33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Application of Higher Order Cumulants to ECG Signals for the Cardiac Health Diagnosis

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Abstract—**Electrocardiogram (ECG) is the P-QRS-T wave which indicates the electrical activity of the heart. The subtle changes in the amplitude and duration of the ECG signal depict the cardiac abnormality. It is very difficult to decipher these minute changes by the naked eye. Hence, a computer-aided diagnosis system will help the physicians to monitor the cardiac health. The ECG is a nonlinear and non-stationary signal. Hence, the hidden information in the ECG signal can be extracted using nonlinear method. In this paper, we have automatically classified normal and abnormal beats using higher order spectra (HOS) cumulants of wavelet packet decomposition (WPD). The abnormal beats are ventricular premature contractions (VPC) and Atrial premature contractions (APC). These HOS cumulant features of the WPD are subjected to principal component analysis (PCA) to reduce the number of features to five. Finally these features were fed to the support vector machine (SVM) with kernel functions for automatic classification. In our work, we have obtained the highest accuracy of 98.4% sensitivity and specificity of 98.9% and 98.0% respectively with radial basis function (RBF) kernel function and Meyer's wavelet (dmey) function. Our system is ready clinically to run on large amount of data sets.**

I. INTRODUCTION

Nowadays cardiovascular disease (CVD) is one of the most common causes of death. 82% of CVD deaths occur in developing countries and takes place equally in men and women [1]. Arrhythmias commonly occur due to cardiac rhythm disturbances. These cardiac arrhythmias can be non-invasively diagnosed using ECG signal. Computer-aided cardiac arrhythmia detection and classification can play a significant role in the management of cardiovascular diseases [2].

VPCs were detected in Holter monitoring ECG data using wavelet transform features and fuzzy neural network to report 99.7% accuracy [3]. APCs were detected on small ECG datasets using autoregressive (AR) coefficients as features and generalized linear model classifier [4]. They reported 96.4% sensitivity for APC detection.

Generally discrete wavelet transform domain features can represent features better than the time domain and frequency domain [5]. Different ranges of higher order spectra features were proposed for various cardiac abnormalities using heart rate signals [6]. They have also proposed unique bispectrum and bicoherence plots for various cardiac classes. The nonlinear and dynamic nature of the higher order cumulant features helps to extract the subtle changes in the ECG. These features capture the information present in the ECG signals beyond conventional approaches which use only first two order statistics.

Transform domain features provide higher discrimination between different classes of data (normal and abnormal). It is shown that DWT features have higher discrimination ability validated by the statistical significance test and subsequent high classification accuracy [5].

Since ECG is a non linear and non stationary signal, the non linear features may represent the signal in a more meaningful sense. Therefore if we use non linear features such as higher order cumulants, the representation would be more appropriate and should provide higher discrimination to result higher accuracy in classification.

In this paper we are proposing a discrete wavelet transform (DWT) domain cumulants computation approach for pattern classification of normal and abnormal ECG signals. The layout of the paper is as follows:

Section 2 provides materials and methods, section 3 explains the results of work and results are discussed in section 4. Finally the paper concludesin section 5.

II. MATERIALS AND METHODS

Figure 1 shows the proposed system used for the automated diagnosis of normal and abnormal ECG beat. The working of each block is explained in the following sections.

In this work, we have used MIT BIH arrhythmia database [7] for the analysis.We have used 606 abnormal (ventricular premature contractions (VPC) and atrial premature contractions (APC)) beats and 641 normal beats. The arrhythmia beats consist of both 298 APC and 308 VPC beats.

A. QRS Complex Extraction

The QRS complex is the most important peak in the ECG, in view of its generation and ease in its detection [8]. This peak serves as the basis for ECG registration [9]. Detection of QRS complex is the first step in most of the automated ECG analysis systems. We have detected the QRS complex using Pan and Tompkins method involving derivatives, moving average filters, second derivative, summing and threshold operations. Derivatives provide slope information, whereas moving average filters remove high frequency noise. Once the QRS complex is detected, the ECG is segmented around R peak such that 99 samples before R peak, 100 samples

Manuscript received June 20, 2011. This work was supported in part by CSIR, Govt of India, India.

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978-1-4244-4122-8/11/$26.00 ©2011 IEEE

after R peak and the R peak itself are chosen to form normal and arrhythmia group segments.

