Subband Higher-order Statistics and Cross-correlation for Heartbeat Type Recognition Based on Two-lead Electrocardiogram

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***Abstract*—Regular electrocardiogram beat classification system usually based on single lead ECG signal. This study designated to add a second lead of ECG signal to the system and apply higher-order statistics and inter-lead cross-correlation features to study the influence of the second lead to the recognition rates and noise-tolerance of the classifier. Discrete wavelet transformation is employed to decompose the ECG signals into different subband components and higher order statistics is recruited to characterize the ECG signals as an attempt to elevate the accuracy and noise-resistibility of heartbeat discrimination. A feed-forward back-propagation neural network (FFBNN) is employed as classifier. When compared with the system that uses only one lead, the second lead raises the recognition rate from 97.74% to 98.25%. We also study the ability of the two-lead system in resisting different levels of white Gaussian noise. More than 97.8% accuracy can be retained with the two-lead system even when the SNR decreases to 10 dB.**

I. Introduction

Discrimination of electrocardiogram (ECG) is vital for clinical diagnosis of heart diseases. Many algorithms have been developed to improve the accuracy of ECG beat classification [1-6]. Recently, we have developed an ECG beat classification method, denoted as HOS-DWT-FFBNN [7, 8], which applies discrete wavelet transform (DWT) to decompose the ECG signals into subband components and then uses higher order statistics (HOS) to characterize them. The DWT decomposes a signal into subband components such that valuable features can be uncovered from the otherwise hidden details. On the other hand, the application of HOS to the QRS complexes was shown to be relatively insusceptible to the variation of ECG morphology among different patients [1, 2] and when contaminated with noises. This method has been demonstrated to successfully discriminating pathological heartbeat types under different types of noise contamination.

However, most ECG-based heartbeat recognition system usually makes decision based on single lead signal. This study attempts to investigate the effects of adding a second lead ECG signal to the classifier. It is reasonable to assume that adding information extracted from the second signal may raise the recognition rates of the original system. Moreover, taking into consideration the relationship between the two ECG signals is likely to increase the noise tolerance capability of the system. Therefore, experiments were designed to test the discrimination power and noise tolerance capability of the system when different sets of features were extracted from the two lead signals. The influence of adding a second lead signal to the system and strategies of extracting effective inter-lead information were investigated.

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II. Method

A. Discrete Wavelet Transform

Wavelet transform (WT) is a powerful tool in representing a signal in different translations and scales. As for discrete-time signals, the dyadic discrete wavelet transform (DWT) can be implemented by low-pass and high-pass FIR filters [9, 10]. There are two well-known DWT implementations, namely the Mallat's and the *à trous* schemes. Mallat's scheme has downsamplers following the filters, which removes the redundancy in the filtered signal, yet also reduces the temporal resolution [11]. On the contrary, the *à trous* algorithm reserves the temporal resolution at the expense of larger memories [10]. Since the calculation of HOS requires signals with sufficient length, we employ the *à trous* algorithm in the study.

B. Higher-order Statistics

Higher order statistics has been applied successfully to extract features of the QRS complex for further classification [1]. Efforts have been made to investigate the effect of combining different features with higher order statistics for ECG classification [2, 8]. By using DWT, it becomes possible to apply higher order statistics to subband signals to delineate subtle features embedded in the QRS complex.

Three cumulant functions that characterize the higher order statistics of the signal were adopted in this study. They are defined separately as follows.

$$c_{2x}(\tau) = E[x(n)x(n-\tau)] \tag{1}$$

$$c_{3x}(\tau_1, \tau_2) = E[x(n)x(n-\tau_1)\, x(n-\tau_2)] \tag{2}$$

$$c_{4x}(\tau_1, \tau_2, \tau_3) = E[x(n)x(n-\tau_1)\, x(n-\tau_2)\, x(n-\tau_3)] - c_{2x}(\tau_1)\, c_{2x}(\tau_3-\tau_2) - c_{2x}(\tau_2)\, c_{2x}(\tau_3-\tau_1) - c_{2x}(\tau_3)\, c_{2x}(\tau_2-\tau_1) \tag{3}$$

