심전도 신호를 이용한 일시적 허혈 예측

Prediction of Transient Ischemia Using ECG Signals

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요 약

본 연구는 신경망에 근거한 패턴매칭 방법을 사용하여 일시적 허혈 에피소드의 자동예측을 다루고 있다. 다층 신경망을 학습하기 위한 알고리즘은 수정된 역전파 알고리즘으로서 이 알고리즘은 학습속도를 향상시키기 위해 뉴런간의 연결계수 뿐만 아니라 뉴런내 비선형 함수의 변수들도 갱신한다. 제안된 방법의 성능은 MIT/BIH long-term 데이터베이스의 심전도(ECG) 신호를 사용하여 평가하였다. 총 15 레코드(237 허혈 에피소드)에 대한 실험결과에 의하면 허혈 에피소드 예측의 평균 sensitivity와 specificity 각각 85.71%와 71.11%이다. 또한 제안된 방법은 실제 허혈 에피소드로부터 평균 45.53초 이전에 예측하였다. 이러한 결과는 패턴매칭 분류기로서의 신경망 접근방법이 일시적 허혈 에피소드 예측에 유용한 도구로 사용될 수 있음을 의미한다.

Abstract

This paper presents automated prediction of transient ischemic episodes using neural networks(NN) based pattern matching method. The learning algorithm used to train the multilayer networks is a modified backpropagation algorithm. The algorithm updates parameters of nonlinear function in a neuron as well as connecting weights between neurons to improve learning speed. The performance of the method was evaluated using ECG signals of the MIT/BIH long-term database. Experimental results for 15 records(237 ischemic episodes) show that the average sensitivity and specificity of ischemic episode prediction are 85.71% and 71.11%, respectively. It is also found that the proposed method predicts an average of 45.53[sec] ahead real ischemia. These results indicate that the NN approach as the pattern matching classifier can be a useful tool for the prediction of transient ischemic episodes.

Key words : transient ischemia, prediction of ischemic episodes, ECG signal, Neural networks

Ⅰ. Introduction

Ischemic heart disease is one of the most common fatal diseases. It is considered to be a major complication of the cardiac function, and a prime cause for the occurrence of myocardial infarction with its severe sequellae of heart failure, arrhythmias, and death[1-3]. Ischemia is caused by insufficient blood flow to parts of the myocardium, due to vessel occlusion or muscle injury. This causes the depolarization of the cellular resting membrane potential of the ischemic region with respect to the resting membrane potential of the normal region. This potential difference is manifested in the electrocardiographic(ECG) by an elevated or depressed ST segment[4,5].

Since, during the last years, ambulatory ECG signal

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has become the most widely used noninvasive test for the patient monitoring and diagnosis, it is important to be able to reliably predict ischemia from ECG analysis. Thus, we want to develop a method that detect early changes of the ST segment, i.e., its timely detection of the point that the ST level starts to change, possible indicating the onset of an acute ischemic syndrome. While in some cases it is easy to discern the ST depression, in other cases the ST depression may not be evident, due to the several reasons. Major problems contributing to poor or incorrect analysis of the ST segment level changes in the ECG can be identified as follows: relative position of the recording point, body position, slow baseline drift, noise, sloped ST changes, patient-dependent abnormal ST depression levels, and varying ST-T patterns in the ECG of the same patient[4,5]. Therefore, for more reliable prediction of the ischemia, other factors such as heart rate and its spectrum, heart rate interval, QRS information can also be considered to compensate these problems.

A number of methods have been proposed in the literature for ischemia detection based on digital filtering, time analysis of the first derivative of the signal and spectrotemporal, wavelet-based and syntactic methods, and neural networks[5-7]. However, the prediction of ischemic episodes has not been studied extensively. A few paper have investigated on the changes in ST segment level, heart rate and its variability preceding ischemic events[8,9]. Those papers investigated the ischemic episodes that were intentionally generated on particular subjects, and focused on specific parameters such as heart rate and its power spectrum. Therefore, it can be said that no study has been fully done for prediction of transient ischemia based on ECG signals.

