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Multi-classification of Cardiac Diseases Utilizing Wavelet Thresholding and Support Vector Machine

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Abstract. Automatic classification of electrocardiogram (ECG) is importance in cardiac disease diagnosis. Support vector machine (SVM) has drawn more and more attention on pattern recognition, including ECG feature extraction and cardiac disease detection. The most prominent advantage of SVM can be represent as its excellent performance on simplification of inner product operation from high dimensional space to low dimensional space, avoiding calculations in high dimension space. In this study, a multi-classification method is proposed utilizing wavelet multi-resolution analysis (WMRA) and SVM. WMRA is applied to eliminate interference with frequency beyond the frequency interval of ECG signals (0.05~100Hz). Meanwhile, WMRA provides detail coefficients and approximation coefficients of different decomposition levels, which are the input features fed into SVM for classification. After that, SVM is employed to recognize 6 types of cardiac beats from MIT-BIH arrhythmia database. Besides, different parameters C and γ are discussed and tested. Experimental results indicate that the classification performance gets better as C increases and γ decreases. When C and γ are set to be 1000 and 0.1 respectively, an overall classification accuracy, sensitivity and positive predictivity of 95.23%, 97.42% and 97.71% respectively are achieved.

Key words: Cardiac disease classification; feature selection; temporal and spectral domain; SVM.

INTRODUCTION

Electrocardiogram (ECG) is a continuous and non-stationary wave that reflects the electrical activity of the heart. In clinical practice, ECG helps to detect the abnormal heart rhythm or cardiac abnormalities. ECG signals of healthy hearts have regular characteristics, while the abnormal ones contain deformation in typical ECG waves and the intervals between them. For example, the QRS complex of premature ventricular contraction (PVC) is widened and not associated with the proceeding P wave, and the T wave is inverted after PVC [1].

On account of the high mortality of heart diseases, early detection of abnormal ECG signals and real-time therapy is essential for the treatment of patients with potential heart problems [2]. Support vector machine (SVM) developed by Vapnik [3] is gaining more and more popularity in pattern recognition due to many attractive features and promising empirical performance. Its basic model can be represented as a linear classifier with largest margin between two categories in feature space [4]. SVM classifiers maximize the margin between training data and the decision boundary (optimal separating hyper plane), and it can be formulated as a quadratic optimization problem in feature space. The subset of patterns closest to the decision boundary are called support vectors. Unlike other machine learning algorithms such as back-propagation artificial neural network (BP-ANN) that may has high-intensive calculation in high dimension, SVM avoids the dimensionality disaster by mapping inner product operation of input features into low dimensional space [5].

One challenge of cardiac disease classification is the feature selection fed into SVM. Different features will contribute to generate various SVM classifiers. To confirm the influence of feature selection scheme on the performance of SVM, researchers have conducted numerous studies aiming to find out the optimal features [6]. In [7],

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the authors suggested totally 42 morphological features for heart beat classification. In [8], the author reduced the quantity of ECG feature to 10, including 5 amplitudes and 5 positions of typical waveforms such as P-peak, Q-valley, R-peak, S-valley and T-peak. In addition to morphology methods, more and more researchers adopted HRV analysis and wavelet multi-resolution analysis to extract features from ECG signals. In [9] and [10], the authors integrated HRV features and wavelet coefficients to determine SVM input vectors from both of time and frequency domain. Besides, loss factor C and gamma-value γ of kernel function also affect significantly on classification accuracy [11, 12].

In this study, a multi-classification method is proposed taking advantage of wavelet multi-resolution analysis (WMRA) and SVM. An ECG signal is pre-processed by WMRA to enhance ECG representation, simultaneously, interference with frequency beyond the frequency interval of ECG signal is also removed. Meanwhile, WMRA provides detail coefficients and approximation coefficients in different decomposition levels, which are the input features fed into SVM. Six types of cardiac beats from MIT-BIH arrhythmia database are used to test the proposed method. Parameters C and γ are aslo discussed to verify their influence on classification performance.

MATERIALS AND METHODS

Wavelet Features

WMRA represents a signal in multiple scales and provides simultaneous localization of time and frequency [13]. This is achieved by the decomposition of the signal over dilated (scale) and translated (time) versions of a prototype wavelet. An input signal is decomposed by using a low pass filter and high pass filter followed by down sampling in each stage. The high pass filter gives the detail coefficient, and the low pass filter gives the approximation coefficient.

By using WMRA, frequency bands below 0.05 Hz and above 100 Hz should be excluded from an ECG signal. These intervals are not the ECG frequency bands and most interference is concentrated in these intervals. In addition, according to the Nyquist criterion, sub-frequency band presented by each decomposition level is directly related to the sampling frequency. Consequently, the ECG signals, sampled at 360Hz as illustrated in [14], are decomposed up to 8 levels using bior6.8 wavelet in this study.

