Two Layered Classification Using Qualitative and Quantitative Attributes for QRS Complex Analysis

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Abstract

QRS complex classification in Holter electrocardiogram have been developed using the correlation coefficient methods. However, the accuracy of this traditional classification is not fully satisfied the clinical needs. In this paper, we propose a two-layered classification using qualitative and quantitative attributes. In the first layer, 24 components in a FFT power spectrum for each beat are calculated as the quantitative attributes and are classified using K-means algorithm. In the second layer, the numbers of low, middle and high peaks before/after an R wave are computed as the qualitative attributes and are also classified by the same way. We evaluated our method for ten cases from MIT-BIH arrhythmia databases and compared with a standard cross correlation coefficient method. The classification error rate of the correlation coefficient method and proposed method is 1.10% and 0.79%. We confirmed that the accuracy in our method for the QRS complex analysis is significantly improved.

1. Introduction

QRS complex classification in Holter electrocardiogram (ECG) have been developed using the correlation coefficient methods [1-4] with the quantitative attributes such as power spectrum from heart beat time series signal data. However, the accuracy of this traditional classification is not fully satisfied the clinical needs. Because the quantitative attributes in this traditional classification are not reflected clearly the features in beat wave classifications by human for QRS complexes. In this paper, we propose a two-layered classification using qualitative and quantitative attributes [5]. Two layer classifications are combined to improve the classification accuracy. The first layer is classified with a conventional power spectrum in frequency domain as the qualitative attribute. The second layer is the different classification based on wave shape information and the appearance time as the quantitative attributes, which is not expressed in the quantitative attribute. We experimented our two layered classification method using MIT-BIH arrhythmia database [6] and compared with a standard cross correlation coefficient method with the quantitative attributes. The improvements of the two layered classification error rate means that the proposed method is effective for QRS complex classification.

2. Feature extraction

2.1. Quantitative attributes

The quantitative attribute in our method is the power spectrum as the frequency characteristics of each heart beat in ECG. A single heart beat is digitized at 64 sampling points before/after the R-peak, which cover the most of the single heart beat. To calculate the time series frequency characteristics in the single heart beat, the beat signal data are multiplied by the hanning window function. And these values are transformed to the power spectrum which consists of the 24 components by FFT.

2.2. Qualitative attributes

The qualitative attributes are the numbers of low, middle and high peaks before/after R-peak, the R-R, Q-R, R-S interval times and the height of R wave. We select from the R-60th to the R+100th sampling points to calculate the qualitative attribute value. Over 0.1mV peaks are detected and categorized to "low"(less than 0.25mv), "middle"(less than 1mv), "high"(over 1mv). After the qualitative peak height categorization, the numbers of the low, middle and high peaks are counted around the R-peak in the single heart beat. It means that the single heart beat is roughly categorized to the qualitative beat features such as the different type of peak numbers and interval times.

3. Classification

It the two layered classification, the qualitative and quantitative classifications are combined, that is, the frequency feature and the cognitive wave shape feature are used to improve the classification accuracy (Figure 1). The problem is the number of categories depending on the accuracy of each classification. The categories are tuned in each layer accordingly. In first layer, the frequency feature based classification is performed using K-means algorithm. However, some results with the frequency feature is not correspond to human cognitive sense. We add the second classification layer with the qualitative attributes. It implements a human cognitive measure to complement the first layer. K-means algorithm is also used in the second classification.

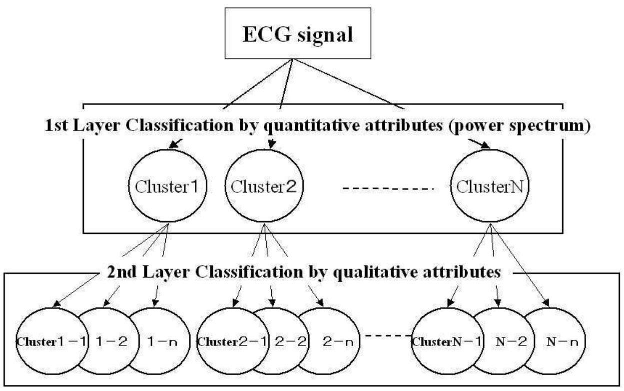


Figure 1. Two layered classification

4. Experiment

4.1. Dataset

In this experiment, we used ten 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). The ECG signal of channel 1 and five kinds of the beat cords, 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 by 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	108	Noise	1,489
2	116	VPC+Noise	2,016
3	200	VPC+Noise	2,168
4	212	RBBB+Noise	2,284
5	214	LBBB+Noise	1,877
6	219	VPC(Multi)	1,772
7	223	VPC(Multi)	2,198
8	228	VPC(Multi)	1,703
9	230	Transient WPW	1,858
10	231	Transient RBBB	1,277
	Total		18,642

4.2. Results

The dataset described in 4.1 was examined by the two-layered classification method using the quantitative and qualitative attributes. In the first layer, all beats in the dataset were classified to 10 categories. The beats of each category in the first layer were classified to 3 categories in the second layer. Finally all beats were classified to total 30 categories. The comparison with the standard classification using cross correlation coefficient, and single layer classification method with power spectrum and our two layered classifications is described in the following section. We use the short names to these method, called "standard," "single layer" and "two-layered" for each. The threshold of the correlation coefficient was used 0.9.

