A Study of ECG Characteristics by Using Wavelet and Neural Networks

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Abstract:

ECG consists of various waveforms of electric signals of heat. Machine Learning methods such as the MLP classification have proven to perform well in ECG classification. In this study, preprocessing was performed through wavelet transform, and in classification several characteristics were evaluated using BP algorithm that applied generalized delta rules to MLP. In order to decide wavelet generating function that can remove baseline by minimizing the distortion of raw signals, this study removed baseline by applying various wavelet generating functions. To evaluate the results above according to the learning method, learning iteration and learning rate of neural networks, various experiments were conducted.

Keywords:

ECG, data mining, wavelet, BP

1. Introduction

Pattern classification, one of data mining techniques, is largely divided into future extraction, which automatically finds specific information from given data, and classification, which classifies given data into several groups and identifies their characteristics [1].

BP (Back Propagation) algorithm has been applied most frequently in solving pattern classification problems using neural networks, but it has delicate problems such as the delay of convergence affecting approximation and convergence rate [2].

ECG (Electrocardiogram) is a very important means for non-invasive diagnosis. It is one of bio-potential signals, with amplitude of several mV and frequency less than 250Hz. Research on ECG system design and signal processing began in the early 1960s in the U.S.A. Since then, there have been researches on designing hardware such as multi-channel ECG for automatic diagnosis, Holter ECG that monitors patients with cardiac disorder for 24 hours a day, stress ECG that diagnose cardiac disorders under exercise stress, and developing accurate algorithms. In Korea, research on ECG system design and signal processing began in the early 1980s. With 10 years' accumulation of fundamental technologies, the development of ECG was fully activated from the early 1990s, and currently 12-channel diagnosing ECG, Holter ECG, stress ECG, patient monitoring equipment and other heart-related diagnosing machines are being studied. Despite a great deal of research efforts, misdiagnosis is still frequent in relation to myocardial ischemia (ischemia is a restriction in blood supply) and myocardial infarction (AMI or MI). Diagnosis of such diseases is based on the up and down of the level or the gradient of ST segment of ECG signal.

Figure 1 below shows the location of ST segment. Because ST segment has a frequency band below 1Hz, it shares the same frequency band with the baseline variation noise of low frequency and muscle artifact that exists in every frequency band. Thus inaccurate removal of noises causes signal distortion, which in turn causes misdiagnosis. Currently available pre-processing methods to remove baseline variation noise are spline interpolation technique, FIR filtering, adaptive filtering, neural network, wavelet transform technique, etc. These techniques minimize signal distortion and remove baseline variation noise. Among the methods, wavelet transform processes signals in multiple resolution, and transformed signals have high resolution in the domains of time and frequency. Thus the method is suggested as an advantageous method for analyzing non-stationary signals. Because the entire process of wavelet transform is performed through mother wavelet, even if the same wavelet transform method is used, the wrong selection of the generating function may bring about the severe distortion of signals[3][4][5]. And this study applied various parameters, which were extracted from the characteristics of ECG pattern in order to classify the signals.

This paper is organized as follows: section 2 describes ECG classification algorithm used as base classifiers, wavelet transform and existing researches on classifying ECG signals. In section 3 results of our experiments are provided and discussed. Finally, Section 4 summarizes the results and draws conclusion.

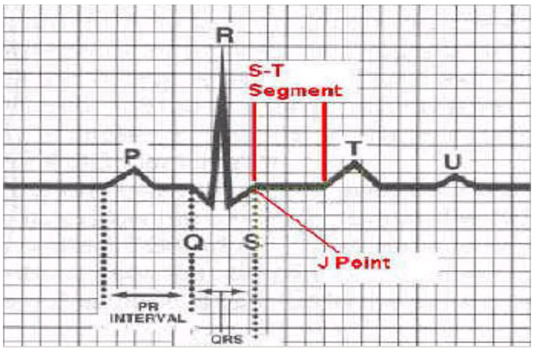


Figure 1 ST segment of ECG signal

2. Preliminaries

2.1. Existing researches on classifying ECG signals

Existing researches on classifying ECG signals are divided into those based on neural networks and those based on signal processing.

One of neural networks based researches is Heden [6] used BP algorithm, in which the initial learning rate (μ) was set at 0.5, training was performed so that the learning rate, a constant adjusting the variation of weight, gradually decreased. The performance was verified using k-fold cross test. Because of a serious error of data in the measuring program, however, the network was not expressed appropriately.

