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Discrimination of ECG Abnormality based on a Normal ECG Wave Model Implementing a Denoising Model

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***Abstract*— Automatic detection of abnormal electrocardiogram (ECG) is a key issue in the field of medical engineering because it is essential for diagnosis of heart disease. Typically ECG data contains noises due to body movement and muscle contractions, and hence it makes difficult to detect original abnormal signal. To address this problem, we propose a new method for discriminating abnormality from noisy ECG data. This method discriminates ECG abnormality based on a normal ECG wave model implementing a denoising model. In the experiment, the proposed method is applied to ECG data of healthy subjects, myocardial infarction (MI) patients and arrhythmia patients. As a result, it is shown that implementation of the denoising model is effective for improving discrimination accuracy of ECG abnormality.**

***Index Terms*— ECG, abnormality detection, denoising**

I. Introduction

RECENTLY, many abnormal detection methods for electrocardiogram (ECG) data have been proposed aiming at discriminating heart diseases [1-3]. However, in many cases, ECG data contains noises due to body movement and muscle contractions, and hence it makes difficult to detect original abnormal signal. To address this problem, Rodrigues et al. proposed an ECG denoising method based on a feed forward neural network and applied it to arrhythmia ECG data [4]. However this method is limited to application to ECG data whose type of heart diseases is known beforehand.

In this paper, we propose a new method for discriminating abnormality from noisy ECG data. This method discriminates ECG abnormality based on a normal ECG wave model implementing a denoising model. Major feature of this method is to be applicable to various ECG data regardless of types of heart diseases because of learning only normal ECG data with noise. In this study, the proposed method is applied to ECG data of healthy subjects, myocardial infarction (MI) patients and arrhythmia patients. In the experiments, the discrimination accuracy of abnormal ECG data is shown, and the effectiveness of implementing the denoising model is discussed.

The rest of the paper is organized as follows. Section II briefly explains ECG data. Section III describes the denoising model and the normal ECG wave model. Section IV provides the method for discriminating ECG abnormality using the above two models. Section V explains the evaluation method of discrimination accuracy, and Section VI presents experimental results and discussion. Section VII provides an overall summary.

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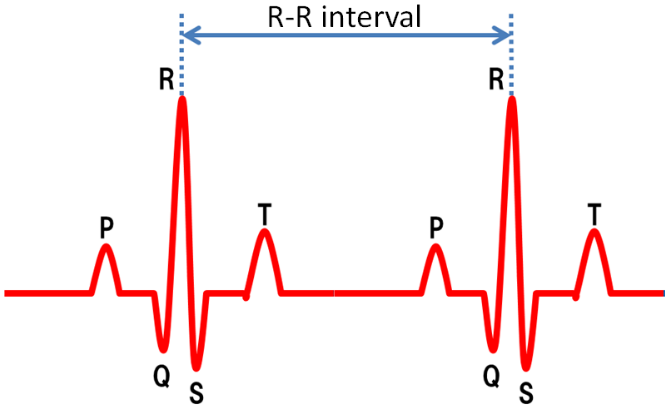

Fig. 1. Basic wave and R-R interval

II. Electrocardiogram (ECG)

ECG is a graphic recording of the heart's electrical activity. Figure 1 illustrates a normal ECG waveform. Each heart beat in Fig.1 is called a basic wave. A basic wave is composed of five waves, P, Q, R, S and T. In ECG data of healthy subject, regular waves periodically appear at equal intervals. On the other hand, ECG data of patient with heart disease shows abnormal waveforms deviating from normal ECG waveform.

III. Construction of Denoising Model and Normal ECG Wave Model

Here we constructed a denoising model to reduce noise in ECG data and a normal ECG wave model to learn waveform of normal ECG. These models were built based on backpropagation neural network [5].

