QRS Morphological Analysis using Two Layered Self-Organizing Map for Heartbeat Classification

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Abstract

QRS morphological analysis in Holter electrocardiography has been developed using correlation coefficient methods. However, the accuracy of automated classification for QRS complexes, does not fully satisfy the clinical needs. In this paper, we propose a two-layered classification using self-organizing map (SOM). In the first layer, each beat is divided in sections. The average level, height, amplitude of the peak, maximum and minimum slope are calculated as the characteristics of the section. By learning these characteristics in the first SOM, the sections are classified in qualitative attributes. In the second layer, QRS complexes are reconstructed as a line of the qualitative attributes and classified by the second SOM. We evaluated our method using MIT-BIH arrhythmia database 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 0.75% and 0.41% respectively. We confirmed that the accuracy in our method for the QRS complex analysis has significantly improved.

1. Introduction

Holter electrocardiogram has spread widely with medical institutions to be able to detect transient arrhythmia and ischemia. Because of the large quantity of data, recorded for 24 hours, it is necessary for the data to be analyzed automatically. The correlation coefficient methods have been developed to classify QRS complex [1-4]. However, the accuracy of this classification does not fully satisfy the clinical needs. Because the quantitative attributes in this traditional classification are not reflecting clearly the features in the human heart beat classifications for QRS complexes. In this paper, we propose an application of a two-layered self-organizing map (SOM) to classify QRS complex [5-6]. SOM is a type of artificial neural network that is trained using unsupervised learning methods to produce a low-dimensional representation from high-dimensional data [7]. In the first layer, each beat is divided in sections and the characteristics of the section are calculated. By learning the characteristics in the first SOM, each section is classified in qualitative attributes. In the second layer, QRS complexes are reconstructed as a line of the qualitative attributes and classified by the second SOM.

We experimented our two-layered SOM classification method using a MIT-BIH arrhythmia database [8] and compared it with a standard cross correlation method. The improvements of the two-layered SOM classification error rate mean that the proposed method is effective for heart beat classification.

2. Methods

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

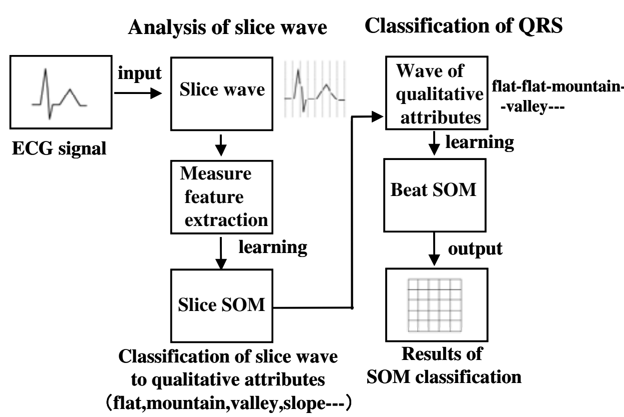

Figure 1. Two layered SOM classification

2.1. First SOM (Slice SOM)

Each beat is divided in 10 sections (slices) to extract partial characteristics. Heartbeat consists roughly of a combination of a flat line, mountain, valley and a slope. The following 6 parameters (Xi) are measured to extract and quantify the above qualitative characteristics for each section.

The six parameters are the average level (X1), height (X2), amplitude of the mountain (X3) and valley (X4), maximum slope (X5) and minimum slope (X6). These parameter's values were normalized to 0-1 and used as an input vector (X).

$$X = \{x_1, x_2, x_3, x_4, x_5, x_6\} \quad (1)$$

In the first SOM (slice SOM), all input vectors (all heart beats x 10 slices) are used for learning, and each slices is classified in qualitative attributes (flat line, up slope, down slope, mountain, valley etc). The weight vector (Wj) of the SOM is initialized to random values. The learning of SOM is repeated with the following steps sequentially. Also the euclidean distance (Dj) between weight vector and input vector is computed. A unit with weight vector most similar to the input vector is decided as the best matching unit C.

$$\mathrm{Dj} = \sqrt{\sum_{i=1}^{n} (x_i - w_{ji})^2} \quad (2)$$

$$\mathrm{C} = \min_j D_j \quad (3)$$

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

$$W_j^{new} = W_j^{old} + \eta h(j,c)(X - W_j^{old}) \quad (4)$$

$$h(j,c) = \exp\left\{-\frac{|j-c|^2}{\sigma^2}\right\} \quad (5)$$

$$\sigma^2 = \frac{\alpha}{t} \quad (6)$$

η is the learning coefficient and h(j,c) is the neighborhood function.