Silipo [7] compared the performance of statistical classification methods with that of neural network based classification. Ambulatory ECG (AECG) was analyzed and European Database was used. It was designed so that training was stopped when RMS (Root Mean Square) went below 0.6. The result is not considered accurate, however, because the error tolerance limit is too large, which should have been at least 0.001.

One of signal processing based researches, Sternickel [8] proposed automatic detection of ECG time series data pattern. It expressed multi-resolution using wavelet variation, and tested using a Holter ECG recorder to improve the reliability of time series data. In P-wave detection, it used coiflet6 as wavelet generating function and HAAR as a generating function to find QRS Complex. Because the selection of wavelet generating function is an extremely important factor, a wrong selection of the function may distort the diagnosing parameters of ECG.

2.2. Methodology

One of the major advantages of neural networks is their ability to generalize. This means a trained net could classify data from the same class as the learning data that it has never seen before. Therefore, the training patterns have to provide a sufficient characterization of the desired system behavior.

The Wavelet transform is a relatively new mathematical took that has proven useful in the analysis of various types of signal.

2.2.1. Classification using Neural Networks. BP algorithm is a multi-layered learning algorithm used in feed forward neural networks and it utilizes generalized Delta rule which is supervised learning. That is, it requires input data and desired output data for learning. Neural networks learning using BP algorithm is carried out in three steps. The first step is to enter learning input patterns into the neural networks and produce output. The second step is to obtain the difference between the output and the target. The third is to propagate the difference backward and change the connection strength of the output layer and that of the hidden layer. Although learning may take a long time, once learning has been completed, results come out quickly in the step of application. Figure 2 is shown Architecture of the MLP neural network.

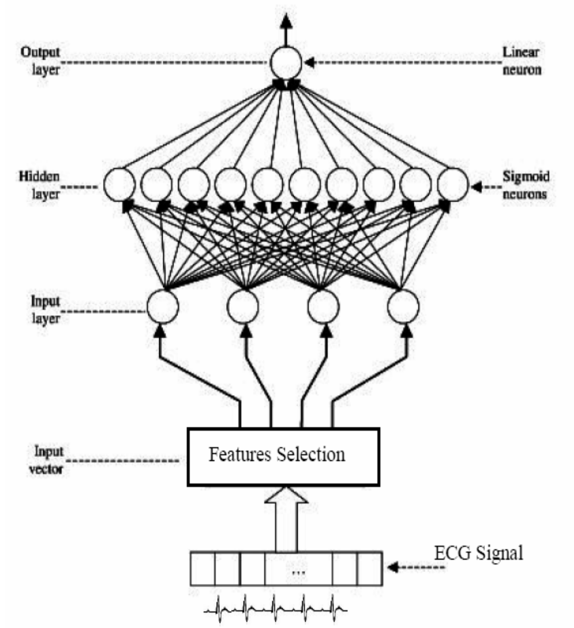


Figure 2 Architecture of the MLP neural network (0: normal, 1: abnormal)

2.2.2. Wavelet Transform. Wavelet transform can be effectively used in processing of non-stationary signals such as ECG signals. Published works dealing with time-frequency ECG processing can be found in two areas:

i) analysis of time-frequency decomposed signals with no requirement on reversibility of the transform used, and

ii) filtering of wavelet coefficients requiring reversibility of the transform.

3. Empirical Comparisons

3.1. The Data Sets

This study used European ST-T database for experiment. Training data and test data in the 1st to 5th columns are ST0, ST60, ST80, the slope of ST segments and the area of ST segments respectively, and training data in the 6th column indicates if the result of the data is normal (0) or abnormal (1). In addition, the test data do not include data of the 6th column.

3.2. Feature Extraction

In order to decide wavelet generating function that can remove baseline by minimizing the distortion of raw signals, this study removed baseline by applying various wavelet generating functions.

ST segment was set at 160ms from 60ms after R-peak if the RR interval is larger than 600ms or from 40ms if not. In order to extract the characteristics of ST segment, we took candidate parameters representing the characteristics of ST segment ST0 [amplitude on the starting point of ST segment (R+60 or R+40 ms)], ST60, ST80 [amplitude at R+140 or R+120 ms], the gradient of ST segment, and the area of ST segment (the area surrounded by ST segment and isoelectric level in the interval of ST segment).

According to the result of the experiment, the best wavelet generating functions were db8 (diff.: 27.12), coif5 (diff: 25.32) and sym7 (diff: 25.13), and it was found that diff (meanSNR - meanRSE) less than 23 is unusable because it distorts even the diagnosing parameters of ECG.