In this paper, we present the prediction of transient ischemic episodes using neural networks based on pattern matching approach. As mentioned, main characteristic of ischemia is changes of ST segment level. However, we found in preliminary survey that the use of only ST segment might not be sufficient to predict ischemic episodes for all records. It is reported that different ECG changes related to the evolution of ischemia have been described, including T wave amplitude changes, ST deviations and even alterations in the terminal portion of QRS complex[10]. These facts mean that the use of other representations better characterizes ischemic prediction patterns[11,12], and yields better prediction of an occluded artery. Thus, we decided to use multiple parameters such as heart rate and its power spectrum, instead of using only a ST segment. Another difficulty is that the change patterns of these parameters prior to ischemic episodes are not consistent in inter-patients and intra-patient. Thus linear parametric methods like autoregressive moving average model do not work to characterize these change patterns. As an alternative approach, we decided to use neural networks to cope with variability of these changes.

Neural networks have been successfully applied in the field of complex pattern recognition or classification. Since the neural networks consist of distributed neurons to process nonlinearity and have the ability to learn from its environment, neural network-based pattern matching approach is potentially useful for classification of diverse patterns with inherent nonlinearity. In this paper, dynamic multilayer recurrent neural networks(RNN) have been applied for recognition of prediction pattern of ischemic episodes. In network learning, we used the modified gradient descent algorithm. The connecting weights as well as the parameters of the node activation function are simultaneously updated with the error backpropagation algorithm.

The performance of the proposed method is evaluated using the MIT/BIH long-term database recorded from ischemic patients[13]. The database contains the ischemic episodes manually annotated by cardiologists. The prediction points determined by the proposed method are compared with annotated episodes, and then evaluated with respect to prediction time, sensitivity, and specificity. Based on experimental results, it has been verified that the proposed method is useful to predict transient ischemic episodes.

II. Methods

Fig. 1 shows the general configuration of the prediction system used in this paper. The approach to predict transient ischemic episodes consists of three procedures: detection of transient ischemic prediction candidates, feature data collection at prediction candidates, and decision of true ischemic prediction points among prediction candidates using the neural networks.

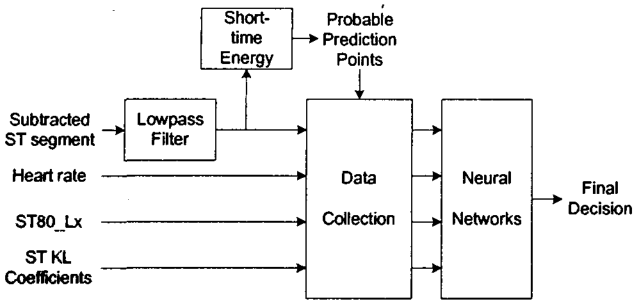


Fig. 1. Block diagram for prediction of transient ischemic episodes

A. Detection of ischemic prediction candidates

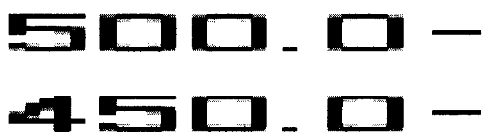
Ischemic prediction candidates indicate timing points that the ST segment level begins to decrease or increase. They can be considered as probable prediction points although they contain both true and false prediction points of ischemic episodes. Since there are a lot of fluctuations in the ST segment, it is not reasonable to test all variations in the ST segment level. The reason of collecting prediction candidates is that we want to choose more definite prediction timing points showing dominant decrease or increase of the segment level. Thus, all prediction candidates are determined in this step.

In order to detect candidate points, the short-time energy(STE) function on subtracted ST segment is computed, and then marked changes in amplitude are detected by threshold. These thresholding points are selected as the prediction candidates. The amplitude of the raw ST segment signal fluctuates appreciably with time. Thus, we apply a lowpass filter to ST segment in order to alleviate the fluctuation, and then the STE is computed on filtered ST segment. The STE function provides a mean of enhancing signal amplitude differences between normal ST segment and depressed or elevated ST segment. The STE is defined as

$$\begin{aligned} STE &= \frac{1}{2N+1}\sum_{k=-N}^{N}\{x(n)w(n-k)\}^2 \\ &= \frac{1}{2N+1}\sum_{k=-N}^{N}x^2(n)h(n-k) \end{aligned} \tag{1}$$