B. Wavelet Packet Decomposition

Since Fourier transform provides high frequency resolution and no time resolution, there is a need to decompose the signal with varied time and frequency resolutions to capture the information present in the signal at different scales. Wavelet transform is one kind of time frequency representation which can provide both time and frequency resolutions aiding to multi resolution analysis [10]. Wavelet decomposition of a signal involves translation and dilation of a basic wave shape, called mother wavelet, whose translates provide the wavelet coefficients at a given scale, the dilation of it provide the coefficients at other scales.

If $\psi(t)$ is the mother wavelet, the basis function at scale a and translation b is given by,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{1}$$

The inner product of the basis function at different scales and translates with the signal provide the full spectrum of wavelet coefficients and this transform is continuous wavelet transform (CWT).

Discrete wavelet transform (DWT) is sampled on a dyadic grid and is given by,

$$\psi_{m\,n}(t) = 2^{-m/2}\psi\left(2^{-m}t-n\right) \tag{2}$$

where m and n are called discrete dilation and translation parameters. A given signal is decomposed using DWT into approximation (low frequency content) and detail (high frequency content) coefficients at first level. The approximation coefficients are further decomposed to obtain the next level approximation and detail coefficients to provide DWT representation at a higher level of decomposition. The detail coefficients are not decomposed further in DWT representation.

In wavelet packet decomposition, both approximation and detail coefficients are further decomposed into various nodes as shown in Fig. 2. The first level detail coefficients D_1 are decomposed further into AD_2 and DD_2. The process is continued further at various levels of decomposition. In this study, up to 4 levels of decomposition is used (In Fig. 2 only first three levels of decomposition are shown).

C. Higher Order Cumulants Computation

The first and second order statistics have gained significant importance in bio-signal processing field. For nonlinear signals first two order statistics are not sufficient for representing it. Hence third and fourth order statistics are used in this analysis.

The nth order moment can be calculated as the expectation over the process multiplied by lagged versions of itself as,

$$m_1^X = E\left[X(n)\right]$$
$$m_2^X(i) = E\left[X(n)X(n+i)\right]$$
$$m_3^X(i,j) = E\left[X(n)X(n+i)X(n+j)\right] \tag{3}$$
$$m_4^X(i,j,k) = E\left[X(n)X(n+i)X(n+j)X(n+k)\right]$$

where m_1^X, m_2^X, m_3^X and m_4^X are the first four moments. Using the moments, the cumulants can be computed as non linear combinations as,

$$C_1^X = m_1^X$$
$$C_2^X = m_2^X(i)$$
$$C_3^X = m_3^X(i,j) \tag{4}$$
$$C_4^X(i,j,k) = m_4^X(i,j,k) - m_2^X(i)m_2^X(j-k) - m_2^X(k-i) - m_2^X(k)m_2^X(i-j)$$

where C_1^X, C_2^X, C_3^X and C_4^X are the first four order cumulants. Here $X(n)$ is assumed to be zero mean process.

D. Principal Component Analysis (PCA)

The PCA is performed on the three cumulant features obtained at every first eight nodes at the 4th level of decomposition of the wavelet tree. PCA consists of first computation of data covariance matrix. Then the covariance matrix is decomposed using eigen value decomposition to obtain eigen values and eigen vectors. The eigen vectors are sorted in the descending order of eigen values. Finally the original data is projected in the direction of these sorted eigen vectors. The first few components consist of highest variability present in the data and rest will contain less. Hence only first few components are chosen such that they contain 99% data variability.

E. SVM classifier

SVM is a single layered, nonlinear network having generalization ability in the sense that it can classify the datasets which are not there in the training set more accurately [11]. In this classifier the distance between the patterns in each group to the class separation boundary is simultaneously maximized. Before maximizing the distance generally the features are mapped into a high dimensional kernel space using kernel transformation. Generally polynomial, quadratic, and radial basis function kernels are used. In this study linear, polynomial order 2, polynomial order 3 and RBF kernels are used for kernel transformation.

The k fold cross validation is used, where the dataset is divided into three non overlapping subsets, first two subsets are used for training the classifier, and the rest one subset is used for testing the classifier. The process is repeated two more times such that every subset is chosen for testing. Finally the average classification accuracy is computed as the average over the three folds. The advantage of this method is that the bias in choosing training and testing sets is removed.

