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Heart Sound Analysis for Diagnosing Cardiovascylar Disorder

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Abstract— **Assisting physicians in the auscultation of the patients by providing less costly, automatic and accurate signal processing module for the heart event detection and recognition is of great importance. This paper presents a complete heart sound analysis system covering from the segmentation of beat cycles to the final determination of heart conditions. A basic task for the diseases diagnosis from the phonocardiogram is to detect the exact timing location of the events present in the cardiac cycle, especially in pathological cases. This paper also presents a new algorithm for segmentation of S1 and S2 heart sounds without using ECG as a reference signal. The decision making process is insured by support vector machine (SVM) classifier utilizing the features based on wavelet coefficients so that the signals of PCG are classified into five categories: normal heart sound, AS, AI, MS and MI using a small training dataset and tested with an enormous testing dataset to show the generalization capability of the scheme.**

Key-Words— Phonocardiogram (PCG), Heart sounds (HSs); Automatic segmentation of heart sounds, Classification, Support Vector Machine

I. Introduction

According to the World Health Organisation estimates of 2003, cardiovascular disease accounts (cvd) for approximately 73 million deaths worldwide, which equals over 78% of all deaths globally [1]. These facts alone show that cvd is a major global threat and any development to aid the prevention of these disease is of great importance [2].

Phonocardiogram (PCG) signals are heart sound signal which are produced due to the vibrations of the heart and thoracic systems [2].These PCG signals contain vital information about the health of the heart and can be used effectively in diagnosing various pathological conditions of the heart valves.

The heart sound signal or the phonocardiogram (PCG) signal of a normal heart is comprised of two distinct activities namely: the first heart sound S1, and the second heart sound S2. In the case of an abnormal heart, there could be several other signal activities between the first and the second heart sounds. The extraneous signal activities which occur between S1 and S2 may be the tow abnormal sound signals, namely S3 and s4, or murmurs, clicks and snaps. In general, the activities of the PCG are S1, S2, S3, S4, murmurs, clicks and snaps. The first and the second heart sounds will be referred to as fundamental activities. It may be noted that S3 may be considered as a physiological sound for subjects under the age of 30.However, for this dissertation, S3 sound is treated as an abnormal sound signal.

With the development of computer science, the cardiac sound signal can be analyzed in an automatic way. The cardiac sound signals should be segmented into some specific features for the automatic analysis and classification in this case [3].

Our aim is to detect a single cardiac cycle of PCG signal and segment it into four parts (S1, Systolic period, S2 and Diastolic period), extract the features, and then classifies them. In this paper classification of heart sounds is achieved using multiclass Support Vector Machines.

Due to the absence of publicly available database of the healthy heart sound signals required to evaluate the proposed approach, our PCG signals were collected from [4-9], namely normal heart sound (NHS), aortic stenosis (AS), aortic insufficiency (AI), mitral stenosis (MS), and mitral insufficiency (MI). Some normal heart sounds were recorded in the Laboratory of Biomedical Signal Processing (University of Technology, Dalia, China). These heart sounds were injected with four different levels of white Gaussian noise (10, 15, 20, 25 dB) in order to simulate the real situation when heart sound records were acquired together with background noise [10-12]. The noisy and original heart sounds were filtered and segmented then fed into the multiclass Support Vector Machines for classification.

II. Signal Pre-Processing

The recorded PCG signal is first pre-processed before performing segmentation. PCG signal is down sampled to 8000 Hz and normalized according to (1).

$$x_{norm}(t) = \frac{x_{8000}(t)}{\max(|x_{8000}(t)|)} \qquad (1)$$

Where $x_{8000}(t)$ is the down sampled signal. Normal and abnormal HSs have a frequency range of 20 to 700 Hz, higher frequencies are not of clinical significance for analysis and diagnosis, hence a band pass Chebyshev type I filter with cut off frequency at 15-750 Hz was designed. After filtering in the forward direction, the filtered sequence is then run back through the filter to obtain zeros phase distortion [10], [13].