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To further characterize the relationship between the two-channel ECG signals, we modified the 2nd cumulant function defined for single-channel signal into cross-correlation function of two-channel signals. Given two signals $x(n)$ and $y(n)$, the cross-correlation function of them was defined as

$$cc_{xy}(\tau) = E[x(n)y(n-\tau)] \tag{4}$$

The signals x and y were zero-mean (with mean value subtracted) and then decomposed into six subband contents with five levels of DWT filtering. To eliminate low-frequency baseline wander and high-frequency power line interference, only the three mid-band signals, D3, D4, and D5, were considered. For each single-channel signal, three HOS functions were calculated from each subband components, resulting in totally nine features from each QRS complex. The cross-correlation function between the same subband components of the two signals added three more functions for feature extraction.

C. Feature Extraction

We recruited four sets of cumulant-related features and three RR interval-related features in this study. Denoting the j^{th} order cumulant of the D_i subband as c_{ij}, where $i \in \{3, 4, 5\}$ and $j \in \{2, 3, 4\}$, the features are defined as follows.

(1) Standard Deviation of the Cumulant (*CSD*): The variance of a cumulant represents the energy within the cumulant. With time lag L, the variance of a cumulant is defined as

$$\sigma_{ij} = \sqrt{\frac{1}{2L}\sum_{l=-L}^{L}\left[c_{ij}(l) - \bar{c}_{ij}\right]^2} \tag{5}$$

where $\bar{c}_{ij}$ is the sample mean of the cumulant and l is the time shift ranging from $-L$ to $+L$.

(2) Normalized Summation (*NS*): The normalized summation is defined as the summation of a cumulant divided by the area between the cumulant function and the zero line. For a cumulant c_{ij} the normalized summation NS_{ij} is defined as

$$NS_{ij} = \sum_{l=-L}^{L} c_{ij}(l) \Bigg/ \sum_{l=-L}^{L} \left|c_{ij}(l)\right| \tag{6}$$

which ranges between -1 and +1, depending on the relative allocation of the function in the negative and positive directions.

(3) Number of Zero-Crossings (*NZC*): The number and position of zero-crossing are important in characterizing a signal. We considered the number of zero-crossing in cumulants c_{52}, c_{53}, and c_{54} in the feature vector.

(4) Symmetry (*SYM*): The symmetry of a signal is defined as

$$SYM_{ij} = \sum_{l=1}^{L} \left|c_{ij}(l) - c_{ij}(-l)\right| \Bigg/ \sum_{l=-L}^{L} \left|c_{ij}(l)\right| \tag{7}$$

which equals zero with the 2nd order cummulents, i.e. $j = 2$. Therefore, we considered only the *SYM* of the 3rd and 4th order cumulants.

(5) RR Interval-related Features: The RR interval is defined as the time elapse between two adjacent R peaks. Certain ECG arrhythmias, such as PVC, APB, VEB, and VFW, show shorter or irregular RR intervals. In this study, we employed three RR interval-related features, including the instantaneous RR interval, the ratio between the instantaneous and the previous ones, and the ratio between the pervious and the one before it [8].

The features for the cross-correlation function are defined similarly, except that c_{ij} in eqs. (5), (6) and (7) represents the subband cross-correlation functions of the two signals.

As a result, the feature vector for single channel signal contains 27 cumulant features, including nine *CSDs*, nine *NSs*, three *NZCs*, six *SYMs*, and three RR interval-related features. By adding the 2nd lead to the system, we can certainly calculate its 27 cumulant features. Besides, three CSDs and three NSs are calculated from the cross-correlation functions of the three subband components. Experiments were designed to investigate the roles of different feature sets to the performance of classifier.

D. Normalization

A normalization process is necessary to standardize all the features to the same level. The hyperbolic tangent sigmoid function [8] is used to transform each feature to the same scale with a range of [-1, +1]. The mean and the standard deviation of each component in the feature vectors are calculated from the training dataset and used throughout the experiments.

