Classification of Premature Ventricular Contraction based on Discrete Wavelet Transform for Real Time Applications

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Abstract — Develop of wearable cardiac monitors is becoming an important field of research because Cardiovascular disease is the leading cause of morbidity and mortality in the world. Real time arrhythmias detection algorithms are necessary to improve this kind of devices. This article presents a premature ventricular contraction detection method based on Discrete Wavelet Transform for preprocessing, segmentation and feature extraction. Discrete Wavelet Transform (DWT) is used to perform baseline wander and powerline noise reduction algorithm. Three different feature spaces based on wavelet coefficients are tested. Principal Component Analysis (PCA) is applied to reduce dimension into a lower feature space. K Nearest Neighbor (KNN) and Support Vector Machine (SVM) are developed and compared in terms of both accuracy and computational cost. Specificity of 97.18% and sensibility of 96.47% with a prediction time of 0.47ms are accomplished. Computational burden is measured and compared with other methods to ensure that the developed method can be implemented in real time.

Keywords —Arrhythmia, Premature Ventricular Contraction, Discrete Wavelet Transform, KNN, SVM.

I. INTRODUCTION

Cardiovascular disease is the leading cause of morbidity and mortality in the world, while coronary artery disease remains the leading cause of death [1]. Cardiac arrhythmias are a consequence of the cardiovascular disease; ventricular tachyarrhythmias have a greater risk since they can lead to cardiac arrest or sudden death. In patients with cardiovascular risk, it is necessary to have a constant monitoring of cardiac electrical activity to detect the onset of fatal arrhythmias and to give time to the patient and the medical staff to take measures that may lifesaving.

Diagnosis of cardiac arrhythmias is performed through Electrocardiogram (ECG), a noninvasive method that allows biopotential acquisition, which reflects electrical events at the cellular level [2].

Development of algorithms for ECG signal processing requires three stages: preprocessing, feature extraction and classification. Techniques for ECG signal preprocessing are addressed to four key problems: Remove baseline artifacts, eliminate high frequency noise, remove power line interference and reduce noise with spectral components in the same bandwidth of ECG signals, such as white noise or thermal noise.

In this regard, the advantage of DWT to eliminate distortions from ECG signals is that it can remove noise from the same ECG frequency band [3]. Likewise, the DWT has been widely used to extract the baseline artifacts [4].

For removing the power line noise, elaborated techniques based on the estimation of 60Hz interference have been proposed to avoid suppression of informative ECG spectral components. Particularly, in [5], an adaptive filtering method is discussed that extracts the sinusoidal interference from the ECG signal. In [6], a technique based on the Kalman filter is developed to estimate the interference signal. The proposed method considers separate models for ECG signal and interference from the power line.

The feature extraction stage for beat classification is based mainly on the detection of the QRS complex and R wave which defines a window for processing. To detect QRS complex, Dib et al. also implement a technique based on Discrete Wavelet Transform using a mother Wavelet DB4 given the high correlation of this Wavelet with the QRS complex. [7].

Concerning the classification stage, Ince et al. use a feed-forward artificial neural network for the detection of Premature Ventricular Contractions (PVC); they use the result of PCA technique applied of discrete Wavelet transform coefficients [8]. Rua et al. implement an ANN and SVM in a microcontroller and they showed that both prediction algorithms could be implemented for real time arrhythmias detection [9].

Dutta et al. discuss an algorithm for beat classification using correlation techniques and SVM to classify between normal beats and PVC [10], SVM with different kernels for ectopic beat classification has been proposed by other authors [11].

Techniques for preprocessing, segmentation, feature extraction and classification have been developed with different methods, however, for real time detection, to reduce computational cost, it is better if few methods are used in order to have a simpler algorithm.

This paper presents a method to PVC detection based in DWT, which is used for preprocessing, segmentation and feature extraction, in such a way that only one decomposition stage is necessary. This method is compared with other algorithms in terms of its computational cost and distortion measures. Three different feature spaces and two classification methods are evaluated in order to select the one with lowest computational cost and better performance.

II. METHODS

A. Experimental Set-Up

A method to PVC detection is developed looking for a compromise between computational cost and performance. A signal processing method using fast DWT is implemented, wavelet domain is used for denoising, based line removal, segmentation and feature extraction making simpler the algorithm and with low computational cost. The specific combination of proposed techniques has not been done before and provides a relation between accuracy and computational cost suitable for real-time implementations. Fig. 1 shows a scheme of the PVC detection proposed in this paper. During the classification stage, KNN and SVM are used and compared.

