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Arrhythmia Detection and Classification using Morphological and Dynamic Features of ECG Signals

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Abstract* -- *Computer-assisted cardiac arrhythmia detection and classification can play a significant role in the management of cardiac disorders. In this paper, we propose a new approach for arrhythmia classification based on a combination of morphological and dynamic features. Wavelet Transform (WT) and Independent Component Analysis (ICA) are applied separately to each heartbeat to extract corresponding coefficients, which are categorized as 'morphological' features. In addition, RR interval information is also obtained characterizing the 'rhythm' around the corresponding heartbeat providing 'dynamic' features. These two different types of features are then concatenated and Support Vector Machine (SVM) is utilized for the classification of heartbeats into 15 classes. The procedure is applied to the data from two ECG leads independently and the two results are fused for the final decision. Compare the two classification results and the classification result is kept if the two are identical or the one with greater classification confidence is picked up if the two are inconsistent. The proposed method was tested over the entire MIT-BIH Arrhythmias Database [1] and it yields an overall accuracy of 99.66% on 85945 heartbeats, better than any other published results.

I. Introduction

Cardiac arrhythmias are abnormal heart rhythms, which cause the heart to beat too fast (tachycardia) or too slow (bradycardia) and to pump blood less effectively [2]. Some types of arrhythmia are life-threatening medical emergencies that can trigger cardiac arrest and sudden death. Therefore, automatic cardiac arrhythmia detection and classification can play a vital role in the monitoring of patients. In the past few years, there has been many works focused on the automatic classification of heartbeats. These works explored to characterize heartbeats using various features, including wavelet features [3], waveform shape features [4][5], autoregressive features [6] etc. Besides, a number of machine learning algorithms have been proposed for classification, such as neural networks [3], linear discriminants [4], decision tree [5] and support vector machine [6].

This paper presents a method for the recognition of various categories of cardiac arrhythmias based on the morphological and dynamic features extracted from ECG signals. Wavelet transform and independent component analysis are applied to obtain the morphological information, while RR interval features are computed to obtain a characterization of the 'dynamics' information. The motivation comes from that arrhythmias could be discriminated from the normal heartbeats in terms of both of morphology and dynamics. A support vector machine (SVM) is developed to classify 15 classes of heartbeats. The decisions from the two ECG leads are fused to make the final decision so as to improve the classification confidence.

II. Theoretical Framework

A. Wavelets and Multi-Resolution Analysis

Since we propose to use wavelet transform for extracting features, we provide a short summary of the relevant material. For any function $f(x) \in L^2(R)$, wavelet function $\Psi(x)$ and the corresponding scaling function $\varphi(x)$, we can define its wavelet series expansion as

$$f(x) = \sum_k c_{j_0}(k)\varphi_{j_0,k}(x) + \sum_{j=j_0}^{\infty}\sum_k d_j(k)\Psi_{j,k}(x) \qquad (1)$$

where j_0 represents an arbitrary starting scale, j is the index of any scale higher than j_0. $c_{j_0}(k)$ and $d_j(k)$ are referred to as approximation coefficients and detail coefficients. The first sum provides a coarse approximation of $f(x)$ at the scale j_0 ; the second sum contains the details of the signal. For each higher scale $j \geq j_0$ in the second sum, a finer resolution is added to the approximation to provide increased detail.

The multi-resolution analysis nature of discrete wavelet transform (DWT) is suitable for characterizing the energy distribution of non-stationary signals, such as ECG signals. We choose Daubechies wavelets of order 8 due to their similarity with most characteristic QRS waveform that contains the most significant information in one heart cycle. The sampling frequency of MIT-BIH Arrhythmias Database is 360 Hz, indicating that the highest possible frequency presented in the ECG signals is 180 Hz. It has been shown that the bandwidth of ECG signals is 0.5-40 Hz [8]. After applying the 4-level wavelet decomposition, this frequency range corresponds to the detail coefficients at level 3 (D3) and 4 (D4) as well as the approxima coefficients at level 4 (A4), which are chosen as the wavelet features to characterize the shape of the heartbeat waveform.