where $h(n) = w^2(n)$. The signal $x^2(n)$ can be interpreted as being filtered by a linear filter with impulse response $h(n)$, which corresponds to the rectangular window. The choice of the window length determines the nature of the STE representation. A short window energy function is preferred for separating ST episodes from background with high resolution. However, it has the disadvantage of being too sensitive to local amplitude variability. To alleviate this, the cascade of two STE processing blocks with different window length has been used. Detecting amplitude changes, which we call an ischemia prediction candidate, at the output of these STE blocks may become sensitive to the values of windows lengths. We experimentally found that the first STE is dominant to determine prediction candidates and the threshold is not crucial since the amplitude changes abruptly near the points corresponding to prediction candidates. The threshold is determined by viewing the signal segment in the beginning of the record.

(a) Subtracted ST segment and its filtered signal



(b) Energy function on filtered ST segment

Fig. 2. Detection of prediction candidates

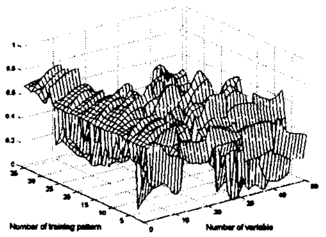
Fig. 2 shows an example to detect ischemic prediction candidates. Fig. 2(a) shows ST segment overlapped with its filtered signal. Fig. 2(b) shows the output of cascade STE functions on the filtered ST segment and prediction candidates (denoted as probable prediction points in the figure) by threshold. Now we have to decide that the probable prediction candidates are real prediction points or not. This is achieved using a neural network which will be explained in section C.

B. Feature data collection at prediction candidates

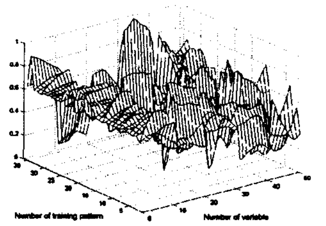
In this step, we collect informative feature data for prediction candidates determined in step A. The informative data such as ST changes, KL(Karhunen-Loeve) coefficients, heart rate and its power spectrum are collected for one minute interval before prediction candidates. The data collected at a prediction candidate are used as the input to the neural network to identify whether they are true or false prediction points.

The database[13] contains several information: ST segment level at the point ST+80[msec] and ST+20[msec], heart rate and its power spectrum with 5 different frequency bands, 5 KL coefficients[11] on

ST segment and QRS waves, fiducial points for P, Q, J, and T waves, and so on. The preliminary survey of several records reveals that signal changing patterns of some of these variables are not consistent in the given interval before ischemic episodes. This inconsistency of signal changing patterns happens in inter-records or intra-record. Based on experimentation, we decided to use five variables although they are not always useful to determine prediction points for all the records. The five informative data used in this paper are as follows: lowpass filtered signal of subtracted ST segment, heart rate, ST segment level at J-point+80 (denoted as ST80_Lx in Fig. 1), and the first two KL coefficients for ST signal (denoted as ST_KL in Fig. 1). The subtracted ST time series is the signal that subtracts linearly approximated ST time series from original time series to compensate for ST baseline movement. ST80_Lx means that ST segment level at the point 80[msec] from J-point for lead x. Each variable consists of 10 data, i.e., averages of 6[sec] interval in 1[min], and each data is normalized to have the value between 0 and 1. Thus, the total number of data for a prediction candidate is 50(10 data x 5 variables). These normalized data are sent to the NN for classification as true or false ischemic prediction points. Fig. 3 shows representative patterns of feature data for typical ischemic and nonischemic prediction candidates.



(a) Ischemic episodes



(b) Nonischemic episodes

Fig. 3. Example of graphical representation of feature data

C. Decision of true or false ischemic prediction points using neural networks

One of the successful applications using neural networks is a pattern classification field. In this final step, the neural networks classify prediction candidates as true or false prediction points based on pattern matching of given feature data.

The neural network used in this paper is the Elman's recurrent neural networks with modified learning algorithm. Fig. 4 shows the structure of fully connected RNN. It consists of three layers. All the units in a layer are connected to all the units in the following layers, i.e., they are one-to-many variable connecting weights. In the input layer, it has external inputs and additional inputs that are fed from the outputs of all neurons of the hidden layer with one-to-one weight connection. These recurrent connections improve the dynamics of the neural networks in order to efficiently process temporal characteristic of the input patterns.