3.3. Evaluation

In this context, suppose that we measure the quality of t, as a measure of the center of the distribution, in terms of the mean square error

$$\mathrm{MSE}(t) = \frac{1}{n}\sum_{i=1}^{k} f_i (x_i - t)^2 = \sum_{i=1}^{k} p_i (x_i - t)^2$$

MSE (t) is a weighted average of the squares of the distances between t and the class marks with the relative frequencies as the weight factors. Thus, the best measure of the center, relative to this measure of error, is the value of t that minimizes MSE.

3.3.1. The learning method based MSE. Comparing speed and memory of BP algorithm training methods provided by MATLAB 7.0. This study selected the best four methods and applied them to ECG data. Here, traincgf is Fletcher Powell Congugate Gradient, trainlm is Levenberg Marquaedt, trainbfg is BFGS Quasi Newton, and trainrp is Resilient Back propagation.

Description

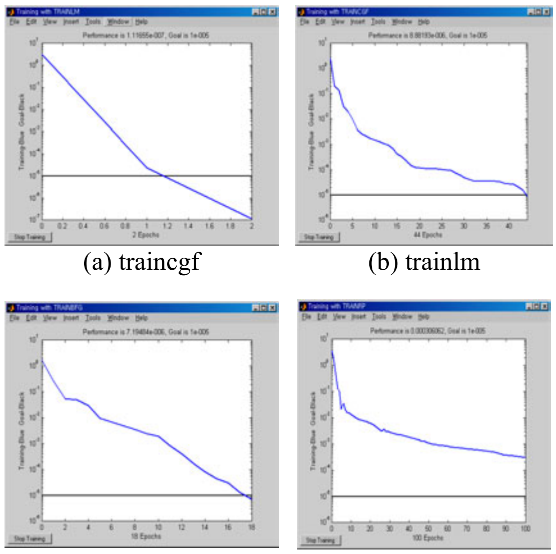
TRAINLM is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization.

TRAINCGF is a network training function that updates weight and bias values according to the conjugate gradient backpropagation with Fletcher-Reeves updates.

TRAINBFG is a network training function that updates weight and bias values according to the BFGS quasi-Newton method.

TRAINRP is a network training function that updates weight and bias values according to the resilient back propagation algorithm

Figure 3 shows the result of convergence. In the figure, (b) and (c) shows fine convergence at 10^{-5}. But (a) and (d) are over-fitting and under-fitting respectively, so they are not fit for problems to which they are to be applied. According to the result of experiment, the application of traincgf was found to produce the most appropriate convergence among BP algorithm training methods.



(a) traincgf (b) trainlm

(c) trainbfg (d) trainrp

Figure 3 The results of convergence for four methods

3.3.2. The learning iteration based MSE. With the increase of the number of training times, learning takes a longer time. Thus it is necessary to set the number of training times so that learning stops when error does not decrease any more. In Figure 4, MSE decreases exponentially with the increase of the number of training times and the rate of MSE decrease becomes slow after 10,000 times of training.

3.3.3. The learning rate based MSE. Learning rate is usually between 0.01~1. Because the result of learning is different according to the characteristic of problems to which the neural network is applied. However, it is necessary to perform an experiment to find the optimal learning rate for the characteristic of ECG signals. Thus, this study carried out an experiment by varying learning rate from 0.1 to 0.7 by increasing by 0.2. According to the result, the distribution of MSE was smallest at around 0.1. Thus we again tested with learning rate ranging from 0.01 to 0.1 by increasing by 0.01. Figure 5, 6 below is the results of experimenting on data e0105 and e0111 with different learning rates and 5,000, 10,000 and 15,000 training times.