B. Independent Component Analysis

Another tool used for feature extraction is Independent Component Analysis (ICA). ICA is a method originally proposed to solve the blind source separation (BSS) problem, which aims to separate the mixed signals into a set of underlying independent sources given very little, if any, prior information [9].

ICA assumes that underlying sources are statistically independent and non-Gaussian. ICA can be formulated as

$$x = A \cdot s \qquad (2)$$

where x represents the N observed signals, A is referred as the mixture matrix and s contains the M sources. Each observation is modeled as a linear combination of underlying sources. The underlying independent components are estimated via maximizing some metric quantifying the statistical independence.

The use of ICA for ECG signal has been justified in [10] and [11]: atrial activity (AA) and ventricular activity (VA) are generated by independent physiological sources; both of them exhibit non-Gaussian distribution given the sub-Gaussian statistical character of AA as opposed to the super-Gaussian behavior of VA. Following previous literature [7], 18 ICA bases are trained using approximately 10,000 normal heartbeats.

C. RR Interval Features

Features such as wavelet features and ICA features are morphological features since they are extracted from a waveform of a single heartbeat. We are motivated by the fact that arrhythmias are different from the normal heartbeats in terms of both morphology and dynamics. Four dynamic features are introduced to characterize the rhythm near a heartbeat, namely, previous RR interval, post RR interval, local RR interval and average RR interval, following previous literature [4]. The previous RR interval is defined as the interval between the given heartbeat and the previous heartbeat while the post RR interval refers to the interval between the given beat and the following beat. Local RR interval is defined as the average of ten RR intervals around the given beat. Each record is divided into six 5-min intervals and the average RR interval is determined by averaging the RR intervals in the corresponding 5-min interval (Figure 1).

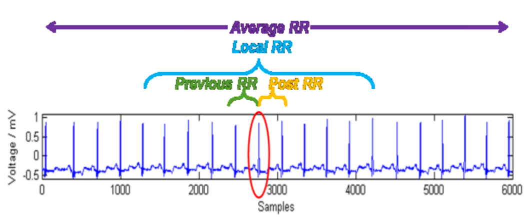

Figure 1: the previous RR, post RR, local RR and average RR features for one particular heartbeat

III. Database & Methodology

A. MIT-BIH Arrhythmias Database

The MIT-BIH Arrhythmias Database is regarded as the benchmark database in the topic of cardiac arrhythmias detection and classification. However, none of previous works [3]-[7] seem to have used the entire database. In our experiments, all 48 half-hour records are utilized and almost all heartbeats are extracted corresponding to the normal and other 14 classes of arrhythmias[1]. There is an annotation file associated with each record, indicating the location of each R peak and the type of each heartbeat. Each record includes an upper lead signal and a lower lead signal. As described in the database directory, normal heartbeats are usually more prominent in the upper signal while the ectopic beats are more visible in the lower one. It suggests that we might find some information from the lower lead to supplement the upper lead, though the two signals are highly correlated.

B. Data Preprocessing

The data was at first preprocessed to correct the baseline wander and then filtered with a band-pass filter [12] to remove high-freq and low-freq artifacts. The data was subsequently segmented based on annotation information. A sample size of 300 (0.83 seconds) was used, consisting of 100 samples before the R peak and 200 samples after the R peak. This appears to be sufficient to capture most if not all of the information from a particular heart cycle. A total of 110076 heartbeats are extracted, corresponding to 15 heartbeat categories. We divide the data by randomly picking up 24131 beats for training and the number of each heartbeat category in training data are present in Table 1. The rest heartbeats are used for evaluation.

C. Feature Extraction

Daubechies wavelet of order 8 is chosen for wavelet analysis. Wavelets coefficients of D3, D4 and A4 are extracted with a total number of 118 wavelet features for each heartbeat segment. In addition, 9753 Normal beats are used to train 18 ICA bases using the FastICA [13] algorithm, which are used to extract 18 ICA coefficients for each heartbeat. The two types of morphological features are concatenated and principal component analysis (PCA) is employed to reduce the feature dimensionality to 26, which accounts for 99.32% variance. The four RR interval dynamics features are concatenated to the 26 morphological features. PCA is introduced before the concatenation since the number of morphological features (i.e., 136) is much larger than the one of dynamic features (i.e., 4) and these

[1] (1) 110,076 beat instances are extracted while 48 instances are abandoned at the beginning and the end of each record which are not qualified because of the length requirement that there are 100 samples before the R peak and 200 samples after the R peak for each segment;
(2) We do not include the heartbeat class of "Q" corresponding to unclassifiable heartbeat as well as the class of "S" which represents supraventricular premature beat as there are only 2 beat instances of these in the whole database.

two sets of features focus on different characteristics (i.e. inside the heartbeat and between the heartbeats).