The automated classification of slice wave was done by repeating these processes.

2.2. Second SOM (Beat SOM)

Using the slice SOM classification results, QRS complexes are then reconstructed as a line of qualitative attributes. As a characteristic of SOM, same kind of slice waves are gathered and classified in the close lattices (Figure 2-b). The heartbeat is reconstructed as a line of the slice SOM number and expressed qualitatively (Figure 2-a). In the second SOM (beat SOM), qualitative beats are learned and classified automatically (Figure 2-c).

3. Experiment

3.1. Dataset

In this experiment, we used 17 cases of MIT-BIH arrhythmia database which includes frequent VPC, noisy ECG and transient abnormal beats (Right Bundle Branch Block, Left Bundle Branch Block, WPW). 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	201	VPC	1,558
6	203	VPC(Multi)	2,481
7	207	LBBB +VPC	1,932
8	210	VPC	2,204
9	212	RBBB＋Noise	2,284
10	214	LBBB＋Noise	1,877
11	215	VPC(Multi)	2,795
12	219	VPC(Multi)	1,772
13	223	VPC(Multi)	2,198
14	228	VPC(Multi)	1,703
15	230	Transient WPW	1,858
16	231	Transient RBBB	1,277
17	233	VPC(Multi)	2,561
	total		33,362

3.2. Results

The size of SOM is 5x5 in slice SOM and 6x6 in beat SOM. A single heartbeat is digitalized from the R-100ms to R+300ms to cover the most of QRS-T complex. The heartbeat is divided in 10 slices every 40ms. The comparison with the standard classification using cross correlation coefficient, and single layer classification method with power spectrum and our two layered SOM classification is described in the following section. For the FFT method, 24 components of power spectrum were used and classified to 30 categories by K-means algorithm. For the correlation coefficient method, a 0.9 threshold was used.

The total Er of the standard method was 0.75%, FFT 1.30%, SOM 0.41% respectively (Table 2). In the case of MIT212 dataset, the Er of the standard method was 4.16%. Because it did not classify the S waves in the RBBBs. The N and RBBB beats were mixed in the same categories. The two layered SOM classification improved the Er to 1.01%. The S wave feature in RBBB was extracted and classified by the qualitative attribute (valley and upslope) in slice SOM (Figure 3). In the case of MIT223 dataset, the Er of the standard method was 4.00%. The shapes of the QRS in the N and V beats were similar. The method could not separate them. The Er of

Table 2. Results of QRS classification by the cross correlation, FFT and two layered SOM methods.

		Cross Correlation			FFT			SOM		
	. MIT	#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
2	108	89	7	0.47	30	12	0.81	28	8	0.54
3	116	24	0	0.00	30	2	0.10	28	3	0.15
4	119	6	0	0.00	30	0	0.00	23	0	0.00
5	201	20	0	0.00	30	0	0.00	30	0	0.00
6	203	173	34	1.37	30	159	6.41	36	44	1.77
7	207	21	0	0.00	30	0	0.00	31	1	0.05
8	210	34	7	0.32	30	62	2.81	32	23	1.04
9	212	17	95	4.16	30	49	2.15	31	23	1.01
10	214	13	21	1.12	30	17	0.91	27	5	0.27
11	215	11	1	0.04	30	5	0.18	23	5	0.18
12	219	6	9	0.51	30	11	0.62	29	8	0.45
13	223	21	88	4.00	30	57	2.59	26	16	0.73
14	228	98	2	0.12	30	6	0.35	32	4	0.23
15	230	11	3	0.16	30	5	0.27	30	2	0.11
16	231	5	0	0.00	30	0	0.00	25	0	0.00
17	233	15	12	0.47	30	54	2.11	24	5	0.20
Average		34.5	16.5	0.75	30	28.6	1.30	28.7	8.9	0.41

