A Radial Basis Function Neural Network for the Detection of Abnormal Intra-QRS Potentials

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Abstract

Abnormal intra-QRS potentials (AIQP) in signal-averaged electrocardiograms have been proposed to be a potential noninvasive index for the diagnosis of the risk of ventricular arrhythmias. This study tries to develop a nonlinear neural network using radial basis functions (RBF) to approximate the normal QRS complex and then to estimate the AIQP using the approximation error, and further to quantify the estimation error of the AIQP. Different spread parameters of the Gaussian kernel function in the hidden layer have been adopted to evaluate the approximation accuracy of the RBF neural network. The study group of AIQP was constructed by adding a white noise with a root-mean-square value of 5 μV into the QRS complexes of the normal subjects to simulate the presence of AIQP. The study results illustrate that the mean root-mean-square values of the estimated AIQP in the AIQP group were 2.5 μV, 3.5 μV, 2.9 μV and 2.3 μV larger than those in the normal group using the spread parameters of 5, 10, 15 and 20, respectively. Hence the maximum accuracy of the proposed RBF neural network for the estimation of AIQP can reach 70% (3.5 μV compared to the ideal value of 5 μV).

1. Introduction

Signal-averaged electrocardiograms (SAECG) have became an important noninvasive tool for diagnosing the risk of ventricular arrhythmias [1-2]. In addition to the analysis of the conventional ventricular late potentials, the abnormal signals hidden in the entire QRS complex, called abnormal intra-QRS potentials (AIQP), have been proposed to be a new potential index to improve the diagnostic performance of SAECG [3-8]. Several studies have applied a linear autoregressive moving average model (ARMA) in the discrete-time cosine transform domain to model the normal QRS components and then extract the AIQP by the modeling error [3-6]. Our previous studies further proposed the linear ARMA and finite-impulse-response (FIR) prediction models to detect the signals with sudden slope change within the QRS complex induced by AIQP for the diagnosis of high-risk patients with ventricular tachycardia [7-8]. The common point of the previous studies is the use of the linear model to estimate the smooth and predictable normal QRS components, and then to analyze the AIQP by the residuals. However the possibility that the normal QRS wave belongs to a nonlinear model cannot be eliminated from a complicated heart system. The purpose of this study is to develop a nonlinear model based on a radial basis function (RBF) neural network [9-11] to approximate the normal QRS components and then analyze the AIQP by the approximation error.

2. Methods

2.1. Data acquisition

The high-resolution electrocardiograms were recorded at rest with patients in a supine position using a commercially available Simens-Elema Megacart® machine and a bipolar, orthogonal X, Y and Z lead system [1-2]. The input electrocardiograms were further digitized by an analog to digital converter with a sampling rate of 2 kHz and a resolution of 12 bits, and a 10 min digitized ECG signal was stored on a computer hard disk for subsequent off-line analysis. According to the standards of SAECG analysis recommended by the 1991 ESC, AHA and ACC Task Force and the 1996 ACC committee, the signal averaging technique was applied to reduce the effects of random noise, and a bidirectional Butterworth filter with 40 to 250 Hz frequency band was used to extract high frequency components of SAECG. The final noise level of SAECG was lower than 0.7 μV. The starting point (onset) and end point (offset) were obtained by using the analysis of vector magnitude [1-2].

Two study groups consisting of the normal and AIQP groups were recruited to test the performance of the proposed RBF neural network for the detection of AIQP. The normal group consisted of the X-lead SAECG of 42 normal Taiwanese. Because all the normal subjects had a normal clinical history, physical examination, and 12-lead

ISSN 0276−6574

ECG and echocardiogram, they had a very low possibility of presenting AIQP in the SAECG. The AIQP group was constructed by adding a white noise with a root-mean-square value of 5 μV into the adjusted QRS complexes of the normal subjects in order to simulate the presence of the broad-band and random AIQP, and had the same root-mean-square values of the QRS complexes in the normal group after adjustment.

2.2. AIQP analysis using the RBF neural network

An RBF neural network has an input layer, a hidden layer and an output layer. The transformation from the hidden layer to the output layer is linear. The output signal of the output layer is the linear combination of the output signals of the hidden layer. However the transformation from the input layer to the hidden layer is nonlinear. Each neuron in the hidden layer contains an RBF whose output is inversely proportional to the distance between the input of the input layer and the center of the RBF. Figure 1 shows a block diagram of an RBF neural network which has a *p*-dimension input signal in the input layer, *M* neurons in the hidden layer and only one output in the output layer. In the approximation analysis of the QRS wave, the target signal is the QRS wave, and the input signal of the input layer is the discrete time variable $x = 1, 2, \cdots, p$, where the dimension *p* depends on the length of the QRS wave. The optimized output signal of the output layer is applied to approximate the QRS wave, and the approximation error is defined as the difference between the target signal and output signal of the output layer.