D. SVM Classification

A support vector machine (SVM) with a Gaussian radial basis function (RBF) kernel was chosen as the classification tool. At first, model parameters (i.e., the penalty parameter for the SVM and the width parameter for the kernel) were selected using the 10-fold cross validation in a grid search scheme. Afterwards, a SVM classifier was trained based on the training data. The trained SVM classifier was then utilized to evaluate testing data. All SVM algorithms are implemented using the well-known LIBSVM [14] package.

E. Multi-lead Fusion

The same procedure was separately applied to the data from both leads (namely, the upper lead and the lower lead) so that there are two classification results for each heartbeat. There are two different approaches to fuse the results from two leads. The first is to reject the heartbeats for which the two leads give different classification results (i.e., no classification decision is made). Another possibility is to use the LIBSVM [14] package for estimating the probability of each class producing the given observation. For those inconsistently classified heartbeats, the classification result which has higher probability (i.e. classification confidence) is picked up.

IV. Results and Discussion

In separate experiments on individual leads, 85300 beats out of 85945 test heartbeats are correctly classified based on the upper lead signal with an average accuracy of 99.25%. The performance of the test based on lower lead is slightly worse but still close, with 85158 heartbeats got correctly classified as an average accuracy of 99.08%. It appears that the performance of both leads are close, consistent with the intuition that the signals of two leads are highly correlated as they are two observations of the same physiological activity. On the other hand, the performance on the upper lead is slightly better than the lower lead. In a real time application, it might be adequate to use only the upper lead, given its slightly superior performance, to halve the computational cost of the algorithm while still providing sufficient accuracy. It is worth noting that the single-lead performance has been shown better than that of any previous work [3]-[7], even before the information fusion of two ECG leads.

As mentioned in section III, two different schemes have been investigated for the fusion of the classification results from two ECG leads. The first scheme is to reject inconsistently classified heartbeats. By excluding the 1.44% (1238) inconsistently classified beats, we obtain the final arrhythmias detection accuracy as 99.93% (84644/84707), i.e. normal vs. arrhythmias, and final heartbeat classification accuracy as 99.91% (84630/84707), i.e. between 15 classes of heartbeats. It is believed that the information of inconsistent classified heartbeats is not reliable enough for the classifier to make correct decisions and the exclusion of a small portion of 'unreliable' information is not expected to have any fundamental impact on the arrhythmia detection and the subject diagnosis scenario. The second fusion method is to solve inconsistencies by choosing the classification result with higher classification probability, yielding an average classification accuracy of 99.66%. In this case, the classification confidence is boosted and none of heartbeats is rejected. The performances of two different fusion schemes are summarized in Table 1 and Table 2.

Table 1: The summary of performance on each heartbeat category: total number, training portion, number of rejections, sensitivity 1 and specificity 1 (if the fusion scheme 1 is used), sensitivity 2 and specificity 2 (if the fusion scheme 2 is used)