A. Creation of normal ECG wave template

Prior to construction of the above two models, a template waveform of normal ECG data was created. The template waveform was used as a teacher waveform of the two models

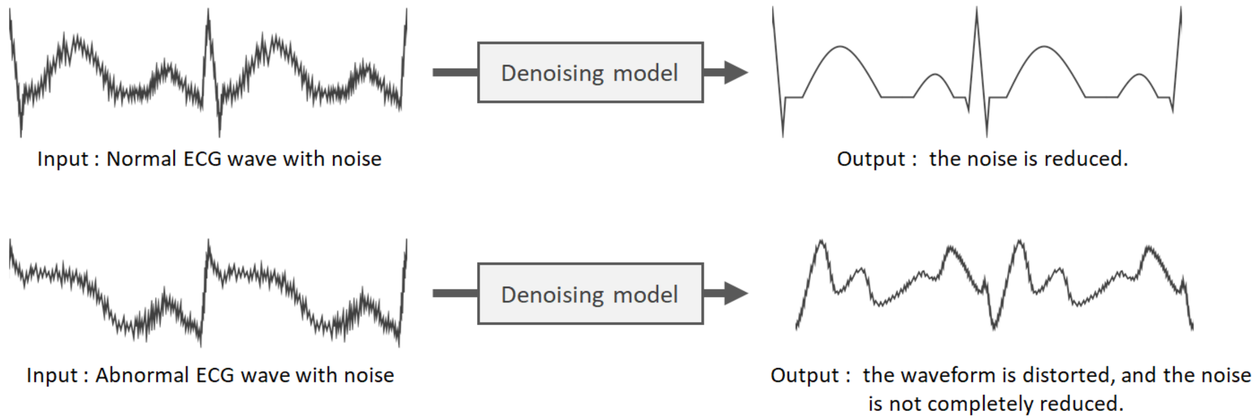

Fig. 2. The outline of the denoising model

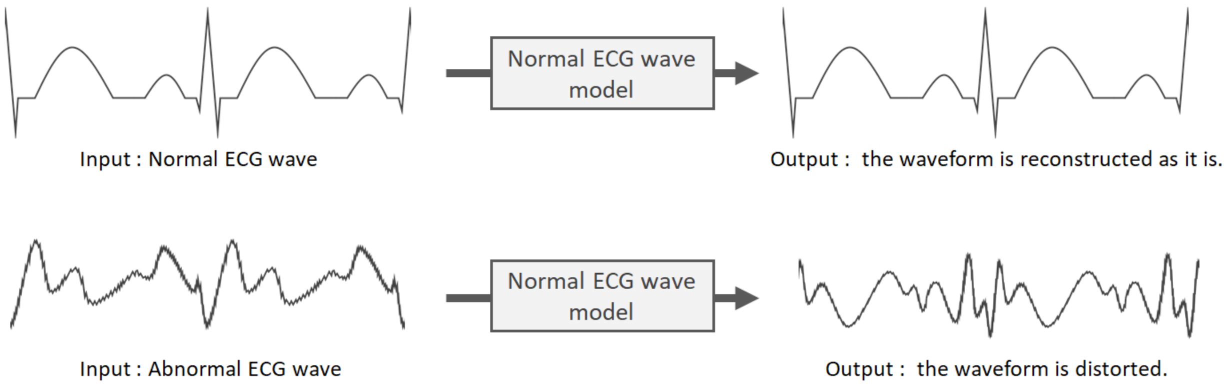

Fig. 3. The outline of the normal ECG wave model

and was created in the following procedure. First, normal ECG data of five healthy subjects were collected from the PTB Diagnostic ECG Database [6]. Next, R-R interval waves were segmented from each ECG data. After that, each R-R interval waves was converted into a sequence data of the uniform length by resampling process which matched the number of data points of each wave with that of the wave with the minimum number of data points. Subsequently, median values were calculated for each time point of the resampled R-R interval waves. Next, copies of the sequence of the above median values were created. Finally, those copies were simply concatenated, and the template waveform of 768 data points was created.

