Article (Ref Link).

EunKwang Jeon is a M.S student in the Department of Computer Science and Engineering at Soonchunhyang University. He received his B.S. in Department of Computer Software Engineering from Soonchunhyang University in 2016. His research interests include machine learning, deep learning, neural network, and wellness.

Bong-Keun Jung received doctoral degree in occupational therapy from Washington University in St. Louis, Missouri, the USA. He is a professor in the department of Occupational Therapy at Soonchunhyang University. His current research interests include rehabilitation engineering, driving rehabilitation, and disability policy

Yunyoung Nam received the B.S., M.S., and Ph.D. degrees in computer engineering from Ajou University, Korea in 2001, 2003, and 2007 respectively. He was a senior researcher in the Center of Excellence in Ubiquitous System (CUS) from 2007 to 2010. He was a research professor in Ajou University from 2010 to 2011. He also spent time as a postdoctoral researcher at Center of Excellence for Wireless & Information Technology (CEWIT), Stony Brook University, New York from 2009 to 2013. He was a postdoctoral fellow at Worcester Polytechnic Institute, Massachusetts from 2013 to 2014. He is a director at ICT Convergence Rehabilitation Engineering Research Center at Soonchunhyang University from 2017. He is currently an assistant professor in the Department of Computer Science and Engineering at Soonchunhyang University. His research interests include multimedia database, ubiquitous computing, image processing, pattern recognition, context-awareness, conflict resolution, wearable computing, intelligent video surveillance, cloud computing, biomedical signal processing, rehabilitation, and healthcare system.

HwaMin Lee is a professor in the Department of Computer Software Engineering at Soonchunhyang University. She received her B.S., the M.S. and the Ph.D. degrees in Computer Science Education from Korea University in Seoul, Korea in 2000, 2002, and 2006, respectively. Her research interests include Cloud computing, deep learning, IoT, mobile computing, wellness, and resource management and fault tolerant system for large-scale distributed systems.