Bias —

$x_1(n)$—

•

Fig. 4. RNN structure

The learning of the network is an extension of the gradient descent algorithm. It is modified to improve the learning speed. The connecting weights between neurons as well as the parameters of the node activation function such as the gain, slope, and delay of the function are updated simultaneously using the error backpropagation algorithm. All neurons in the hidden and output layers use sigmoid transfer functions. The output of a neuron is defined as

$$y(n) = f(v_l(n)) = \frac{g(n)}{1 + e^{-s(n)\{v_l(n) - d(n)\}}} \quad (2)$$

$$v_l(n) = \sum_{m=1}^{N} w_{lm}(n) x_m(n) \quad (3)$$

where $v_l(n)$ is the internal state of a neuron, $w_{lm}(n)$ and $x_m(n)$ are the connecting weights and input to the neuron l, and $g(n)$, $s(n)$, and $d(n)$ represent the gain, slope, and delay of the activation function, respectively. They are considered as time-varying parameters in the network.

The error of the network is as follows.

$$E(n)=\frac{1}{2}\sum_k e_k^2(n)=\frac{1}{2}\sum_k\{d_k(n)-y_k(n)\}^2 \quad (4)$$

The purpose of the training algorithm is to reduce the error, $E(n)$ by adaptively adjusting weights $w_{lm}(n)$ and parameters $g(n)$, $s(n)$, and $d(n)$. The changes of the weights $\Delta w(n)$ and parameters $\Delta p(n)$ are defined and obtained as follows.

$$\Delta w(n)=-\eta_w\frac{\partial E(n)}{\partial w(n)}=\eta_w\delta(n)y(n) \quad (5)$$

$$\delta(n)=-\frac{\partial E(n)}{\partial v(n)}=e_k(n)\frac{\partial f(v(n))}{\partial v(n)} \quad (6)$$

$$\Delta p(n)=-\eta_p\frac{\partial E(n)}{\partial p(n)}=\eta_p e_k(n)\frac{\partial f(v(n))}{\partial p(n)} \quad (7)$$

Above equations show the incremental weights and parameters of the output layer. The weights and parameters of the hidden layer can be derived the same way as those of the output layer. The η_w and η_p $(=\eta_g, \eta_s, \eta_d)$ represents the update rates for weight and parameters. The incremental connecting weights $\Delta w(n)$ and the parameters $\Delta p(n)$ $(=\Delta g(n)$, $\Delta s(n)$, $\Delta d(n))$ of the activation function are updated at every iteration in the training process. The momentum term is added to change only the weights to speed up the learning of connecting weights.

The number of neurons of the input, hidden, and output layers was chosen to be 50, 65, and 1, respectively. The number of neurons of the input layer corresponds to the number of input variables. The number of the hidden layer was determined experimentally, so as to accelerate the training time and stabilize the performance of the neural networks. So the total number of neurons of the input layer including feedbacks from the hidden layer and bias is 116. Other parameters are as follows: η_w=0.035, η_g =0.001, η_s=0.001, η_d= 0.0001, momentum rate of 0.0015. For network training, the desired output is set to $d(k)$=1 if the input pattern belongs to the ischemic episode class, and is set to $d(k)$=0 if it belongs to the nonischemic episode class. The network is trained to reach a stable error level, beyond that level the error does not reduce much as iteration continues.

The success of the network implementation relies on the collection of training set and good training. The difficulty in constructing the training set is the definition of nonischemic class events. Nonischemic class events are selected at a timing point in the ST segment more than 20[msec] away from ischemic episodes annotated in the database. Sometimes nonischemic episodes are selected in the middle of absolute ischemic and nonischemic intervals.