Heartbeat Type	Type Annotation	Total Number	Training Ratio	Number of rejected beats	Final Sensitivity1	Final Specificity1	Final Specificity2	Final Specificity2
Normal Beat	N	75017	13%	789	99.95%	99.96%	99.84%	99.49%
Left Bundle Branch Block	L	8072	40%	23	100%	99.99%	99.94%	99.99%
Right Bundle Branch Block	R	7255	40%	12	99.99%	100%	99.84%	99.99%
Aterial Premature Contraction	A	2546	40%	93	99.65%	99.97%	96.81%	99.95%
Premature Ventricular Contraction	V	7129	40%	228	99.26%	99.99%	98.24%	99.83%
Paced Beat	P	7024	40%	4	100%	99.99%	99.88%	99.99%
Aberrated Atrial Premature Beat	a	150	50%	8	92.86%	99.99%	86.30%	99.99%
Ventricular Flutter Wave	!	472	60%	21	100%	99.99%	100%	99.99%
Fusion of Ventricular and Normal Beat	F	802	50%	22	99.73%	99.99%	95.60%	99.96%
Blocked Atrial Premature Beat	x	193	50%	6	100%	99.99%	98.89%	99.99%
Nodal (junctional) Escape Beat	j	229	50%	13	100%	100%	90.60%	99.99%
Fusion of Paced and Normal Beat	f	982	50%	12	100%	99.99%	98.57%	99.99%
Ventricular Escape Beat	E	106	50%	1	100%	99.99%	100%	99.99%
Nodal (junctional) Premature Beat	J	83	50%	4	97.06%	99.99%	92.11%	99.99%
Atrial Escape Beat	e	16	50%	2	100%	100%	85.71%	99.99%
Total	15	110076	22%	1238	-	-	-	-

	N	L	R	A	V	P	a	!	F	x	j	f	E	J	e	∑
N	**64447**	0	0	5	23	0	0	0	0	0	0	0	0	0	0	**64475**
L	0	**4819**	0	0	1	0	0	0	0	0	0	0	0	0	0	**4820**
R	0	0	**4341**	0	0	0	0	0	0	0	0	0	0	0	0	**4341**
A	18	0	1	**1412**	3	0	0	0	0	0	0	0	0	0	0	**1434**
V	6	0	0	0	**4043**	0	0	0	0	0	0	0	0	0	0	**4049**
P	1	0	0	0	0	**4209**	0	0	0	0	0	0	0	0	0	**4210**
a	2	0	0	0	0	0	**65**	0	0	0	0	0	0	0	0	**67**
!	0	0	0	0	0	0	5	**162**	0	0	0	0	0	0	0	**167**
F	2	0	0	0	0	0	0	0	**376**	0	0	0	0	1	0	**379**
x	0	0	0	0	3	0	0	0	1	**86**	0	0	0	0	0	**90**
j	0	0	0	0	0	0	0	0	0	0	**101**	0	0	0	0	**101**
f	1	0	0	0	0	0	0	0	0	0	0	**478**	0	0	0	**479**
E	1	0	0	0	0	0	0	0	0	0	0	0	**51**	0	0	**52**
J	4	0	0	0	0	0	0	0	0	0	0	0	0	**33**	0	**37**
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**6**	**6**
∑	**64482**	**4819**	**4342**	**1417**	**4073**	**4209**	**70**	**162**	**377**	**86**	**101**	**478**	**51**	**34**	**6**	**84707**

(a)

	N	L	R	A	V	P	a	!	F	x	j	f	E	J	e	∑
N	**65158**	0	2	38	43	0	1	0	8	0	11	2	0	0	1	**65264**
L	1	**4838**	1	0	3	0	0	0	0	0	0	0	0	0	0	**4843**
R	2	0	**4345**	3	2	0	0	0	0	0	0	0	0	1	0	**4353**
A	32	0	1	**1488**	5	0	1	0	0	0	0	0	0	0	0	**1527**
V	26	2	0	3	**4236**	0	1	0	8	0	0	1	0	0	0	**4277**
P	1	0	0	0	1	**4208**	0	0	0	0	0	4	0	0	0	**4214**
a	6	1	0	1	3	0	**63**	0	0	1	0	0	0	0	0	**75**
!	0	0	0	1	2	0	6	**179**	0	0	0	0	0	0	0	**188**
F	18	0	1	0	12	0	0	0	**369**	0	0	0	0	1	0	**401**
x	0	0	0	2	3	0	1	0	1	**89**	0	0	0	0	0	**96**
j	5	0	1	1	0	0	0	0	0	0	**106**	0	0	1	0	**114**
f	3	0	0	0	2	5	0	0	0	0	0	**481**	0	0	0	**491**
E	1	0	0	0	0	0	0	0	0	0	0	0	**52**	0	0	**53**
J	5	0	1	0	0	0	0	0	0	0	0	0	0	**35**	0	**41**
e	2	0	0	0	0	0	0	0	0	0	0	0	0	0	**6**	**8**
∑	**65260**	**4841**	**4352**	**1537**	**4312**	**4213**	**73**	**179**	**386**	**90**	**117**	**488**	**52**	**38**	**7**	**85945**

(b)

Table 2: (a) Final confusion matrix using the fusion scheme 1; (b) Final confusion matrix using the fusion scheme 2

Table 3 makes a comparison between previous work and our proposed method, which clearly shows improvement over previous published results [3]-[7].