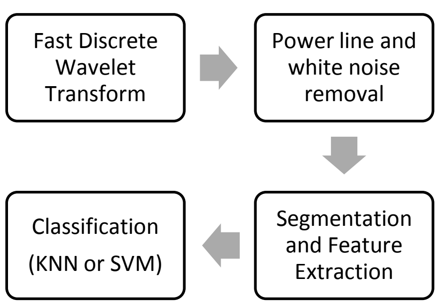

Fig. 1: PVC detection Diagram

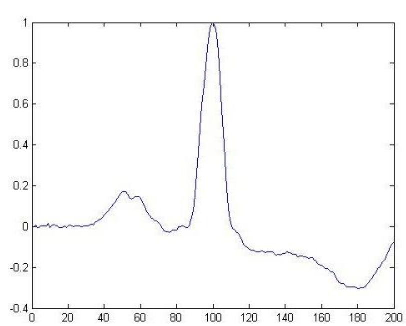

Fig. 2. Normal heartbeat

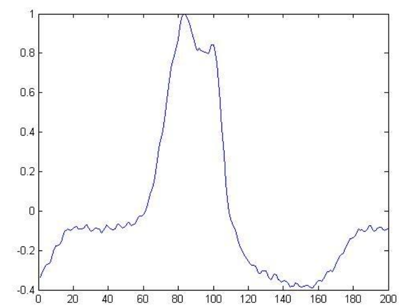

Fig. 3. Ventricular beat.

B. Database

MIT-BIH Arrhythmia Database is used [12]. Only ventricular beats and normal beats are considered. 2538 beats are extracted to the training set, 850 beats to the test set and 846 beats for the cross validation set. Each set is constructed with the same number of normal beats than PCV beats. Fig. 2 shows a normal beat and Fig. 3 shows a PVC beat extracted from the database.

C. *Preprocessing*

Fast DWT is used for noise reduction, baseline wander removal and to reduce power line interference. Fast DWT works like an array of high pass $h(n)$and low pass $l(n)$ filters as shown fig. 4, the coefficients of the filters are selected according to the mother Wavelet and with cut frequency in the middle of the spectrum of the input signal [13]. Fast DWT is implemented with eight decomposition levels; Daubechies and Symlets with different orders are used as mother Wavelet and checked.

The algorithm for noise reduction based in Wavelet consists in decomposing the signal into frequency scales using fast DWT and thresholding according to the level of signal/noise ratio. Thresholding is applied on the detail coefficients cD1-cD8 [3].

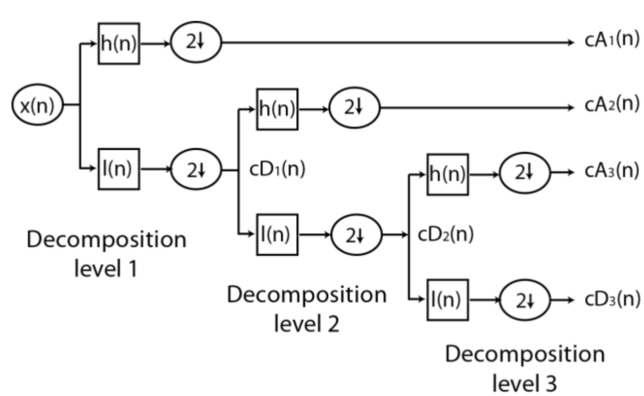

Fig. 4. Fast DWT with three levels of decompositions.

Approximate coefficients cA8 corresponds to lower frequencies and contain the baseline wander, then, these coefficients are removed.

D. Segmentation and Feature extraction

An algorithm based on Wavelet transform is used to detect the R peak according to [7]; the sum of the reconstructed detail coefficients cD2, cD3, cD4, cD5 is used to detect the QRS complex. These wavelet scales corresponds to the main frequency components of the QRS complex, where the amplitude of the T wave is markedly decreased. The absolute value of the reconstructed signal is calculated and the peaks are detected using the adaptive threshold proposed by Pan and Thompkis [14]. After identifying the R-peak, 200 points around the peak R are extracted.