Multilayer neural networks compute the estimation of a posteriori probability[14, 15]. The least square error E_{LS} between the network's actual output y and desired output d is

$$E_{LS}=\frac{1}{N}\sum_{i=1}^{N}[y_i(\boldsymbol{x}, \boldsymbol{w})-d_i(\boldsymbol{x})]^2 \quad (8)$$

where $\boldsymbol{x}$ and $\boldsymbol{w}$ represent vectors of input and weights of the network. This equation reduces into the following equation by applying stochastic variable theory.

$$E_{LS}=E[y(\boldsymbol{x}, \boldsymbol{w})-P(C\mid \boldsymbol{x})]^2 \quad (9)$$

where E represents an expectation operator. Above equation means that assuming that the training is performed successfully, the output of neural networks can compute the estimation of a posteriori probability $P(C\mid \boldsymbol{x})$ with respect to least square error between actual network output and ideal output. Thus, for the input vector of each prediction candidate, the network can classify whether the given prediction candidate belongs to true prediction points of ischemic episode or not.

III. Experimental Results

The algorithm was tested using the MIT/BIH long-term ST database[13]. The database consists of ECG signals measured from ischemic patients and their derived parameters such as ST segment time series, Karhunen-Loeve(KL) coefficients of the ST segment and QRS complex, heart rate and its frequency spectra. It also contains linearly approximated ST segment level time series and subtracted ST segment level time series. Each record contains complete long-term two- and three-lead ECG signals, annotated beat-by-beat with respect to ST episodes, rhythm changes, and signal quality changes, ranging in length from 14 to 24 hours. The annotated ischemic episodes have been validated and annotated manually by cardiologists. All tests have been done on one-lead ECG signal.

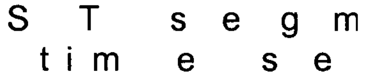


Fig. 5. Definition of ST episode

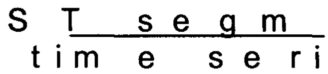
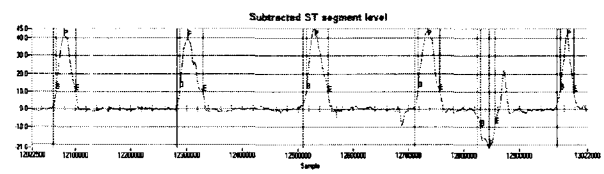


Fig. 6. Example of nested ST episodes

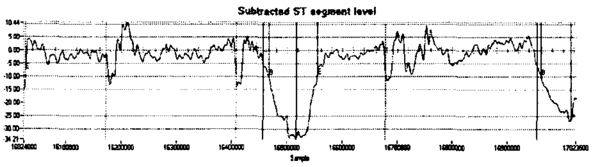
The performance of the algorithm was tested based on the following protocol of transient ischemic episode used by Jager et al.[13]. Fig. 5 shows a criterion on ST segment time series for definition of a transient ischemic episode: $V_{min} = 75[\mu V]$, $T_{min} = 30[\text{sec}]$. In some records of the database, nested transient ischemic episodes exist. These nested episodes are not predicted in this study. Fig. 6 illustrates an example of one nested episode (denoted as episode #2) and the episode points to be predicted in this paper. Another assumption is that the episode within 10[min] from the end of a previous episode will not be predicted since it can be considered a part of a long transient ischemia.

(a) ST segment depression, #1

(b) ST segment depression, #2



(c) ST segment elevation



(d) Erroneously predicted points

Fig. 7. Examples of prediction results

In order to train the NN, we collected training data set from 8 records. The first half and the second half of each record are used training and test data, respectively. The total number of training set is 456, consisting of real ischemic episodes of 110 and nonischemic episodes of 346. The total number of test set is 237 episodes from 15 records, 112 episodes from 8 training records and 125 from other 7 records. Fig. 7 illustrates typical examples of true and false ischemic episodes. The B, P, and E in the figure represent the beginning, peak, and end of the ischemic episode. The long line before B represents the ischemic prediction point determined by the neural networks. Fig. 7(d) shows three erroneously predicted points due to the insufficient T_{min}.

The annotated ischemic episodes in the database have been validated and annotated manually by cardiologists. The prediction points determined by the proposed method are compared with these annotated episodes. Table 1 shows the prediction results for training data set. 107 episodes among 110 episodes are predicted correctly and 3 episodes are not. The system predicts erroneously 36 episodes which do not exist in the database. Average prediction time was computed on correctly predicted episodes by taking absolute mean of time differences between onset points of the annotated episodes and prediction points determined by the proposed system. For training data, the system predicts the ischemic episodes 54.64[sec] ahead in average.