Table 2. Results of QRS classification by the cross correlation method.

No.	MIT	# of Classes	Error Beats	Error Ratio
1	108	89	7	0.47%
2	116	24	0	0.00%
3	200	50	10	0.46%
4	212	17	95	4.16%
5	214	13	21	1.12%
6	219	6	9	0.51%
7	223	21	88	4.00%
8	228	98	2	0.12%
9	230	11	3	0.16%
10	231	5	0	0.00%
	Average	33.4	23.5	1.10%

The total Er of the standard method was 1.10%, the single layer 0.87%, the two layered 0.79% respectively. In the case of the MIT211 dataset, the Er of the standard method was 4.1%. Because it did not classify the S waves in the RBBBs. The N and RBBB beats were mixed in the same categories. The single layer classification improved the Er to 1.4%. The S wave feature in RBBB was extracted by the low components (from 1st to 6th) in the power spectrums (Figure 2). In the MIT223 dataset, the standard method error rate Er was 4.0%. The shapes of the QRS in the N and the V beats were similar. The method could not separate them. The Er of the single layer classification was 2.2%. The difference between the QRS shape and T wave in the frequency domain was not enough to classify. In the two layered method, the qualitative attributes have the effect to recognize P wave appearance. The Er reached to 1.0%. N beat was expressed as one low peak before R-peak (P wave), one low peak after R-peak (T wave) and middle RR interval

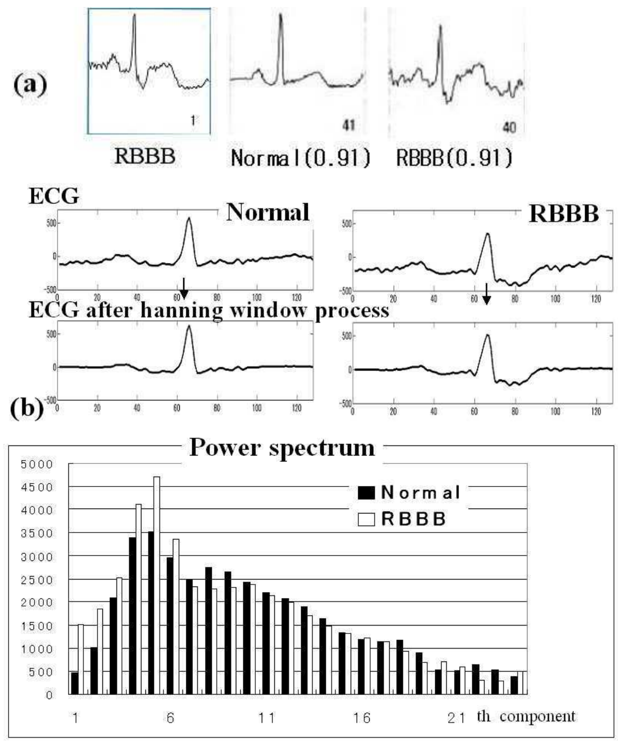
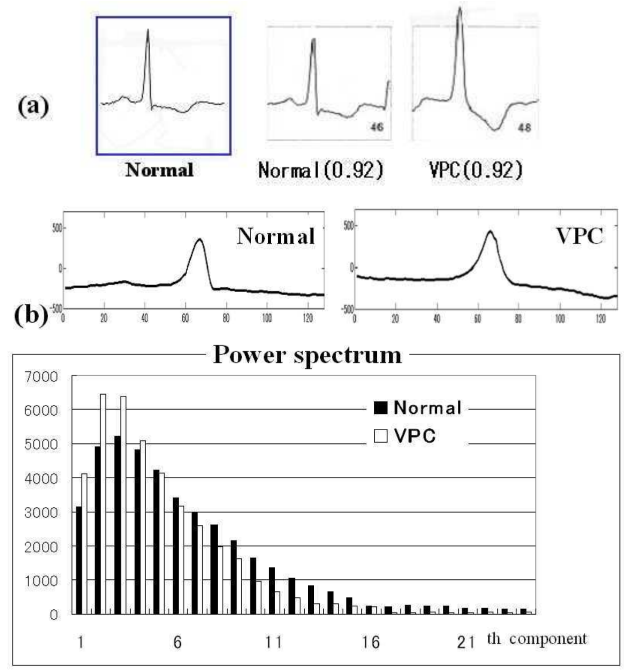


Figure 2. MIT212:(a):Examples of the error classification by the correlation method. The inside numbers of ( ) are the cross correlation coefficient between the template ECG (left window) and each beat. Normal and RBBB are classified as the same template. (b):Example of the power spectrum. Characteristics of S wave in RBBB are extracted by spectrum of low components.

Table 3. Results of QRS classification by the 1 layered classification.

