QRS Complex Analysis Using Wavelet Transform and Two Layered Self-Organizing Map

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Abstract

Many kinds of methods have been developed to classify QRS complex in Holter electrocardiogram. However, the accuracy of these methods dose not fully satisfy the clinical needs. In this paper, we developed an automated classification methods using a wavelet transform and two-layered Self-Organizing Map (SOM) to improve the accuracy. A discrete wavelet coefficient is used as a characteristic parameter for the heart beat and the two-layered SOM is used for classification. First, each beat is divided in eight sections and the discrete wavelet coefficients of level 1-5 are calculated using a Haar mother wavelet for each section. By learning these characteristics in the first SOM, each section is classified automatically. Second, the QRS complexes are reconstructed as a line of the classified class in the first-SOM and classified by the second SOM. We evaluated our method using MIT-BIH Arrhythmia database of 16 cases (32,032 beats) and compared it with the accuracy of a standard cross correlation coefficient method. The classification error rate of the correlation coefficient method and proposed method is 0.82% and 0.39% respectively. We confirmed that the accuracy of our method for the QRS complex analysis has significantly improved.

1. Introduction

The Holter electrocardiogram has spread widely to be able to detect transient arrhythmia and ischemia. However, it is very difficult for medical expert to analyze the ECG recording beat by beat, because of the large quantity of data recorded over 24 hours (over 100,000 heart beats). Therefore, many automated classification algorithms have been developed [1-3]. For the feature extraction of QRS complex, time domain parameters (QRS height, width, area etc) and frequency domain parameter (power spectrum by FFT) have been used. For the classification methods, a correlation coefficient method, neural network, K-means algorithm and support vector machine have been used. However, the accuracy of these methods does not fully satisfy the clinical need. Different kinds of beats such as Normal, VPC, transient Right Bundle Branch Block, Left Bundle Branch Block and WPW beat are mixed in the same category, because the extraction and classification of partial abnormalities (a notch of R wave, S wave, delta wave etc) are insufficient [4].

We have previously developed the two-layered SOM classification system which classified the partial abnormalities in the first SOM and entire QRS-T complex in the second SOM using time domain parameters [5-7]. This time, we propose a wavelet coefficient which is a superior technique of time-frequency analysis for the feature extraction and apply it to the two-layered SOM for the classification.

2. Methods

Our QRS complex analysis system consists of a two-layered SOM (Figure 1).

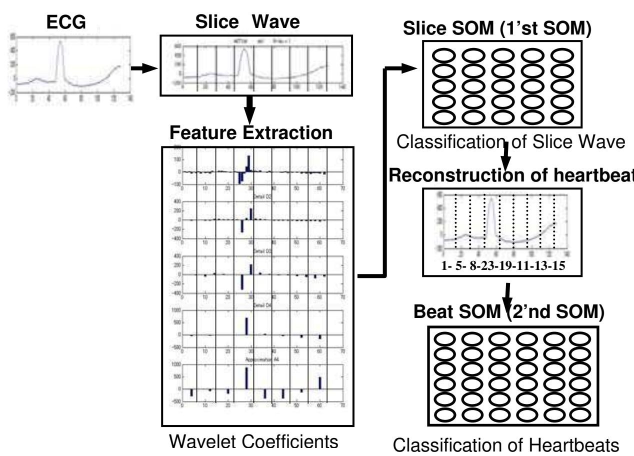

Figure 1. Two-layered SOM classification

2.1. Feature extraction

A single heart beat is digitized at 128 sampling points which include the P, QRS and T wave. A discrete wavelet to transform the extracted heart beat f(n) is performed using Haar mother wavelet ψ . And wavelet coefficients $W(j,k)$ are calculated (1=<j=<5 : level).

$$W[j,k]=\sum_{n=0}^{N-1} f(n)\psi_{j,k}[n] \tag{1}$$

$$\psi_{j,k}[n]=\sqrt{2j}\psi(2^{j}n-k) \tag{2}$$

2.2. Two-layered SOM classification

The extracted heart beat is divided in 8 sections (slices). Wavelet coefficients W of each section are normalized to 0-1 and used as an input vector.