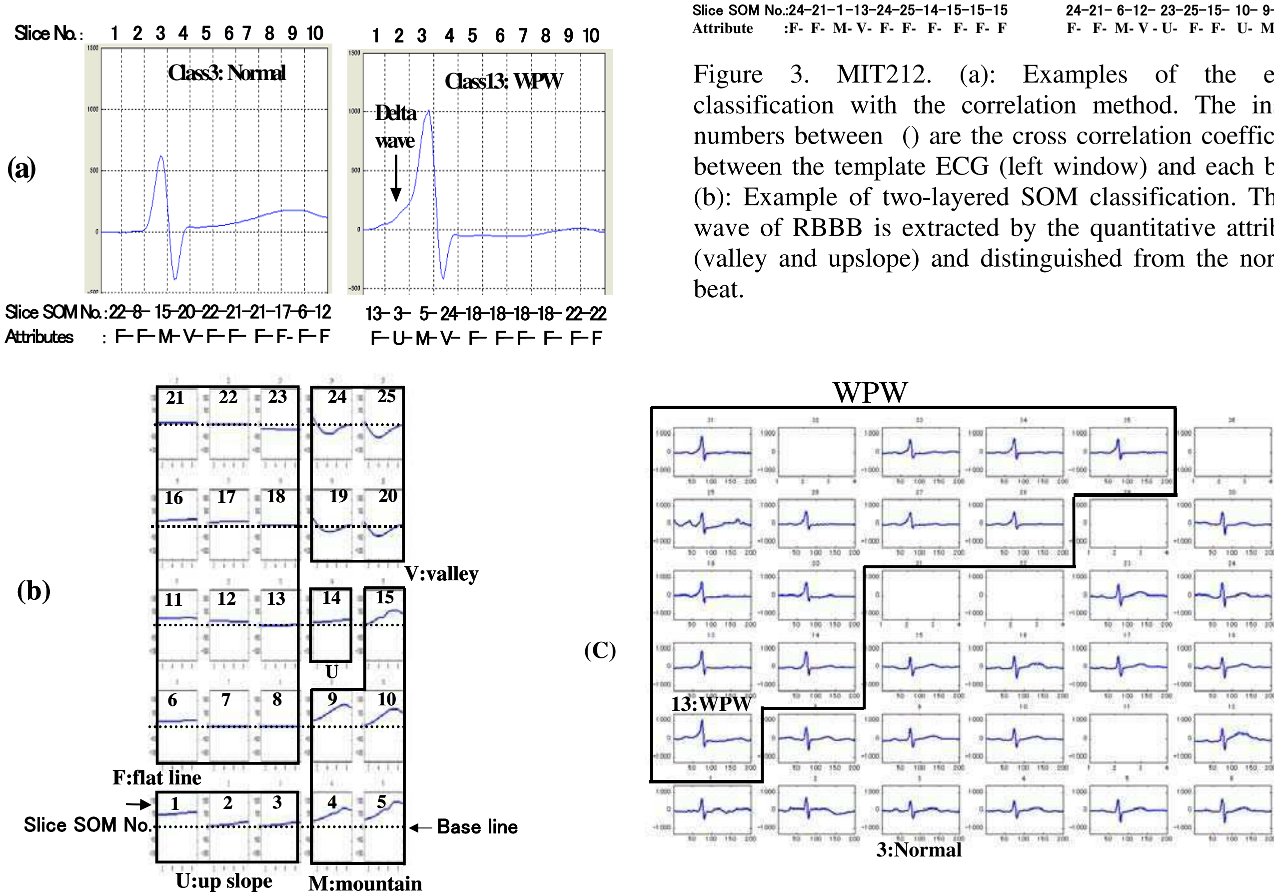

Figure 2. MIT-230. (a): Examples of two layered SOM classification. The delta wave of WPW beat is expressed as an upper line at the second slice in slice SOM and distinguished from the normal beat. (b): Results of the slice SOM classification. Slices are classified in the quantitative attributes (upslope, flat line, mountain etc). (c): Results of the beat SOM classification. WPW and normal beats are distinguished and classified between upper left and lower right block in the beat SOM.

the FFT method was 2.59%. The difference between the QRS shape and T wave in the frequency domain was not enough to be classified. The two layered SOM method improved the Er to 0.73%. Because, the difference of the S and T wave shapes were extracted as up slope and down slopes by the slice SOM (Figure 4). The total