III. SEGMENTATION OF HEART SOUNDS

The segmentation of the phonocardiogram signal is the first and the most important step in the automatic diagnosis of heart sounds. The majority of the attempts in segmenting the heart sounds use the ECG (electrocardiogram) signal pulse as reference ; the first heart sound (S1) was defined as the first signal peak after the QRS complex, and the second heart sound (S2) as the signal peak after the T-wave in the ECGs[10]Fig.1.

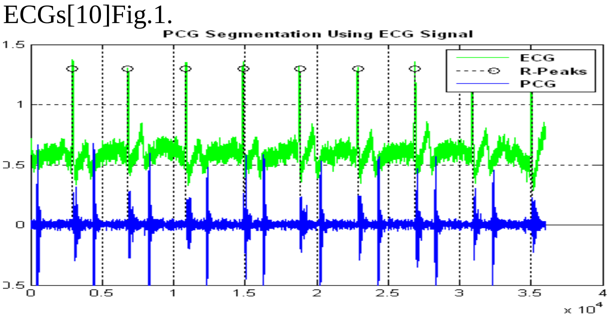

Figure 1.Segmentation of PCG signal using ECG.

The idea here is to implement the segmentation based on the heart sound signal itself without a reference to the ECG using a set of PCGS recordings. Three steps have been developed for splitting PCG signal into short segments.

A. First step: Short Time Energy

Short Time Energy is calculated similarly to a moving window, using a 0.02 second with 0.01 second overlapping according to:

$$STE = \frac{1}{L}\left(\sum_{l=0}^{L-1} x[l]^2\right) * W(L) \qquad (2)$$

L is the length of window and l sample number

B. Second step: RMS Envelope Detection

The envelope of the Short Time Energy is calculated using Root Mean Square (RMS) according to:

$$RMS = \sqrt{\left(\frac{1}{L}\sum_{n=0}^{L-1} STE[n]^2\right)} \qquad (3)$$

C. Second step: RMS Envelope Detection

After envelope detection a low-pass Fire filter of cut off frequency 0-15 Hz is applied in order to smoothing the envelope. The choice of threshold is very important in order to have interesting results, in this paper the proposed threshold is calculated as:

$$Thr = (SRMS * 0.1) + 0.12 \qquad (4)$$

SRMS is the smoothed RMS envelope.

D. *Fourth step: Segmentation and identification of S1 and S2*

For normal heart rates, the diastolic period is longer than the systolic period. Consequently, it is assumed the longest interval between two sounds corresponds to the diastolic period and the immediate sound following that interval corresponds to an S1 while the immediate sound preceding it corresponds to an S2.

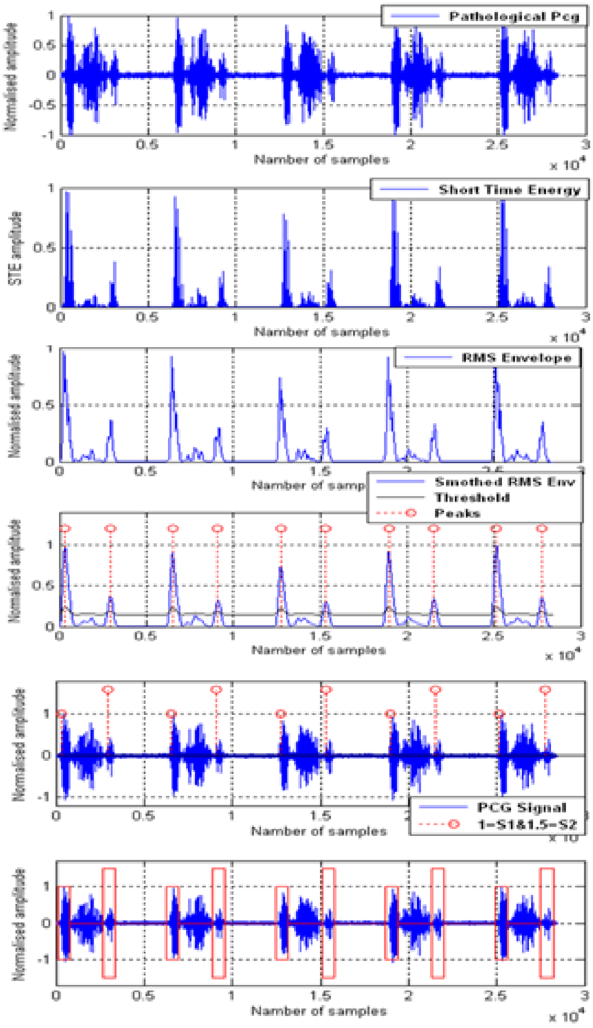

Figure 2*. Segmentation and identification of S1 and S2*

The segmentation results are illustrated in table 1.