Fig. 1 shows the decomposition procedure of eight-level WMRA by using bior6.8 wavelet and the corresponding ECG frequency bands. cD_2~cD_8 consist of frequency components in range of 0.70-90 Hz, which is the ECG frequency band of interest. cD_1 with frequency band 90~180 Hz and cA_8 with frequency band 0~0.70 Hz are beyond the ECG frequency, they are not the considered coefficients containing baseline drift and other interference. Consequently, cD_1 and cA_8 are set to zeroes, $cD_2 \sim cD_8$ are preserved for reconstruction. The kept detail coefficients are then filtered by the wavelet shrinking threshold algorithm [15]. In fact, there are two thresholding approaches: hard thresholding and soft thresholding. In this study, soft thresholding is adopted due to its good continuity and no Gibbs phenomenon on step points [16].

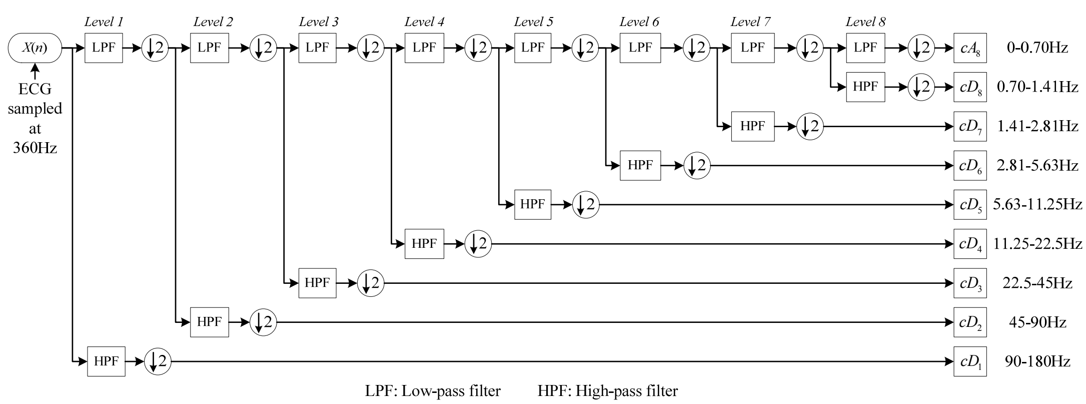

FIGURE 1. Decomposition process of the eight-level WMRA. The sampling frequency is decomposed into two sub-bands: high frequency of detail coefficient (cD_jcD_j) and low frequency of approximation coefficient (cA_jcA_j), both in Level j.

SVM Multi-Classification

One-versus-one SVM, which can be implemented in multi-classification applications, is an enhanced classifier derived from SVM. Since the inherent property of SVM can only determine one hyperplane of two classes, the hyperplane corresponding to each class should be trained individually. By using a popular SVM training tool that determines the support vectors for each hyperplane, the remaining process is how to make the final decision for each class based on the classification results of all hyperplanes.

One-versus-one SVM uses the majority voting scheme to categorize all the hyperplanes, with which the classification result is determined by selecting the maximum likelihood class. For an test set S, if there are n classes, the total number of hyperplanes constructed among these classes is "n(n-1)/2" . The class having the most votes given by all the hyperplanes is recognized as the outcome of the corresponding hyperplane. For instance, if the classification output of a hyperplane indicates that the input set S should be in class C, then class C gets one vote from this hyperplane. The set S is predicted to be in class C if this class get the maximum number of votes φ(C, S), which is defined as

$$\varphi(\boldsymbol{C}, \boldsymbol{S}) = \sum_{p=1}^{n(n-1)/2} v(p, \boldsymbol{C}, \boldsymbol{S}) \tag{1}$$

$$v(p, \boldsymbol{C}, \boldsymbol{S}) = \begin{cases} 1 & \text{if } \delta(p, \boldsymbol{S}) = \boldsymbol{C} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Where p denotes the index of a hyperplane, $v(\mathrm{p, C, S})$ represents the Boolean function for the vote corresponding to the p-th hyperplane, and $\delta(\mathrm{p, S})$ is the class index of the classification result for the p-th hyperplane.