No.	MIT	# of Classes	Error Beats	Error Ratio
1	108	30	12	0.81%
2	116	30	3	0.15%
3	200	30	44	2.03%
4	212	30	33	1.44%
5	214	30	18	0.96%
6	219	30	11	0.62%
7	223	30	48	2.18%
8	228	30	5	0.29%
9	230	30	5	0.27%
10	231	30	0	0.00%
	Average	30	17.9	0.88%

by qualitative attributes. V beat was expressed as no peak before R-peak, one middle peak after R-peak (T wave) and short RR interval. N and V beats which QRS complexes were similar could be distinguished by differences of peaks before/after R-peak and intervals using qualitative attributes. The data that number of classification was many were MIT108 (89) and MIT228 (98) in the standard method. For influence of noises, the number of the classified categories increased.



(c)

		Normal	VPC
Peaks	before R	low 1	no
	after R	low 2	middle 1
Intervals	R-R	middle	short
	RS	middle	no

Figure 3. MIT223. (a): Examples of the error classification by the correlation method. The inside numbers of ( ) are the cross correlation coefficient between the template ECG (left window) and each beat. (b): Examples of quantitative attributes. The differences of QRS width and shape of T wave in the frequency domain are not enough to classify. (c): Examples of qualitative attributes. Normal and VPC are distinguished by defferences of peaks and intervals.

4.3. Discussions

The Er was improved from 1.10% to 0.79% by using the new method (Figure 4). Correlation coefficient methods are classified using total similarity of QRS - T wave. Therefore, partial abnormalities such as S wave of transient bundle branch block are hardly expressed in the total similarity. For this problem, S wave of transient RBBB was distinguished by spectrums. In the case of similar QRS complexes between N and V, it is difficult to classify them by the standard method. However, P wave and QRS width are different between them. By using the new method, they were distinguished by differences of spectrum components in frequency domain quantitative attributes and the rough recognition of T wave and P wave in time domain qualitative attributes. By the influence of noise, same kinds of beats are classified as different kinds of beats, and the number of classifications increased in the standard method. We were able to suppress the influence of noise by rough characterizations with qualitative attributes. A present problem is that each beat is classified to 30 categories in any cases, even if there is one kind of beat code. Optimization of the classification number is needed.

Table 4. Results of QRS classification by the 2 layered classification.

No.	MIT	# of Classes	Error Beats	Error Ratio
1	108	30	13	0.87%
2	116	30	3	0.15%
3	200	30	57	2.63%
4	212	30	36	1.58%
5	214	30	15	0.80%
6	219	30	6	0.34%
7	223	30	21	0.96%
8	228	30	6	0.35%
9	230	30	4	0.22%
10	231	30	0	0.00%
	Average	30	16.1	0.79%

5. Conclusions

We developed two-layered classification system using quantitative and qualitative attributes for QRS complex. The two enhancements of partial abnormality detection and similar shape classification of QRS were enabled by the combination of the quantitative attributes and the qualitative attributes. The classification error rate was improved by new method, in comparison with the standard approach using the correlation coefficient method. We confirmed that our new methods are effective for QRS complex classification in Holter electrocardiogram.

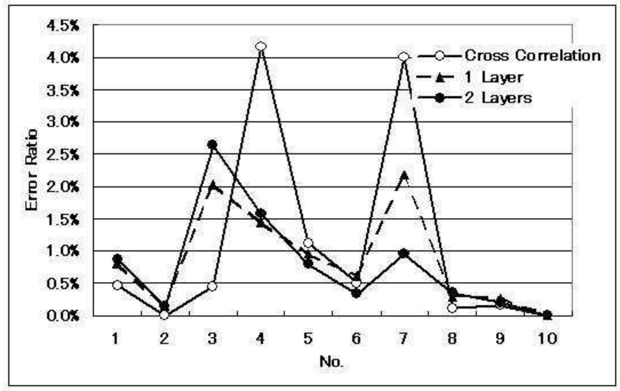


Figure 4. Error ratio of QRS classification

References

[1] Arnold JM, Shah PM, Clark WB. Artifact rejection in a computer system for the monitoring of arrhythmia. Computers in Cardiology 1975;163-166.

[2] Lewis JW, Mayer JL, Gradma AH. An Evaluation of Template Matching Alogorithms for Arrythmia Quantification. Computers in Cardiology 1979;33-36.

[3] Stanley BH, Raymond LW. A Minicomputer Based System for the Quantification of Ventricular Arrhythmia. Computers in Cardiology 1978; 355-358.

[4] R Dillman, N. Judell, S Kuo. Replacement of AZTEC by Correlation for More Accurate VPB Detection. Computers in Cardiology 1978; 29-32.

[5] Fumiaki Iseri, Tetsuya Sasaki, Mutsuo Kaneko, Takafumi Gotoh, Naomichi Sueda. A hierarchical classification using qualitative and quantitative attributes for ECG analysis. Information Processing Society of Japan 2008, Hinokuni Symposium.

[6] R Mark. R. Wallen. AAMI-recommended pactice: Testing and reporting performance results of ventricular arrhythmia detection alogorithms. Association for the Advancement of Medical Instrumentation, Arrythmia Monitorring Subcommittee, AAMI ECAR, 1987.

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