PCG	Cycles	Correct	Incorrect	Performance (%)
NHS	270	270	0	100
AR	321	301	20	93.76
AS	380	330	50	86.84
MR	235	195	40	82.97
MS	120	109	11	90,83
Totel	1326	1195	122	90.214

The segmentation algorithm was tested on five classes original and noisy heart sounds: Normal, aortic stenosis (AS), aortic insufficiency (AI), mitral stenosis (MS) and mitral insufficiency (MI). The results are as tabulated in Table 1. High intensity murmurs and high background noise could cause the segmentation algorithm to fail. The incorrectly segmented cycles were hand segmented to enable feature extraction and classification [14].

IV. WAVELET ANALYSIS OF PCG SIGNAL

A heart sound is non-stationary signal. Therefore, we applied the wavelet transform, which is a time-frequency representation method that is very suitable for analyzing non-stationary signals. A wavelet transform is superior to time Fourier transform, Wigner_ville distribution because, not only is it capable of providing time and frequency information simultaneously, it has a varying time and frequency resolution.

In wavelet transform (WT) the time domain waveforms are mapped into a frequency-time domain while preserving both frequency and time information. The main idea of wavelet analysis is to measure the degree of similarity between the original waveform x (t) and the basic function of the WT, also called the mother wavelet, through wavelet coefficients computation. The calculation process is performed on a shifted version of the mother wavelet, thus moving along the time, and on stretched or compressed version of the mother wavelet thus varying the frequency. Continuous wavelet transform (CWT) is defined as the convolution between the original signal x(t) and a wavelet $\psi_{a,b}(t)$.

$$w_{\psi}(a,b)=\int_{-\infty}^{+\infty} x(t)\overline{\psi_{ab}(t)}dt=\frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\overline{\psi(\frac{t-b}{a})}dt \qquad (4).$$

Where x (t) is the input signal, a is the scaling factor, b is the translation parameter and ψ is the transforming function called mother wavelet. The mother wavelet is given by:

$$\Psi_{a,b}=\frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \qquad (5).$$

The DWT coefficients are usually sampled from the CWT on a dyadic grid. The mother wavelet in DWT is defined as:

$$w_{m,n}(t)=\frac{1}{\sqrt{2^{m}}}\psi\left(\frac{t-n^{2^{m}}}{2^{m}}\right) \qquad (6).$$

DWT analyses the signal by decomposing it into its coarse and detailed information, which is accomplished by using successive high-pass and low-pass filtering operations, on the basis of the following equations:

$$y_{h}=\sum_{n} x(n)h(2k-n) \qquad (7).$$

$$y_{l}=\sum_{n} x(n)g(2k-n) \qquad (8)$$

Where y_h, y_l are the outputs of the high-pass and low-pass filters with impulse response h and g, respectively, after upsampling by 2 [3].

V. FEATURE EXTRACTION

Feature extraction is one of the important steps of pattern recognition because the performance of classifiers will degrade significantly if the features are not chosen properly.

Hence, wavelet transformations are proffered to extract the particular features of the heart sounds. Several orthogonal wavelets are exploited here to decompose one segmented cardiac cycle into different resolution levels using the fast wavelet transform [15], the statistical parameters like standard deviation, kurtosis of the 4th level approximation and detail are calculated for each segmented cardiac cycle to determine a feature vector (FV) for the all categories of signals. I found that fourth level decomposed signal have the characteristics of the frequency spectrum of S1, S2 and murmurs Fig3.