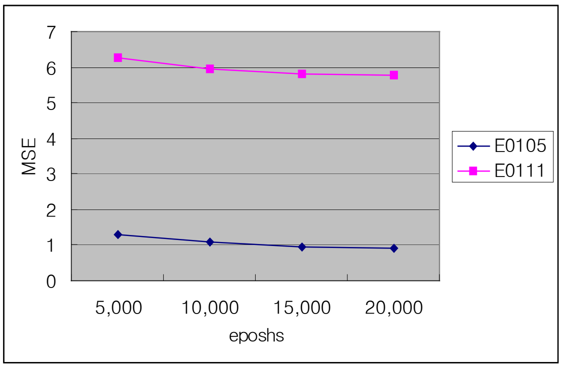


Figure 4 The number of training times and MSE

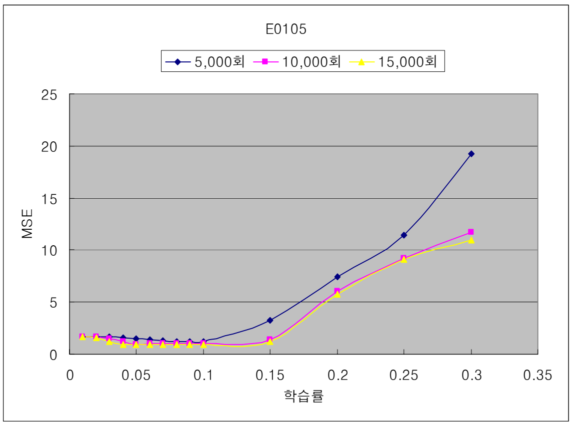


Figure 5 The learning rate and MSE – e0105

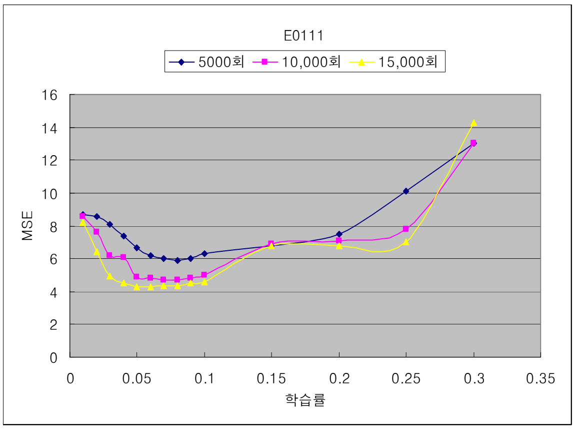


Figure 6 The learning rate and MSE – e0105

4. Conclusion

In this study, In order to classify the pattern of ECG signals, preprocessing was performed through wavelet transform, and in classification several characteristics were evaluated using BP algorithm that applied generalized delta rules to MLP.

To evaluate the results above according to the learning method, learning frequency and learning rate of neural networks, various experiments were conducted. In an experiment with BP algorithm, the use of traincgf resulted in appropriate convergence into a desired point. In addition, the final error, namely, MSE decreased exponentially with the increase of the number of training times and the rate of MSE decrease became slow when the number of training times exceeded 10,000. As for the effects of learning rate and MSE, the optimal learning rate was different according to data but it was roughly between 0.04 and 0.1.

References

[1] C Groselj, "Data Mining Problems in Medicine", Proceedings of the 15 th IEEE Symposium on Computer-Based Medical Systems (CBMS 2002)

[2] F. Vargas, M. Cristina F. de Castro, M. Macarthy, D. Lettnin, "Electrocardiogram Pattern Recognition by Means of MLP Network and PCA: A Case Study on Equal Amount of Input Signal Types ", VII Brazilian Symposium on Neural Networks (SBRN'02) .

[3] Z. Dokur and T. Olmez, "ECG beat classification by a novel hybrid neural network", Computer Methods and Programs in Biomedicine, Volume 66, Issues 2-3, pp. 167-181, 2001.

[4] P. M. Rautaharju, S. H. Zhou, et al., “Comparability of 12-lead ECGs derived from EASI leads with standard 12-lead ECGS in the classification of acute myocardial ischemia and old myocardial infarction”, Journal of Electrocardiology, Volume 35, Issue 4, Part 2, pp. 35-39, 2002.

[5] U. Rajendra Acharya, P. Subbanna Bhat, et al., "Classification of heart rate data using artificial neural network and fuzzy equivalence relation," Pattern Recognition, Volume 36, Issue 1, pp. 61-68, 2003.

[6] B. Heden, “Agreement Between Artificial Neural Networks and Experienced Electro-cardiographer on Electrocardiographic Diagnosis of Healed Myocardial Infarction,” JACC, Vol.28, No.4, pp. 1012-1016, 1996.

[7] R. Silipo, M. Goru, et. al., “Classification of Arrhythmic Events in Ambulatory Electrocardiogram, Using Artificial Neural Networks”, Computers and Biomedical research Vol.28, pp. 305-318, 1995.

[8] K. Sternickel, “Automatic patttern recognition in ECG time series”, Computer Methods and Programs in Biomedicine, Vol.68, pp. 109-115, 2002.