This study adopted a Gaussian RBF to be the neuron in the hidden layer defined as follows [11]:

$$\phi(\|x-c\|) = \exp\left(-\frac{\|x-c\|^2}{2\sigma^2}\right) \tag{1}$$

where *c* denotes the center, σ is the spread or standard deviation, and $\|x-c\|$ represents the Euclidean distance between *x* and *c*. Each output in the hidden layer can be obtained by passing the input signal in the input layer through the transformation of the neuron as follows:

$$z_j(x) = \phi(\|x-c_j\|)\ ,\ j = 1,2,\cdots,M \tag{2}$$

where c_j denotes the center of the *j*th neuron. Then the output signal of the output layer can be derived from the linear combination of the outputs of the hidden layer as follows:

$$y = \sum_{j=1}^{M} w_j z_j(x) \tag{3}$$

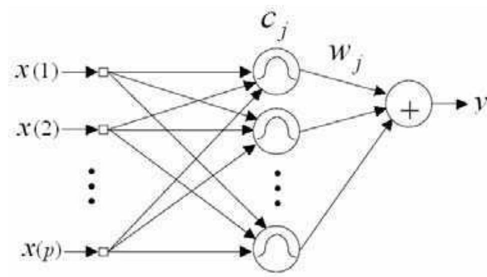

Figure 1. Block diagram of an RBF neural network.

where w_j and z_j denote the *j*th neuron weight and output of the hidden layer, respectively. By substituting equation (2) with equation (3) we can further obtain

$$y = \sum_{j=1}^{M} w_j \phi(\|x-c_j\|) \tag{4}$$

The matrix form of the output signal of the output layer can be represented as

$$\begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(p) \end{bmatrix} = \begin{bmatrix} \phi(\|x(1)-c_1\|) & \cdots & \phi(\|x(1)-c_M\|) \\ \phi(\|x(2)-c_1\|) & \cdots & \phi(\|x(2)-c_M\|) \\ \vdots & \vdots & \vdots \\ \phi(\|x(p)-c_1\|) & \cdots & \phi(\|x(p)-c_M\|) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_M \end{bmatrix} \tag{5}$$

or

$$\mathbf{y} = \mathbf{\Phi W} \tag{6}$$

Because the target signal of the RBF neural network can be obtained by the summation of the approximation error and the output signal of the output layer, it can be expressed as follows:

$$\mathbf{d} = \mathbf{\Phi W} + \mathbf{e} \tag{7}$$

where $\mathbf{e}$ denotes the approximation error vector, $\mathbf{e} = [e(1) \quad e(2) \quad \cdots \quad e(p)]^T$ (*T* indicates the transport operation). This study adopted the minimum mean-square-error method to find the weight vector that can minimize the mean-square value of the approximation error. The optimized weight vector $\mathbf{W}^*$ can be derived as follows [11]:

$$\mathbf{W}^* = (\mathbf{\Phi}^T\mathbf{\Phi})^{-1}\mathbf{\Phi}^T\mathbf{d} = \mathbf{\Phi}^+\mathbf{d} \tag{8}$$

Given the optimized weight vector, the output signal of the output layer can be calculated by

$$\mathbf{y} = \mathbf{\Phi W}^* = \mathbf{\Phi}(\mathbf{\Phi}^+)\mathbf{d} \tag{9}$$

2.3. Definition of the AIQP parameter

This study used the output of the RBF neural network to approximate the normal QRS components and then adopted the approximation error to estimate the AIQP. An AIQP parameter for the quantification of the estimated AIQP was defined by the root-mean-square value of the approximation error as follows:

$$\mathrm{AIQP}_{rms}(\sigma)=\sqrt{\frac{1}{p}\sum_{i=1}^{p}e^{*2}(i)} \tag{10}$$

where σ indicates the spread parameter of the RBF, p is the length of the input QRS wave, and $e^{*}(i)$ denotes the optimized approximation error.

3. Results and discussion

The spread parameter of the Gaussian function determines the width of the RBF waveform. A wider RBF can approximate the smoother components of the QRS wave well, but it can not accurately approximate the rougher components, even if a large number of neurons is used. On the other hand, a narrower RBF can approximate the rougher components of the QRS wave well, but it needs a large number of neurons to approximate the smoother components. The conventional method for designing the RBF neural network used the least mean-square-error method to determine the width of the RBF, but each RBF has the same width (i.e. the same spread parameter) in this study. Hence the approximation error can be considered as the components which are rougher than the RBF and can not be approximated by the RBF. The number of neurons is another parameter which affects the approximation accuracy. In order that the approximation error can be determined as far as possible only by the width of the RBF and not be induced by the insufficient number of neurons, a large number of neurons that is equal to the length of the input QRS wave was adopted for the approximation of the wave.