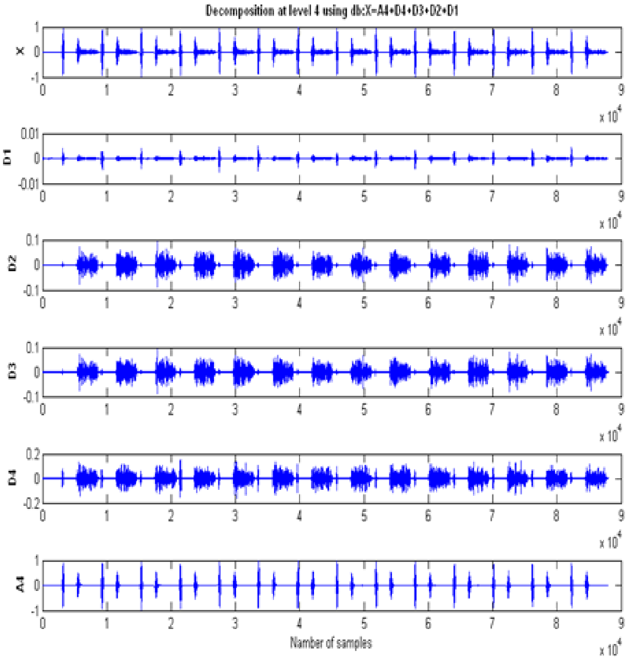

Figure 3. Wavelet detail coefficients at the first-four decomposition levels (D1–D4) and the wavelet approximation coefficients at the fourth level (A4) for normal PCG signal. X(t):segmented cardiac cycle.

VI. HEART SOUNDS SVM CLASSIFICATION

Support Vector Machines (SVM) have been successfully applied to various pattern recognition problem such as image recognition, text classification and bioinformatics since introduced by Vapnik (1995).The SVM was developed based on the idea of structural risk minimization. The basic principle of SVM is to find an optimal separating hyperplane (OSH) to separate two classes of patterns based on the training set and the decision boundary, which can be easily formulated as a quadratic programming (QP) problem in the feature space [3,16-19].

A. Basic Principles of the Support Vector Machines

Consider the problem of separating the training dataset belonging to two separate classes $S=\{(x_i, y_i)\}, i=1 \ldots N$ where $x \in R^n$ is an i-th input vector in n-dimensional input space and only $y_i \in \{-1,+1\}$ is a specified binary target vector .The main goal of the SVM approach is to find a hyperplane $f(x)=\langle w.x \rangle + b$ able to separate classes linearly so that separate the classes linearly so that all the points with the same class are on the same side of the hyperplane. In the non-linear case, which is the most common case since data are often not linearly separable, the two classes are first mapped with a kernel method in a higher dimensional feature space, i.e. $\phi(x) \in R^{\bar{n}} (\bar{n} > n)$ [17, 18].The membership decision rule is based on the function sign [f(x)] represents the discriminant function associated with the hyperplane in the transformed space and is defined as:

$$f(x) = w^{*}.\phi(x) + b^{*} \qquad (9)$$

The optimal hyperplane defined by the weight vector and the bias is the one that minimize a cost function that expresses a combination of two criteria: margin maximization and error. The solution of such optimization problem is a discriminant function conveniently expressed as a function of the data in the original dimensional feature space X:

$$f(x) = \sum_{i \in S} \alpha_i^{*} y_i k(x_i, x) + b^{*} \qquad (10)$$

Where: $\alpha = [\alpha_1, \alpha_2, \ldots \alpha_N]$ is the vector of Lagrange multipliers and K (.,.) is a kernel function. The set S is a subset of the indices corresponding to the non-zero Lagrange multipliers which define the so-called support vectors [17, 18].

The kernel function must satisfy the condition stated in Mercer's theorem so as to correspond to some type of inner product in the transformed (higher) dimensional feature space.

The commonly used kernel functions are:

1. *Linear kernel function*

$$K(x_i, x_j) = x_i . x_j \qquad (11)$$

2. *Polynomial kernel function*

$$K(x_i, x_j) = (x_i . x_j + 1)^q \qquad (12)$$

3. *RBF kernel function*

$$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / 2\alpha^2) \qquad (13)$$

4. *Sigmoid kernel function*

$$K(x_i, x_j) = tanh(\alpha x_i . x_j + r) \qquad (14)$$

In our case, radial basis kernel was used to differentiate between heart sounds. More details about recent developments of SVM can be found in [20].