Table 1. Prediction results for training data set

Record	Number of ischemia prediction				Average pred. time +/- STD (sec)
	Total	Correct	Wrong	Missing	
S20131	8	7	5	1	96.29
S20273	20	20	5	0	80.60
S20401	3	3	0	0	38.00
S20411	6	6	4	0	342.67
S20151	19	19	2	0	13.89
S20171	12	11	7	1	10.91
S20291	17	17	8	0	17.06
S20591	25	24	5	1	21.62
Total	110	107	36	3	54.64 +/- 114.06

We tested for seven more records using the same neural networks trained for 8 records. Table 2 shows the prediction results for test data set. The total prediction results for 15 records are as follows: among total 237 transient ischemic episodes, 214 episodes are predicted correctly, 23 episodes are missed to predict, and 118 episodes are erroneously predicted. The average prediction time for correctly predicted episodes is 45.53[sec], indicating the system predicts 45.53[sec] ahead real ischemic episodes.

Table 2. Prediction results for test data set

Record	Number of ischmia prediction				Average pred. time +/- STD(sec)
	Total	Correct	Wrong	Missing	
S20131	8	0	1	8	00.00
S20273	19	17	7	2	24.59
S20401	3	3	0	0	53.33
S20411	5	4	6	1	72.50
S20151	19	19	6	0	14.11
S20171	12	11	6	1	10.91
S20291	19	16	5	3	26.50
S20591	27	26	8	1	25.00
S20021	26	26	6	0	12.62
S20031	7	7	12	0	84.00
S20041	20	18	8	2	85.00
S20081	6	6	8	0	60.67
S20111	11	11	8	0	93.64
S20121	9	9	7	0	163.33
S20161	46	41	30	5	49.46
Total	237	214	118	23	45.53 +/- 75.46

We present two performance indexes[5]: sensitivity and specificity(or positive predictivity) for ischemic ST episode prediction. Correctly predicted episodes in Table 2 are termed true positive(TP) episodes. Missed episodes are termed false negatives(FN). Erroneously predicted nonischemic episodes are termed false positives(FP). Thus the two indexes are defined as follows.

(1) Sensitivity of ischemic ST episode prediction (ST_{se}) is defined as the ratio of the number of correctly predicted episodes to the number of annotated ischemia episodes in the database. This index expresses the sensitivity of the proposed algorithm to the prediction of ST episodes.

$$ST_{se} = \frac{TP}{TP+FN} \tag{10}$$

(2) Specificity of ischemic ST episode prediction (ST_{sp}) is defined as the ratio of the number of correctly predicted episodes to the number of all episodes predicted. This index is a measure of the inclination to incur false prediction. Here, the denominator is the number of ischemic ST episodes predicted by the NN based pattern matching algorithm.

$$ST_{sp} = \frac{TP}{TP+FP} \tag{11}$$

Table 3 summarizes sensitivity and specificity. In the table, Training and Test #1 columns indicate sensitivity and specificity of training and test data sets for 8 records. Test #2 column indicates those of test data set for 15 records. The sensitivity and specificity for 237 transient ischemic episodes are 90.30% and 64.46%. Comparing with Test #1, the proposed method improves sensitivity by 4.59% and deteriorates specificity by 6.65%. This means that when we test the ischemic prediction on new records which are not included in training records, the proposed method will increase the probability to predict the ST episodes and increase also the probability to incur false prediction.

Table 3. Sensitivity and specificity

	Training	Test #1	Test #2
Sensitivity(%)	97.27	85.71	90.30
Specificity(%)	74.83	71.11	64.46

Ⅳ. Conclusions

The aim of this study is to predict transient ischemic episodes using neural networks based pattern matching method. The ischemic prediction is performed on noninvasively measured signals such as ECG signals and heart rate. This paper is the first study to predict ischemia using MIT/BIH long-term database, thus no paper exists to compare for relative evaluation of the proposed method. However, experimental results such as the sensitivity of 90.30% and prediction time of 45.53[sec] for 15 records indicate that the neural network approach provides a potential tool to predict transient ischemic episodes. For the proposed method to be of practical use, further investigations for more patients with other signals is necessary to verify the robustness and reliability for the ischemia prediction.

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