In the first SOM (slice SOM), all input vectors (all heart beats x 8 slices) are used for learning, and each slice wave is classified. The weight vector (M_l) of the SOM is initialized to random values. The learning of SOM is repeated with the following steps continually. The Euclidean distance (D_l) between weight vector and input vector is calculated. A unit with weight vector more similar to the input vector is decided as the best match unit C.

$$D_l=\sqrt{\sum_j\sum_k \ (W_{j,k}-M_{j,k,l})} \tag{3}$$

$$C=\min_l D_l \tag{4}$$

The weights of unit C and neurons close to it in the SOM lattice are adjusted towards the input vector using the following formula.

$$M_l^{new}=M_l^{old}+\eta h(l,c)(W-M^{old}_l) \tag{5}$$

$$h(l,c)=\exp\left\{-\frac{|l-c|^2}{\sigma^2}\right\} \tag{6}$$

$$\sigma^2=\frac{\alpha}{t} \tag{7}$$

η is the learning coefficient and $h(l,c)$ is the neighborhood function. The automated classification of slice wave was done by repeating these processes. Using the slice SOM classification results, QRS complexes are reconstructed. In the second SOM (beat SOM), heart beats that are expressed as a line of the slice number are learned and classified automatically.

3. Experiment

3.1. Dataset

In this experiment, we used 16 cases of MIT-BIH arrhythmia database which include frequent VPC, noisy ECG and transient abnormal beats (Right Bundle Branch Block, Left Bundle Branch Block, WPW) [8]. The ECG signal of channel 1 and five kinds of beats, Normal (N), VPC (V), Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB) and WPW are used in the experiment. We compared the results of each method using the error rate Er = Eb/Tb. Eb is the number of the classification error beats and Tb is the total number of beat cycle.

Table 1. Dataset

No	MIT	Characteristics	Beats
1	106	VPC(Multi)	1,696
2	108	Noise	1,489
3	116	VPC+Noise	2,016
4	119	VPC	1,661
5	200	VPC+Noise, Run	2,168
6	201	VPC	1,558
7	203	VPC(Multi),VT	2,481
8	207	LBBB+VPC	1,932
9	210	VPC	2,204
10	212	RBBB+Noise	2,284
11	214	LBBB+Noise	1,877
12	219	VPC(Multi)	1,772
13	223	VPC(Multi)	2,198
14	230	Transient WPW	2,858
15	231	Transient RBBB	1,277
16	233	VPC(Multi)	2,561
	Total		32,032

3.2. Comparison of previous methods

We compared our method with the standard classification using cross correlation coefficient, single layer classification method with power spectrum and two layered SOM classification with time domain parameters. For the correlation coefficient method, a 0.9 threshold was used. For the FFT method, 24 components of power spectrum were used and classified in 30 categories by K-means algorithm. For the two layered SOM with time domain parameter method, 6 parameters were measured to extract the characteristics of each section (average level, height, amplitude of the mountain and valley, maximum slope, minimum slope), learned and classified automatically by slice SOM and beat SOM same as the wavelet method.

3.3. Results

The size of SOM is 5x5 in slice SOM and 6x6 in beat SOM. The total Er of the standard method was 0.82%, FFT 1.48%, time SOM 0.55% and wavelet SOM 0.39% respectively (Table 2). In the case of MIT212 dataset

Table2. Results of QRS classification using the cross correlation, FFT, time SOM and wavelet SOM methods.