B. Construction of the denoising model

This model was constructed in order to remove noise from ECG data. Figure 2 illustrates the outline of the denoising model. Training data of this model was created by adding white Gaussian noise into the template waveform. Note that each training data is composed of 768 data points starting from R-peak. In this study, training data with different noise level were generated by changing signal-to-noise ratio. This model minimizes the error between each training data and the template waveform by the backpropagation algorithm and learns the manner of denoising in the training data. If a normal ECG wave with noise is input to this model, the noise will be adequately reduced. On the contrary, if an abnormal ECG wave with noise is input to this model, the noise will not completely reduced, and the distorted wave will be outputted.

C. Construction of the normal ECG wave model

This model was constructed in order to learn typical waveform of normal ECG data. Figure 3 illustrates the outline of the normal ECG wave model. In this model, normal ECG data of healthy subjects was used as the training data, and the template waveform was used as a teacher data. Note that the normal ECG data is composed of 768 data points starting from R-peak. In this model, if a normal ECG wave is input, similar waveform is reconstructed. On the contrary, if an abnormal ECG wave is input to this model, the waveform is distorted and outputted. Hence, we can discriminate abnormal ECG data using similarity between input wave and output wave.

IV. Discrimination Method

In advance, ECG waves of 768 data points were segmented for discrimination test. Hereafter, these waves are called test waves. First, a test wave was input to the denoising model to reduce noise of the wave. Next, the output wave from the denoising model was input to the normal ECG wave model, and the final output wave was obtained. Discrimination of normality or abnormality was conducted based on similarity between the test wave and the final output wave. The similarity is calculated by the correlation coefficient below:

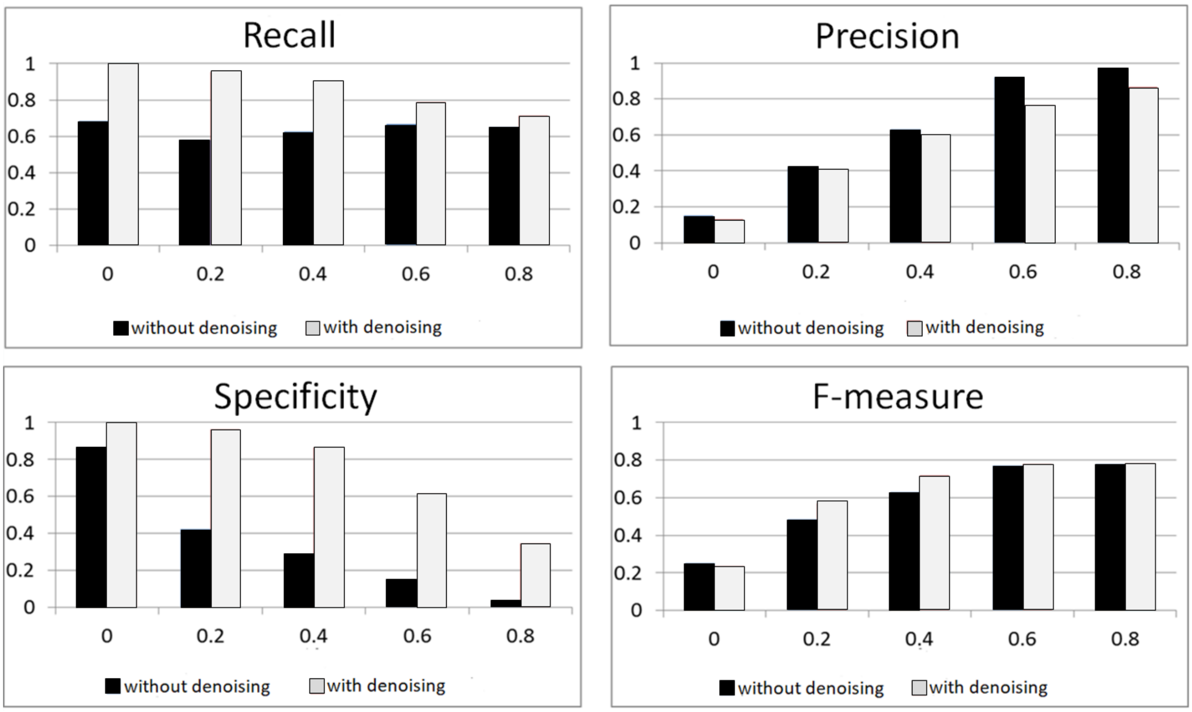

Fig. 4. Discrimination accuracy

$$r = \frac{\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})^2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \bar{Y})^2}}$$

Here X_i and Y_i indicate i-th data in the test wave and the final output wave, respectively. $\bar{X}$ and $\bar{Y}$ are the mean values of the test wave and the final output wave, respectively. N is the number of all data points of the test wave or the final output wave. If r is greater than or equal to the threshold θ, the test wave was judged to be normal; otherwise, it was judged to be abnormal.

V. Experiments

A. Preparation of ECG data for discrimination test

Normal ECG data of 52 healthy subjects and abnormal ECG data of 50 MI patients were collected from the PTB Diagnostic ECG Database [6]. In addition, abnormal ECG data of 48 arrhythmia patients were collected from the MIT-BIH Arrhythmia Database [7]. From these ECG data, test waves of 768 data points were segmented in advance.

B. Discrimination test

In this experiment, discrimination accuracies were compared with and without denoising model. Here the case without the denoising model indicates that the test wave is discriminated using only the normal ECG wave model without prior noise reduction.

Evaluation of discrimination accuracy was conducted using the following four indexes:

$$\mathrm{Precision} = \frac{TP}{TP + FP}$$

$$\mathrm{Recall} = \frac{TP}{TP + FN}$$

$$\mathrm{Specificity} = \frac{TN}{FP + TN}$$

$$\mathrm{F-measure} = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

Here, TP, FP, TN, and FN are true positive, false positive, true negative and false negative, respectively. The discrimination test was performed using leave-one-out cross validation, and for each index the mean score through all the validations was calculated. In this experiment, we calculate the discrimination accuracy when the correlation coefficient r was changed from 0.0 to 0.8.

VI. Results and Discussion

Figure 4 shows the results of the four indexes. The horizontal axis is the correlation coefficient, and the vertical axis is the score of the index. Recall and specificity shows higher score in the case of using the denoising model. In particular, the specificity shows remarkable difference between the cases with and without the denoising model. This is due to the following reason. The case without the denoising model cannot reconstruct normal ECG wave successfully due to influence of noise. On the other hand, the case of using the denoising model enabled to reduce noise of the test wave and reconstruct the original waveform adequately. Precision shows higher score in the case without the denoising model. This is because ECG waves with subtle abnormalities were modified by the denoising model and consequently misjudged as normal ECG wave. F-measure, which is the harmonic mean of recall and precision, was somewhat higher in the case of using the denoising model.

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VII. Conclusion

In this paper, aiming at discriminating abnormal ECG with noise, we proposed a method based on the normal ECG wave model implementing the denoising model. In the experiment, this method was applied to ECG data of healthy subjects, MI patients and arrhythmia patients, and the discrimination accuracy was evaluated. As a result, it was shown that the precision and the specificity of the method were significantly higher than those of the case without the denoising model. This result means that the proposed method not only can correctly discriminate abnormality of ECG waves but also has high detection power for normal ECG wave. However, it was clarified that ECG data with subtle abnormalities could be misjudged to be normal because the abnormalities were modified by the denoising model: hence recall of the proposed method was lower than the case without the denoising model.

In the future, we will increase ECG data for training to deal with overfitting problem and develop a method to improve the recall score.

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