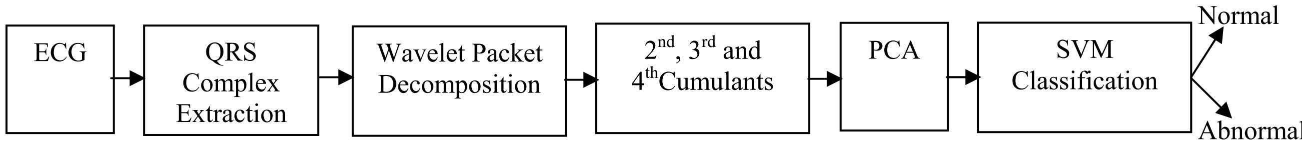

Fig. 1: Block diagram of the proposed system

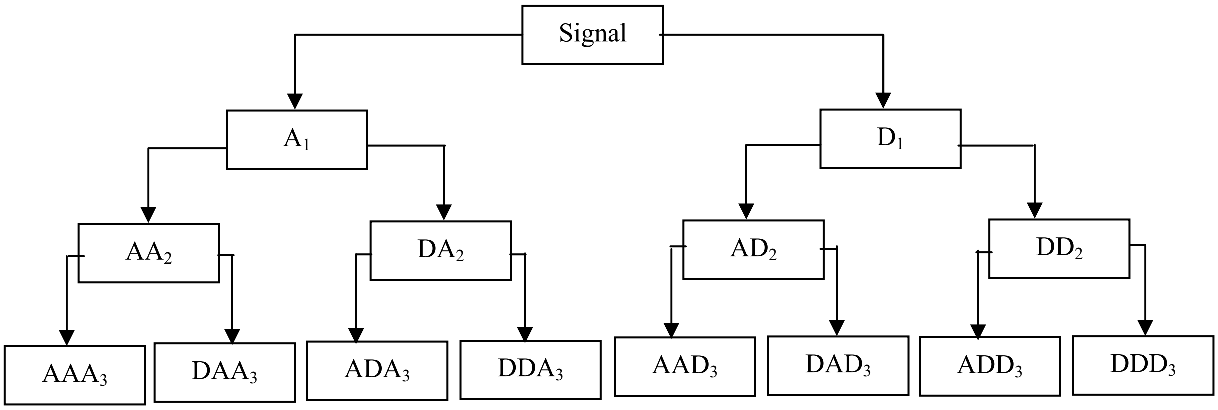

Fig. 2: Wavelet packet decomposition

III. Results

The ECG data were extracted from MIT BIH arrhythmia database. Then the QRS peak was detected using Pan Tompkins algorithm. After the QRS complex detection, the ECG is segmented into 200 sample window for subsequent wavelet packet decomposition. We have performed the WPD using 56 basis functions. They are Haar, Daubechies of order 2 to 10, Symlets of order 1 to 10, Coiflets of order 1 to 5, biorthogonal (bior 1.1, bior 1.3, bior 1.5, bior 2.2, bior 2.4, bior 2.6, bior 2.8, bior 3.1, bior 3.3, bior 3.5, bior3.7, bior 3.9, bior 4.4, bior 5.5, bior 6.8), reverse biorthogonal (rbio 1.1, rbio 1.3, rbio 1.5, rbio 2.2, rbio 2.4, rbio 2.6, rbio 2.8, rbio 3.1, rbio3.3, rbio 3.5, rbio3.7, rbio 3.9, rbio 4.4, rbio 5.5, rbio 6.8) and finite impulse response (FIR) based approximation of Meyer wavelet (dmey). The wavelet coefficients at the first eight nodes at fourth level of decomposition were computed. The 2^{nd}, 3^{rd} and 4^{th}cumulants of DWT coefficients at the first eight nodes were computed and used as features for our further study. In total there were 24 features from 3 cumulants at eight nodes. These 24 features were compressed using PCA into 5 features such that 99.95% variability was preserved. Table 1 shows the features extracted from the dmey wavelet function (after PCA). The eigen value profile during PCA is shown in Fig. 3(a). The three-fold cross validation is used for choosing training and testing sets. It was found that dmey wavelet provide the highest accuracy. The final 5 features are classified using SVM with various kernel functions including linear, polynomial order 2 and 3 and RBF. The SVM classification with RBF kernel performed better than the other kernel functions (Fig. 3(b)) along with the class separating hyper-plane for dmey wavelet. The average performance of classification over three folds is tabulated in Table 2. The performance of the SVM classifier for various kernel functions was evaluated using receiver operating characteristics (ROC) curve (as shown in Fig.4). It can be seen from the figure that, RBF kernel classification using dmey wavelet performed better than the rest with Area under ROC curve (AUC) for RBF kernels higher (0.983) as tabulated in Table 2.