Table 3: The comparison of the proposed method with previous work [3]-[7]

Work Reference	Types	Accuracy	Data Size	Features	Classifier
Prasad	13	96.77%	105,423	WT	NN
Philip	5	96.40%	109,492	Waveform	LD
Rodriguez	14	96.13%	85263	Waveform	DT
Ge	6	97.7%	1,200	AR	SVM
Jiang	14	98.65%	103,898	WT/ICA	SVM
Proposed Method	**15**	**99.91% /99.66%**	**108,838 /110,076**	**WT/ICA/ Interval**	**SVM**

V. Conclusions

We conclude that the proposed method can reliably discriminate between 15 categories of heartbeats based on ICA features, wavelet features and RR interval features; it has been validated over the entire MIT-BIH Arrhythmias Database and it yields an average accuracy of 99.91% or 99.66%, depending on which fusion method is utilized. To the best of our knowledge, either result is better than any others in the literature.

In this paper, we focused on the arrhythmia classification problem and utilized the annotation information to segment ECG signals and obtain the RR interval features; however, in the future work, the design of an effective R-peak detector is important since it has direct impact on the dynamic features.

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References

[1] MIT-BIH Arrhythmia Database (Cited in May 2010): http://physionet.org/physiobank/database/mitdb/

[2] K. Robert *et al.*, *Basis and Treatment of Cardiac Arrhythmias*, 1st ed., Springer, New York, 2006.

[3] G.K. Prasad *et al.*, "Classification of ECG arrhythmias using multi-resolution analysis and neural networks," *IEEE TENCON* 2003.

[4] D.C. Philip *et al.*, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1196-1206, 2004.

[5] J. Rodriguez *et al.*, "Real-time classification of ECGs on a PDA", *IEEE Trans. Info. Tech. in Biomed.*, vol. 9, no. 1, pp. 23-34, 2005.

[6] D.F. Ge *et al.*, “Cardiac arrhythmia classification using autoregressive modeling”, *Biomed. Eng. Online*, vol. 1, no. 5, pp. 1-12, 2002.

[7] X. Jiang *et al.*, "ECG Arrhythmias Recognition System Based on Independent Component Analysis Feature Extraction," *IEEE TENCON* 2006.

[8] N.V. Thakor *et al.*, "Estimation of QRS Complex Power Spectra for Design of a QRS Filter," *IEEE Trans. Biomed. Eng.*, vol. 31, no. 11, pp. 702-706, 1984.

[9] A. Hyvärinen *et al.*, *Independent Component Analysis*, Wiley Interscience, 2001.

[10] A. Bollmann *et al.*, “Frequency analysis of human atrial fibrillation using the surface electrocardiogram and its response to ibutilide,” *Amer. J. Cardiol.,* vol. 81, no. 12, pp. 1439–1445, 1998.

[11] J.J. Rieta *et al.*, "Atrial activity extraction for atrial fibrillation analysis using blind source separation," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 7, pp. 1176-1186, 2004.

[12] J. Pan *et al.*, "A Real-Time QRS Detection Algorithm", *IEEE Trans. Biomed. Eng.*, vol. 32, no. 3, pp. 230-236, 1985

[13] A. Hyvärinen *et al.*, “Fast and Robust Fixed-Point Algorithms for Independent Component Analysis”, *IEEE Trans. Neural Networks*, vol. 10, no. 3, pp. 626-634, 1999. Software available at http://www.cis.hut.fi/projects/ica/fastica/.

[14] C.C. Chang *et al.*, “LIBSVM: a library for support vector machines”, 2001. Software available at http://www.csie.ntu. edu.tw/~cjlin/libsvm.