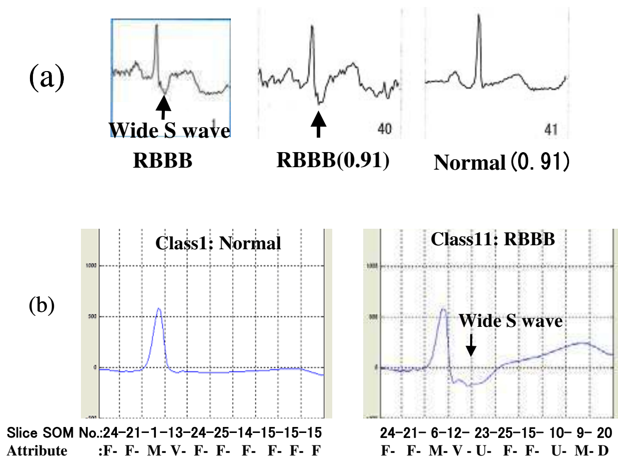

Figure 3. MIT212. (a): Examples of the error classification with the correlation method. The inside numbers between () are the cross correlation coefficient between the template ECG (left window) and each beat. (b): Example of two-layered SOM classification. The S wave of RBBB is extracted by the quantitative attribute (valley and upslope) and distinguished from the normal beat.

number of classifications was 867 for the standard method, 997 for FFT, 488 for SOM. Because of the influence of noise and waveform change, the number of classification increased for the standard and FFT method.

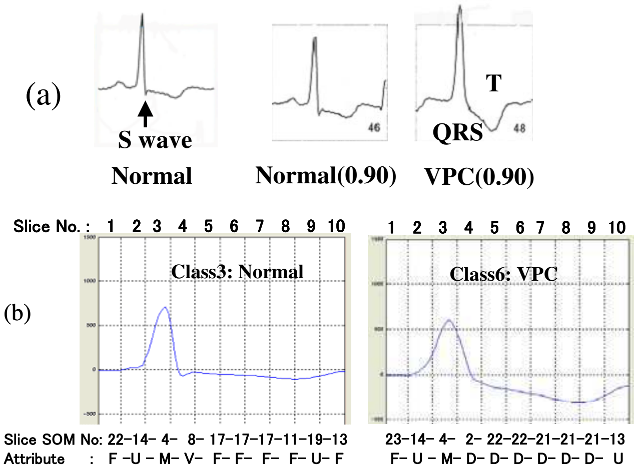

Figure 4. MIT223. (a): Examples of the error classification with the correlation method. (b): Examples of SOM classification. Normal and VPC are distinguished by the qualitative attributes of ST segment and T wave.

4. Discussion

The Er improved from 0.75% to 0.41% using the new method (Figure 5). QRS complexes have been classified by calculating the similarity of the entire QRS-T wave using the correlation coefficient method. Therefore, partial abnormalities such as the S wave of transient bundle branch block are hardly expressed, and the different kinds of beats are mixed in the same category. Regarding this problem, the partial abnormalities were distinguished by the qualitative expression of the section in the first SOM. In the correlation coefficient method, the same kind of heart beats are classified as different kinds of heart beat by the influences of small waveform change and noise, and the number of classifications increased. In our proposed system using qualitative analysis in the first SOM, the sections with noise and the waveform change were roughly characterized, and in the second SOM, the small changes were absorbed and classified. We were able to reduce the influence of the small changes and noise.

5. Conclusion

We developed a two-layered SOM classification system for QRS complex. 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.

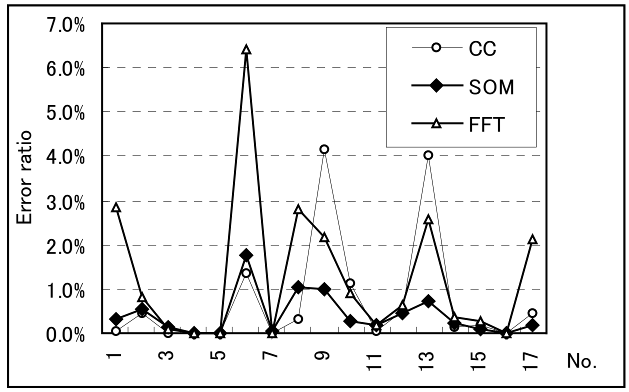

Figure 5. Error ratio of QRS classification using Cross Correlation (CC), FFT and the two layered SOM.

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