No.	MIT	Cross Correlation			FFT			SOM			Wavelet +SOM		
		#of Classes	Error Beats	Error Ratio%	#of Classes	Error Beats	Error Ratio%	#of Classes	Error Beats	Error Ratio%	#of Classes	Error Beats	Error Ratio%
1	106	23	1	0.06	30	48	2.83	33	5	0.29	32	2	0.12
2	108	89	7	0.47	30	12	0.81	28	8	0.54	30	7	0.47
3	116	24	0	0.00	30	2	0.10	28	3	0.15	29	2	0.10
4	119	6	0	0.00	30	0	0.00	23	0	0.00	22	0	0.00
5	200	50	10	0.46	30	44	2.03	32	41	1.89	30	43	1.98
6	201	20	0	0.00	30	0	0.00	30	0	0.00	28	0	0.00
7	203	173	34	1.37	30	159	6.41	36	44	1.77	36	57	2.30
8	207	21	0	0.00	30	0	0.00	31	1	0.05	32	1	0.05
9	210	34	7	0.32	30	62	2.81	32	23	1.04	30	13	0.59
10	212	17	95	4.16	30	49	2.15	31	23	1.01	31	7	0.31
11	214	13	21	1.12	30	17	0.91	27	5	0.27	28	1	0.05
12	219	6	9	0.51	30	11	0.62	29	5	0.45	30	1	0.05
13	223	21	88	4.00	30	57	2.59	26	16	0.73	24	2	0.09
14	230	11	3	0.16	30	5	0.27	30	2	0.11	28	2	0.11
15	231	5	0	0.00	30	0	0.00	25	0	0.00	23	0	0.00
16	233	15	15	0.47	30	54	2.11	24	5	0.46	26	1	0.04
Average		33.0	18.1	0.82	30.0	32.5	1.48	29.1	11.3	0.55	28.7	8.7	0.39

which includes partial abnormal beats (transient RBBB), the Er of the standard method was 4.16%. The Normal and RBBB beats were mixed in the same categories when the cross correlation coefficients were under 0.92 (Figure 2-a). The Er of FFT method was 2.15%. The S wave features of RBBB were extracted a little using low component in the power spectrums (Figure 2-b). The Er of time domain SOM was 1.01%. The S wave of RBBB was expressed qualitatively as valley and upslope (slice SOM No.12 -23) in slice SOM. The small S wave of Normal beat was expressed as small valley and flat line (No. 13-24). Many of RBBB and N beats were able to be classified in different categories. However, 23 beats were mixed in the same categories because the lattice position in slice SOM were close (No .12-23 : 13-24). The wavelet SOM method improved the Er to 0.31%. Using the discrete wavelet transform, the S wave components of RBBB were expressed with wavelet coefficients of each level (remarkable in level 5) at the S wave position. And the high T wave components of RBBB were expressed at the T wave position in level 5 (Figure 2-d). The Normal and RBBB beats were distinguished with different classes by wavelet SOM more correctly.

In the case of MIT-223 dataset which includes similar QRS shapes between N and V beats, the Er of correlation method was 4.00%. The FFT method provided a limited accuracy and the Er was 2.59%, because the differences of the QRS width and T wave in the frequency domain was not enough. In the time SOM method, the Er was 0.73%, because the small S wave of N beat and the differences of T wave amplitude were detected in slice SOM. The wavelet SOM method provided the highest classification accuracy. The wavelet coefficients of normal R wave were higher than VPC in high frequency (level 1-2). And Normal P waves were expressed in low frequency (level 4-5). High T waves of VPC were extracted in level 5. We were able to distinguish N and VPC beats and improved the Er to 0.09%.

4. Discussion

The Er improved from 0.82% to 0.39% by using new method. About the extraction and classification of partial abnormalities, the correlation coefficient method and the FFT method were insufficient to calculate the similarity and the power spectrum of entire QRS-T wave. In the time SOM method, the extraction of the partial characteristics was improved to use the slice SOM. However, similar characteristics such as a wide S wave and small s wave were not able to distinguish in the time domain parameters and mapped on the close lattice position in slice SOM. In the wavelet SOM methods, the characteristics of frequency of P, R and T wave were extracted in each level, by using the wavelet transform as the future extraction. And the position of the characteristics of each wave was able to be expressed on the time scale. Therefore, the extracted characteristics were able to be used effectively as time-frequency information. The classification accuracy of the partial abnormality was largely improved by using two-layered SOM methods which combined the first SOM classification for slice wave and the second SOM classification for the entire beat.