In order to create the sets for training, cross validation and test process, a matrix is built with 200 points beats. We consider only the PCV and normal beats, assigning the label *1* to ventricular beats and label *0* to normal beats. To avoid class imbalance, in the matrix construction, the same number of both 1's and 0's (equal numbers of normal and abnormal beats) is selected randomly. This matrix is divided in a 60% for the training set, 20% for cross validation set and 20% for testing set.

PCA analysis is used to perform the dimension reduction stage. PCA is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables. Geometrically, PCA finds a new coordinate system obtained by rotating the original system which directions represent the maximum variability and provide a simpler description of the covariance structure [15]

E. Classification

KNN and SVM are used during the classification stage, the KNN is a statistical classification algorithms used for classifying objects based on closest training examples in the feature space [16]. This algorithm is one of the simplest learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbor. For this project, KNN is implemented using Matlab Toolbox to obtain the result for each beat.

SVM is a supervised learning machine method which selects the hyperplane that maximizes its distance from the training set patterns of two classes [17]. In an SVM, given X, an input vector with m dimensions, a new feature vector $f \in R^{m-1}$ Is computed depending on the proximity to vectors in the training set. To compute the proximity, a Gaussian kernel is used that is given as follows:

$$k(x,x') = exp\left(-\frac{\|x-x\prime\|^2}{2\sigma^2}\right), \tag{1}$$

The prediction is calculated by the inner product between the new feature vector f and the weights (alpha) of the model θ^T, where the prediction is 1, if $\theta^T \cdot f \geq 0$. SVM is implemented in MATLAB using a simplified version of the SVM algorithm from the Learning Machine online course of Andrew Ng from Stanford University.

F. Computational cost measure

Execution time is measured to be an indicator of the computational cost, MATLAB profile function is used using a 1.67 GHz Inter ® Core ™ Duo CPU with RAM of 3GB and 32 bits Windows 8 operational system.

G. Distortion Measures

Correlation, percentage root-mean-square difference (PRD) and signal to noise ratio (SNR) are used as distortion measures in the preprocessing stage. To make these measures, a synthetic ECG signal with 4550 samples and with a sample frequency of 256 Hz is used; baseline signal and synthetic power line of 60 Hz are added.

III. RESULTS

A. Noise reduction

A comparative analysis is done between the method proposed using DWT with mother wavelet db4, db9, sym9, sym4 and other traditional methods as single median and double median filter baseline wander correction. Single median is applied with an averaging window length of 77 samples, and double median is applied with two averaging windows of 77 samples and 154 samples for the first stage and second stage respectively. Table 1 shows the results of distortion measures applied. Table 2 shows distortion measures for power line interference reduction using several methods like Notch filter, Ziriani filter [5], Kalman filter [6] and DWT. The results show that DWT Method has better performance in order to ensure that the preprocessing stage does not distort the signal morphology with low computational cost.

B. Feature space

Three different features spaces are created and compared. First, Wavelet coefficient of cD3(n) to cD8(n) are used as features, therefore a 160 dimensional vector is used as a feature. Second feature space is created after applied PCA to Wavelets coefficients and the dimension is reduced from 160 to 10 preserving the 81.55% of the variability of the system.

TABLE I
BASELINE WANDER REMOTION

Method	Execution time for 1 second of signal (ms)	Distortion measures		
		Correlation	PRD	SNR
Single Media	11.22	0.9128	41.13	17.76
Double Media	24.48	0.8987	43.13	16.81
Wavelet Sym9	7.71	0.9898	18.71	33.51
Wavelet db9	1.73	0.9492	32.86	22.25
Wavelet db4	1.52	0.8954	45.38	15.80
Wavelet Sym4	1.49	0.9144	42.62	17.41

TABLE II
POWER LINE INTERFERENCE REMOVAL

Method	Execution time for 1 second of signal (ms)	Distortion measures		
		Correlation	PRD	SNR
Notch IIR	0.883	0.9991	4.33	62.77
Ziriani [5]	7.77	0.9669	25.52	27.31
Kalman AR [6]	11.56	0.9999	1.17	88.79
Wavelet	0.99	0.9999	1.10	90.17

In the third feature space, the energy contribution of the Wavelet sub-bands coefficients are extracted to create the feature vector, cD3(n), to cD8(n) and cA8(n) are selected, while cD1(n) and cD2(n) are discarded because they only represent the 2% of the total signal energy. The energy percentage contributions are calculated as features, it results in a vector of eight dimensions.