EXPERIMENTAL RESULTS

The MITDB comprises of 48 ECG records and each record contains a 30-minute ECG signal. The signals are sampled at 360Hz with 11-bit resolution over a 10mV range and band-pass filtered at 0.1~100Hz [14]. In this study, six types of heartbeats: normal (N, Record 101, 115 117), left bundle branch block (L, Record 109, 111, 214), right bundle branch block (R, Record 118, 124, 212), atrial premature contraction (A, Record 209, 222, 232), premature ventricular contraction (V, Record 106, 107, 119), and paced beats (P, Record 102, 107, 219),are used to test the proposed method. Totally 45081 beats are trained and classified including 14057 N beats, 8067 L beats, 7163 R beats, 2371 A beats, 6354 V beats and 7069 P beats.

Experimental results are evaluated in terms of accuracy (ACC), sensitivity (SEN) and positive predictivity (+P), which are defined as

$$ACC = \frac{TP}{TP+FP+FN} \times 100\% \tag{3}$$

$$SEN = \frac{TP}{TP+FN} \times 100\% \tag{4}$$

$$+P = \frac{TP}{TP+FP} \times 100\% \tag{5}$$

where TP (true-positive) is the number of true beats that are correctly recognized, FN (false-negative) is the number of true beats that are recognized as false ones, FP (false-positive) is the number of false beats that are recognized as true ones. Correspondingly, ACC reflects the overall recognition accuracy, SEN is a measure of missing recognition on true beats, and +P is a measure of incorrect detection on true beats. The test results of the 22543 beats are summarized in Table 1.

TABLE 1. Detailed results for multi-classification (C=1000, γ=0.1)

	N	L	R	A	V	P
N	6823	1	3	10	180	12
L	7	3995	0	0	32	0
R	8	2	3551	9	12	0
A	38	1	28	1100	19	0
V	30	4	5	1	3137	0
P	11	2	0	1	64	3457
ACC	95.78829	98.78833	98.14815	91.13505	90.04018	97.46264
SEN	97.06928	99.03322	99.13456	92.74874	98.74095	97.79349
+P	98.64103	99.75031	98.99638	98.12667	91.08595	99.65408

Generally, most of the cardiac beats are correctly classified by the proposed multi-classification scheme. Among the six types of heart beats, the L beat has the highest accuracy with ACC of 98.79, SEN of 99.03 and +P of 99.75. However, the A beat achieves the worst identification performance. Table 1 also shows that most of the wrongly partitioned A beats are recognized as N beats, this is because the A beat has similar waveform morphology as N beat, the only different between them is the RR interval. One solution is to contain more features that distinguish various waveform representation. Besides, it is necessary to reduce redundant input features since superabundant feature quantity will be quite time-consuming.

DISCUSSIONS

The performance of one-versus-one SVM is affected by the loss factor C in dual problem and the kernel width γ in kernel function. The two parameters affect the number of support vectors and the maximization margin. To explore the effect of C and γ on SVM performance, accuracy of multi-classification with difference parameters are tested, and the results are summarized in Table 2.

TABLE 2. Comparative results for accuracy of SVM multi-classification with different C and γ

C \ γ	0.1	0.3	0.5	0.7	0.9
1	96.87	92.56	88.76	86.20	84.38
5	97.40	93.27	89.77	87.25	85.20
10	97.40	93.25	89.76	87.24	85.20
20	97.41	93.23	89.76	87.24	85.20
40	97.42	93.23	89.76	87.24	85.20
60	97.40	93.23	89.76	87.24	85.20
80	97.40	93.23	89.76	87.24	85.20
100	97.40	93.23	89.76	87.24	85.20
500	97.40	93.23	89.76	87.24	85.20
1000	97.40	93.23	89.76	87.24	85.20

As can be seen from Table 2, the performance is likely to become better as C increases and γ decreases. The multi-classification scheme attains an overall accuracy of 97.40% with C = 40 and γ = 0.1. Two innovations of SVM are responsible for the success of the proposed method, namely, the ability to find a hyper-plane that divides samples in to two classes with the widest margin between them, and the extension of this concept to a higher dimensional setting using kernel function to represent a similarity measure on that setting. This makes SVM a practical and effective solution for many pattern recognition and classification problems in bioinformatics

CONCLUSIONS

In this study, a multi-classification scheme on abnormal ECG signal recognition is designed and tested. The method take advantage of WMRA and one-versus-one SVM. The WMRA decomposes the ECG signal into detail and approximation coefficients in different levels, eliminating noises with frequency beyond the frequency band of ECG signal. The coefficients are also the input features fed into SVM for multi-classification. To evaluate the performance of the proposed scheme, six types of cardiac beats from MIT-BIH Arrhythmia Database are used for SVM training and prediction. Experimental results indicate that the classification performance becomes better as C increases and γ decreases. When C and γ are set to be 40 and 0.1 respectively, the proposed method can realize the highest accuracy, sensitivity and positive predictivity of 95.23%, 97.42% and 97.71% respectively.

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