E. Nonlinear Neural Classifier

Feed-forward backpropagation neural network (FFBNN) was employed as the classifier of the system [12]. The typical structure of a FFBNN classifier consists of three layers, namely input, hidden, and output layers. Hyperbolic tangent sigmoid function is used as the activation function and the weights between layers are modified by propagating the error signals layer by layer backwardly. The number of neurons in the hidden layer was empirically chosen as sixty [8].

III. Experimental Design

A. Database

Twelve records attributed to seven beat types were selected from the MIT/BIH arrhythmia database [13] for analysis. The seven heartbeat types were normal sinus rhythm (NSR), left bundle branch block (LBBB), right bundle branch block (RBBB), premature ventricular contraction (PVC), atrial premature beat (APB), ventricular escape beat (VEB), and ventricular flutter wave (VFW).

These records provide ECG signals acquired from the same two-leads, i.e. Lead II and Lead V1. Moreover, since the method of data sample selection can influent the results of ECG beat classification, we followed the profile suggested by [1] and [8] and extracted multiple beat types from each of the records, resulting in a total of 7187 beats.

B. Experimental Procedure

QRS segments with a length of 64 points centered at R peak (31 points on the left and 32 points on the right) were extracted from the records. The DC value of the non-zero mean QRS segment was subtracted. The DC-free signals were than decomposed into six subband signals by five levels of DWT. In view of its shape similarity to that of regular QRS complexes in ECG, the 'sym6' basis was employed as the mother wavelet [4].

To suppress the influences of different artifacts with white or color spectra, only the three midband components, i.e. D3, D4 and D5, were considered. The higher order statistics were then applied to delineate these components. Twenty seven cumulant features, including nine *CSDs*, nine *NSs*, three *NZCs*, six *SYMs* and three RR interval-related features described previously were exploited to characterize individual lead ECG signals. Three cross-*CSD* and three cross-*NS* features were calculated from the three subband cross-correlation functions.

These features were normalized and a non-linear FFBNN was employed to discriminate the heartbeat types based on half-half two-fold cross-validation method. Since the classification result is affected by initial weights, we repeated each experiment setup for five times and the accuracies were averaged.

B. Feature Sets for Experiments

This study intended to investigate the effects of adding the information of a second lead (lead V1) to the system using only the first lead (lead II) in heartbeat recognition. Cumulant features associated with the first lead and the second lead were first calculated. Features related to the two-lead setting were then calculated from the subband cross-correlation functions. These feature subsets were integrated into three feature sets for experiments.

(1) Feature set 1: Cumulant features associated with the first lead (lead II) + RRI-related features

(2) Feature set 2: Feature set 1 + Cumulant features associated with the second lead (lead V1)

(3) Feature set 3: Feature set 1 + correlation features calculated from the two lead signals

C. Contaminating Noises for Experiments

ECG signals usually suffer from different noise contamination coming from internal and external sources [14, 15]. The presence of noises in ECG signals usually influences the visual interpretation of the ECG and degrades the feature extraction and classification processes in automatic ECG classifiers.

TABLE I. RECOGNITION RATES OF DIFFERENT FEATURE SETS

Features	Set 1 [8]	Set 2	Set 3
Feature No.	30	57	36
NSR	97.83	97.71	98.81
LBBB	98.73	98.92	98.90
RBBB	99.08	99.85	99.76
APB	97.76	98.33	98.43
PVC	93.38	94.72	92.02
VEB	92.31	94.71	95.65
VFW	98.81	98.20	98.82
Accuracy (%)	97.74	98.07	98.17

In this study, experiments were designed to compare the noise-tolerant capability of the single-lead and two-lead system when confronted with different levels of white Gaussian noise. The white Gaussian noise can be expressed as a random process with a zero mean Gaussian distribution. It was practically generated by the Gaussian random generator supported by Matlab® and the variance was adjusted according to specific SNR values designed in different experiment settings.

Different levels of artifacts expressed in signal-to-noise ratio (SNR) were added to the original ECG segments and the classification accuracies in different noisy environments were measured. The methods for generating these artifacts are described as follows.