For the third model, PCA is applied in order to find the three directions of maximum variability and visualize the feature space in a 3D plot. Fig. 5 shows the three principal components of the training set which represent the 94.61% of the variance.

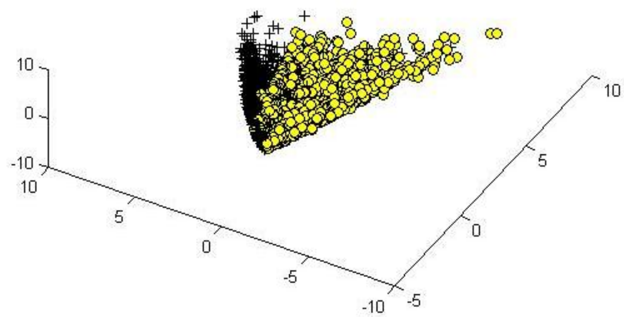

Fig. 5. Third feature Space with 3 Principal Components

C. *Classification performance*

KNN and SVM are applied to three different feature spaces. Different parameters of KNN and SVM algorithms are checked with a cross validation set and parameters with the best performance are selected for the implementation. The parameters tested for KNN are the number of neighbors k and the distance function, whereas the regulation parameter (C) and the standard deviation (sigma) parameter are considered for SVM.

Table III shows the performance and the execution time of three different feature space using KNN and SVM with parameters selected after cross validation stage. Execution time is calculated only for prediction algorithm. The SVM training computational cross is not relevant for real time application because the only prediction algorithm is used when the application is running.

IV. DISCUSSION

At baseline wander the removal stage, table I shows that fast DWT has lower computational cost than single median and double median methods; DWT with the mother Wavelet symlets order 9 had the lowest distortion and it is the technique selected for the implementation.

TABLE III
COMPARATION OF KNN AND SVM PERFORMACE USING THREE DIFFERENTS FEATURE SPACE

Feature space	Classifier	Specificity (%)	Sensitivity (%)	F1 Score	Execution time (ms.)
160 Wavelet Coefficient without cD8 and cD7	KNN with K=1 and correlation function	96.47	97.41	0.9696	1.63
	SVM with C = 10 and Sigma = 0.7	99.06	95.53	0.9725	0.94
10 principal component of Wavelet Coefficient	KNN with K = 3 and Euclidean function	96.24	97.18	0.9672	1.29
	SVM with C = 1 and sigma = 0.7	97.18	96.47	0.9681	0.56
8 Wavelet subbands energies	KNN with K = 3 and Citiblock function	94.82	93.41	0.9404	1.23
	SVM with C = 10 and sigma =1	93.41	92.47	92.91	0.47

To remove power line interferences, DWT has similar performance than the Kalman filter proposed by [6], however, DWT has a lower computational cost. Additionally, using DWT, the algorithm to remove power line and baseline uses the same Wavelet decomposition in order to have a simpler the method.

Table III shows a comparison between KNN and SVM using three different features spaces. The SVM prediction algorithm has lower execution time than KNN in the three feature spaces; KNN has more computational cost because the algorithm to calculate the shortest distance has a lot of iteration. Prediction algorithm of SVM after kernel calculation only executes the dot product between the new feature vector after distance calculation and the trained weight vector.

Feature space with wavelet coefficient (160 dimensions) has the better specificity with 99.06, however the better sensitivity is obtained using 10 principal components after applied PCA to wavelet coefficients. A method using PCA has the best relation between sensitivity, specificity and computational cost and it is the method selected for the final application.

A possible limitation of this work could be that only signals from one database are considered and only normal and PCV beats are used, whence it is possible that the system is overfitting. Additionally, preprocessing stage is tested only with a synthetic signal. For future work we recommend include other databases with different arrhythmias. In the other hand execution times are measured in Matlab, however, computational cost will be improved through the implementation in language C.

V. Conclusion

A method to PCV detection is implemented, DWT is used for preprocessing with a lower computational cost than other tools with similar performance, DWT is also used for segmentation and feature extraction making the method simpler and with low computational cost. 10 principal components of wavelet coefficients are used in the feature vector and SVM is selected as Classifier. The method developed could be implemented in real time application because its computational cost is reduced. In future the developed method will be implemented in embedded system for real time applications in wearable cardiac devices.

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