Figure 2 demonstrates the simulation signals including a QRS wave with the length of 106 ms from one of the normal subjects with a root-mean-square value of 500 μV, and a white noise signal with a root-mean-square value of 5 μV for the simulation of the AIQP. Figure 3 shows the approximation errors using the spread parameters of 10 (dotted line) and 20 (solid line), respectively, for the approximation of the normal QRS without adding AIQP. Obviously, the RBF neural network using the spread parameter of 10 can accurately approximate the QRS wave with only 0.04 μV approximation error. However the spread parameter of 20 has a larger approximation error of 2.29 μV because the wider RBF cannot approximate the rougher components of the QRS wave well. Figure 4 illustrates the approximation error (solid line) using the spread parameter of 10 for the normal QRS added to the AIQP, and the waveform of the original AIQP (dotted line). The QRS wave added to the AIQP

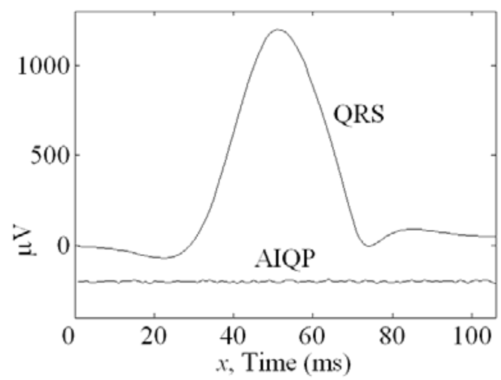

Figure 2. A QRS wave from one of the normal subjects with a root-mean-square value of 500 μV, and a white noise signal with a root-mean-square value of 5 μV for the simulation of the AIQP.

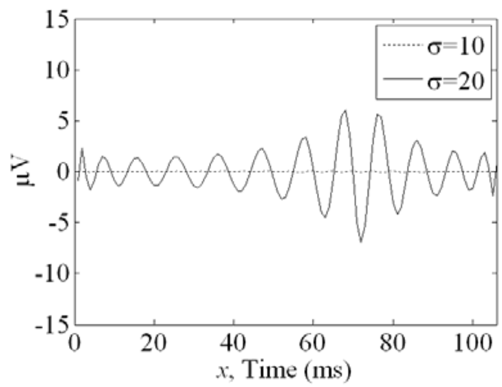

Figure 3. The approximation errors using the spread parameters of 10 (dotted line) and 20 (solid line), respectively, for the approximation of the normal QRS without adding the AIQP.

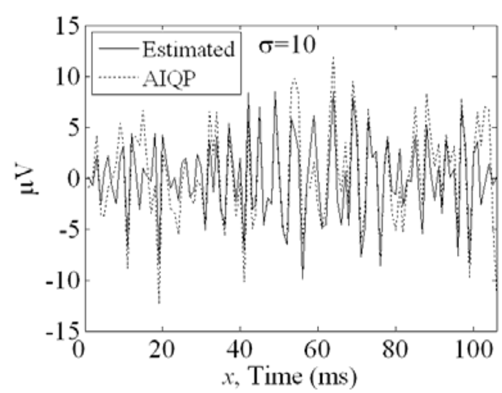

Figure 4. The approximation error (solid line) using the spread parameter of 10 for the approximation of the QRS wave added to the AIQP, and the waveform of the original AIQP (dotted line).

Table 1: Summary results of the AIQP analysis

	Normal	AIQP
QRS_{rms}	537.7 ± 170.4	
$AIQP_{rms}(5)$	0.1 ± 0.1	2.6 ± 0.2
$AIQP_{rms}(10)$	0.5 ± 0.2	4.0 ± 0.2
$AIQP_{rms}(15)$	1.8 ± 1.0	4.7 ± 0.5
$AIQP_{rms}(20)$	3.7 ± 2.1	6.0 ± 1.5

QRS_{rms} denotes the root-mean-square value of the QRS wave, and $AIQP_{rms}(\sigma)$ is the root-mean-square value of the estimated AIQP with regard to the spread parameter σ.

was adjusted to have the same root-mean-square value as the normal QRS wave without adding AIQP in order to avoid the approximation error being dominated by the larger amplitude of the QRS wave. The estimated AIQP is 4.07 μV and has about 80% accuracy compared with the 5.0 μV of the original AIQP.

Table 1 lists the summary results of the AIQP analysis for the normal and AIQP groups. Both study groups have the same root-mean-square value. The mean values of the AIQP parameter using the spread parameters of 5, 10, 15 and 20 in the AIQP group were 2.5 μV, 3.5 μV, 2.9 μV and 2.3 μV larger than those in the normal group, respectively. Hence the maximum accuracy of the proposed RBF neural network for the estimation of AIQP can reach 70% (3.5 μV compared to the ideal value of 5 μV) using the spread parameter of 10.

4. Conclusions

This study has successfully demonstrated that the proposed RBF neural network can be applied to approximate the smooth, normal QRS wave, and the approximation error can be used to estimate AIQP. The proposed RBF neural network can be considered as a special filter using the spread parameter of RBF to determine the approximation capability of the filter. The study results show that a smaller spread parameter would overestimate the AIQP and then have a smaller approximation error, while a larger spread parameter would underestimate the normal QRS and then have a larger approximation error. Further study is required with larger clinical populations to test the usefulness of the proposed method.

Acknowledgements

This research was financially supported by the National Science Council under Grant No. 97-2320-B-167-001.

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