IV. RESULTS AND DISCUSSIONS

A. Discriminarity of Different Feature Sets

Different feature sets were applied to the classifier and the recognition rates of different experimental setting are summarized in TABLE I for comparison.

Feature set 1 contains the cumulant features calculated from the first lead (lead II) and is the same feature set as applied in [8]. The difference is that the data sampled in the present study were chosen from the twelve records, out of the fifteen records employed in [8], which provide records from the same two leads. The recognition rate is 97.74%. When extracting features independently from the two lead signals, feature set 2 achieved a relatively higher recognition rate of 98.07%. When adding only the six cross-correlation features to feature set 1, feature set 3 further elevates the recognition rate to a higher value of 98.17%.

These observations validate the assumption that adding information from a second lead indeed increases the discrimination power of the system. This raise in discriminarity does not need to include the complete features extracted from the second lead. Adding information from the inter-lead correlation can attain even higher recognition rates. When tested with paired t-test, the recognition rates of feature set 1 and feature set 3 is significantly different with a p value of 0.0234, which is well below 0.05.

B. The Effects of Noise

Experiments were designed to test the noise-tolerant capability of different feature sets to the classifier. Different levels of white Gaussian noises ranging from 10~40 dB in SNR were added to the two-channel signals and their effects were investigated. To high-light the contribution of cross-correlation features, only the features calculated from the first lead (feature set 1) and the combination of feature set 1 and features calculated from the subband cross-correlation functions of the two-lead signals (feature set 3) were considered.

Figure 1 depicts the accuracy changes of the classifier with the two feature sets when the ECG signals were confronted with different levels of white-Gaussian noise. At low levels (20~40 dB) of white Gaussian noise, both feature sets shows rather stable accuracy although feature set 3 shows higher recognition rate. As the noise level increases (SNR decreases), feature set 1, which contains features calculated only from the first lead, demonstrates significant decrease in accuracy while feature set 3, which adds features calculated from the cross-correlation functions of the two-lead setting, shows little influence from the noise. High accuracy of 97.81% is still retained even when the two-lead system is situated in a very noisy environment (SNR = 10 dB).

These observations validate the assumption that taking into account the inter-lead information indeed increases the noise tolerance capability of the system. This raise in noise tolerance becomes more evident at higher level of noises. When compared with the original system based on single lead ECG signal, adding only six cross-correlation features can retain the system at significantly higher level of accuracy even when confronted with 10 dB noises, i.e. noise is at the same level as the signal.

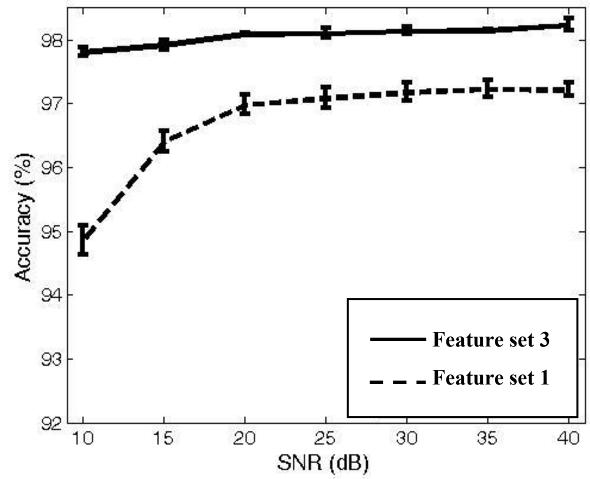

Figure 1. Influence of white Gaussian noise.

V. CONCLUSION

This study investigates the impact of adding a second lead ECG signal to an ECG beat recognition based on one lead. The results demonstrated raise in recognition rates when extra information from the second lead was added. The increase in discriminarity did not require including the complete features extracted from the second lead. Features calculated from the cross- correlation functions of the two lead signals contributed significantly to the enhancement of recognition rates. Moreover, the noise-tolerance of the system was also significantly enhanced by the cross-correlation features. The recognition rates remained stable even when confronted with as high as 10 dB (SNR) white Gaussian noises.

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