B. Multi-class Classification

SVM classifier was originally designed for binary classification problems. In order to deal with multi-class classification, it needs to build up the multi-SVM classifier with a hierarchical structure. One of the frequent used methods is to decompose the M-class problem into a set of binary classification problems and then combine M binary classifiers. Typically, there are two approaches that can be used for this purpose like one-against-all (OAA) Approach and one-against-one (OAO) approach [3].

OAA approach constructs M_{OAA}=M1 binary SVM classifiers, each of which separates one class from all the rest. The i-th SVM is trained with all the training sets of the i-th class with positive labels and all the others with negative labels. OAO approach constructs M_{OAO}=M2 (M2-1)/2 binary SVM classifiers, each of which discriminate between a class A and B. In this study, the OAA approach and OAO approach were combined together to construct M (M1+M2) class problem for classifying the heart sounds [3, 17, 18].

Figure 4depicts the decision-making tree composed of four binary SVM modules classifiers (M_{OAA}=3and M_{OAO}=1).These SVM modules are determined by the training dataset, SVM1module is used to discriminate between the normal sounds and abnormal sounds, SVM2 module is used for searching AS sound, SVM3module for AI sound, and SVM4 is lastly obtained for discriminating between MR and MS sounds.

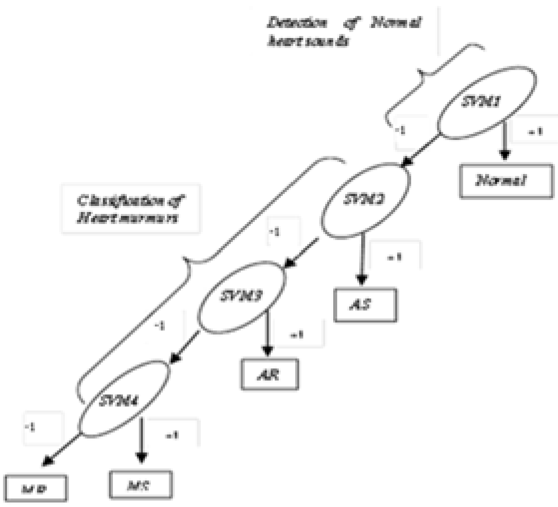

Figure 4. The decision-making tree composed of three SVM modules.

Table 2. The percentage accuracy of the multi-Svm classification approache using divers wavelets

Multi_Svm Classifier	Wavelet	db1	db4	Coif3	Sym5	Rab1.5
Svm1	*Nor(%)*	90.4	**92**	89.56	91.14	88
	Abn(%)	87.5	**88.12**	84	85.51	78.18
Svm2	*As(%)*	65	**82.94**	66.35	50	81.66
Svm3	*As(%)*	68.33	**84.94**	77.13	62	82
Svm4	*Mr(%)*	71	**85.87**	83.7	50.6	68.9
	Ms(%)	84	**89.58**	72.56	67	74

Table 2 compares the classification performance of diverse suitable wavelets. It can be deduced from Table 2 that the db4 wavelet is selected as the best wavelet applied to dignoise PCG signal confirmed with [15].

VII. CONCLUSION

It is vital to identify a single cardiac cycle to obtain information about the health of heart valves and also to detect some heart diseases. At first, the pre-processing procedure was introduced for eliminating the artefact noises lower than 20 Hz and higher than 700 Hz because the frequency band of the cardiac sound signals usually occurred at 20-700 Hz. Secondly, the automatic segmentation of the PCG signal was presented in details. Current techniques use a reference signal like ECG to obtain a single cardiac cycle, or to identify the fundamental activities of the PCG signal. Our algorithm of segmentation based on RMS enveloppe has shown 90.345% of success. Then, the features of the segmented heart sounds based on wavelet transform were obtained and classified using multi-class Support Vector Machines (SVM). Compared to [3],[15], the results of classification were less satisfying because noises were added to our dataset, and the classifier was trained with small training dataset and tested with an enormous dataset .
The main message of this short communication is to prove that the PCG signal can be used as a complimentary tool to the ECG signal for the detection of valve dysfunction pathologies.

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