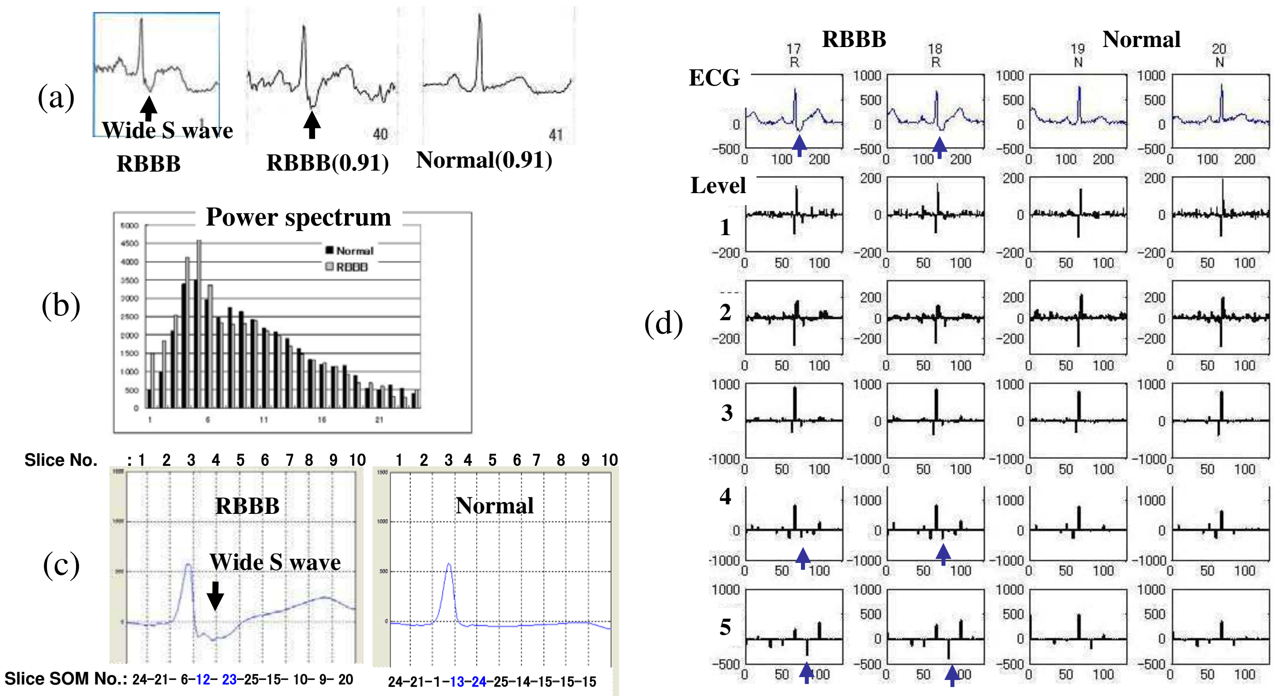

Figure 2. MIT212. (a): Examples of the error classification with the correlation method. The inside numbers between () are the cross correlation coefficient between the template ECG (left window) and each beat. (b): Example of power spectrum. Characteristics of S wave in RBBB are extracted by spectrum of low components. (c): Example of two-layered SOM classification with time domain parameters. The S wave of RBBB is extracted by quantitative attribute (valley and upslope) ,but the slice SOM number was close between the wide S wave of RBBB and the small S wave of N beat (12-23:13-24). (d): Examples of wavelet coefficients. The S wave components of RBBB were expressed with wavelet coefficients for each level at the S wave position.

5. Conclusion

We developed a QRS complex classification system using a wavelet transform and two-layered Self-Organizing Map. The classification error rate improved with the new method, compared with the standard approach using the correlation coefficient method. We confirmed that our new method is effective for QRS complex analysis in Holter electrocardiogram.

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