IV. Discussion

In this work, the features of the ECG beat were extracted using HOS cumulants method in the DWT domain. We have selected dmey wavelet function from 56 wavelet basis functions as it gave the maximum classification accuracy compared to the other wavelet functions.

It can be seen from our results that, our proposed method is able to classify the unknown class with accuracy, sensitivity and specificity of more than 96% for all kernel functions of the SVM classifier. However, RBF kernel performed better than the rest.

Hu et al. [12] proposed mixture of experts approach for classification of 4 beat types provided by AAMI recommended practice. As per AAMI recommendations 4 records containing paced beats and 11 records having no VPCs are excluded. They reported 94% accuracy in classification. They used principal components of QRS morphology features along with the RR interval and QRS interval information.

Sayadi*et al.* [13] modeled the ECG wave as a combination of finite characteristic waveforms, each of which is represented by the sum of Gaussian kernels. Three class classification problems of normal, VPC and other beats is performed using Bayesian filtering. They reported 99.1% accuracy which is a improvement over the previous literatures.

The performance of the proposed method can be tested using other data compression methods like independent component analysis (ICA) and linear discriminant analysis (LDA) along with PCA to select the best features for the SVM classifiers. . The performance can be tested using other classifiers also and with more number of ECG samples. Our proposed method can be extended for normal, abnormal and life threatening classes. It can be used in intensive care units (ICU). We feel that, the system is easy to use and can be used as an adjunct tool for the physicians to cross check their diagnosis. It may be used to detect the efficacy of the cardiac drugs.

V. Conclusion

Our proposed method provides convincing results in the diagnosis of normal and abnormal ECG beats. We have obtained the highest accuracy of 98.4%, sensitivity and specificity of 98.9% and 98.0% respectively with radial basis function (RBF) kernel function and Meyer's wavelet (dmey) function. The performance of the system can be improved with more diverse data and better features. In future one can use other time frequency representations like Wiegner Ville distributions etc. for energy compaction instead of wavelet transform.

Table 1: Summary statistics of features

Feature Index	Eigen value	Normal	Arrhythmia	*p*-value
1	0.4116	0.0314±0.0168	0.0843±0.0848	0.0000
2	0.0379	0.0110±0.0064	0.0017±0.0356	0.0000
3	0.0055	0.0002±0.0061	-0.0018±0.0129	0.0042
4	0.0036	0.0060±0.0039	-0.0042±0.0082	0.0000
5	0.0011	0.0034±0.0033	-0.00003±0.0040	0.0000

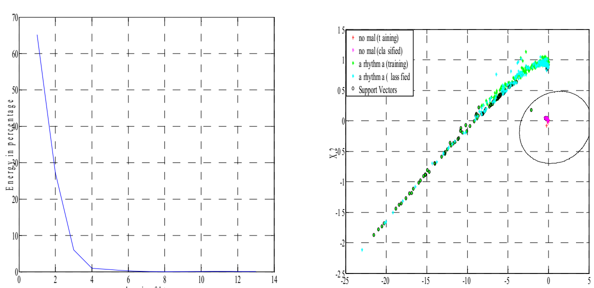

Fig. 3: (a) The eigen value profile of principal components of the features (b) SVM with RBF kernel classification of compressed features

Table 2: Accuracy, sensitivity, specificity, positive predictive value (PPV) and AUC for the SVM classifier with dmey features.

SVM kernel function	Sensitivity (%)	Specificity (%)	Accuracy (%)	PPV (%)	AUC
Linear	97 12	94.38	95.75	94.55	0.95
Polynomial order 2	97.48	96.25	96.87	96.41	0.96
Polynomial order 3	97.79	96.26	97.03	96.41	0.97
RBF kernel	**98.90**	**98.04**	**98.48**	**98.13**	**0.98**

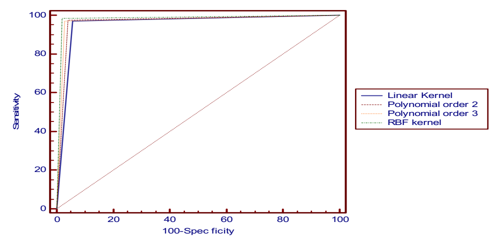

Fig. 4: Receiver operating characteristics (ROC) for SVM classification with various kernels for dmey features

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