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A Time-Frequency Approach for Discrimination of Heart Murmurs

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ABSTRACT

In this paper, a novel framework based on a time-frequency (TF) approach is proposed for detection of murmurs from heart sound signal. First, a high-resolution TF algorithm, matching pursuit, was used to decompose each heart beat into a series of TF atoms selected from a redundant dictionary. Next, representative components of murmurs were identified by clustering the selected atoms of all the beats into a finite number of clusters. Then, Wigner-Ville distribution of the representative components was used to generate a set of 8 features which were fed to a classifier. Experiments with a dataset consisting of heart sounds from 35 normal and 35 pathological subjects showed a classification accuracy of 95.71% in distinguishing murmurs from normal heart sounds.

Keywords*: *Phonocardiogram* (*PCG*), *Murmur*, *Matching Pursuit* (*MP*), *Time-Frequency Atom*, *Clustering

1. Introduction

Mechanical activity of the heart is evaluated by auscultation and analysis of phonocardiogram (PCG) signal, which is a recording of heart sounds. PCG provides valuable information on the structural integrity and function of heart valves. Heart sounds normally consist of two regularly repeated thuds, known as S1 and S2 for every heat beat. An underlying pathology such as diseased valves produces some additional and abnormal sounds which are called murmurs. The automatic detection of murmurs has been widely considered for several decades because of the human auditory limitations in distinguishing them from normal heart sounds [1].

PCG is highly nonstationary signal with multicomponent nature and identification of its components can be performed by a nonstationary signal analysis tool such as time-frequency (TF) analysis methods [2]. Short-time Fourier transform (STFT) is one of the existing techniques that tackles the nonstationarity of the PCG signal by segmenting it into stationary parts [3,4]. Wavelet transform (WT) was used to obtain TF decomposition of PCG signals in previous studies [5,6]. It does not require the fixed data window needed for STFT; however, even wavelet bases are not well suited to exact TF representation of PCG components whose localizations in time and frequency vary widely. Some researchers performed analysis of PCG by using Wigner-Ville distribution (WVD) [7]. A major drawback of the WVD is presence of cross-term artifacts caused by aliasing when analyzing multicomponent signals such as PCG. A true nonstationary TF technique would be one that can give an accurate parametric display of PCG characteristics with satisfactory TF resolution, cross-term suppression, and without segmentation requirements. The parameters of decomposed components could be later used to extract crucial features for identification of murmurs. In this paper, we achieve this goal using a cross-term free high-resolution method, matching pursuit (MP) algorithm. MP is a signal decomposition method whereby a signal is decomposed into a linear combination of TF components (atoms) that are selected from a redundant dictionary [8].

Figure 1 represents the architecture of our proposed framework for heart murmur detection. PCG signal from an electronic stethoscope is processed along with a simultaneously recorded electrocardiogram (ECG) stream as a reference signal. First, preprocessing stage is carried out consisting of filtering, down sampling, and beat segmentation. Next, all the beats are decomposed into a series of TF atoms using the MP algorithm and a redundant Gabor-type dictionary. Each selected atom is described by a set of parameters including the amplitude, position in time, scale, frequency, and phase. Groups of atoms with similar morphology of parameters are then isolated into clusters. For each cluster, atoms are merged together

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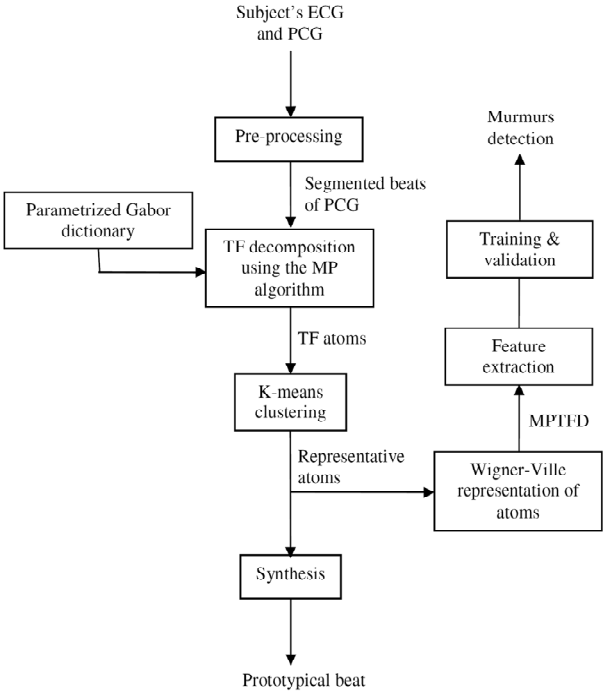

Figure 1. Block diagram of the proposed scheme.

based on the mean values of their parameters to create a single representative atom. Also, a prototypical beat corresponding to the beats of the analyzed PCG can be constructed by synthesizing these representative atoms. MP-based TF decomposition (MPTFD) of the PCG signal is obtained by taking the WVD of the resulted atoms. Features are derived from the MPTFD followed by classification using a MLP-based classifier.

The paper is organized as follows. In Section 2, theory of the utilized method for murmurs detection is introduced and our data set of typical murmurs is described. The obtained results on murmurs detection are presented in Section 3 and conclusion in Section 4 is the final part of this paper.

2. Materials and Methods

2.1. Matching Pursuit

In the MP method, a discrete-time signal $x(n)$ is decomposed into a sum of TF atoms selected from a redundant dictionary

$$x(n)=\sum_{m=1}^{M} a_m g_m(n)+e(n) \tag{1}$$

where

$$g_m(n)=e^{-\pi\left[(n-p_m)/s_m\right]^2}\cos\left[2\pi f_m(n-p_m)+\phi_m\right] \tag{2}$$

and $g_m(n)$ is a Gabor-type TF atom which has good time-frequency localization. The scale factor s_m is used to control the width of the mth atom, and the latency parameter p_m controls the temporal placement. The parameters f_m and ϕ_m are frequency and phase, respectively and the amplitude factor a_m is the expansion coefficient. The collection of atoms with all possible combinations of scaling, translations, modulations, and phase-shifting, forms a redundant dictionary. The first part in (1) denotes the sum of TF atoms till M iterations of the MP algorithm, and the second part is the residue to be decomposed in the subsequent iterations. At first iteration the signal is projected over the dictionary of atoms and the best correlated atom that can model the maximum possible function of the signal energy is selected. The selected atom is then subtracted from the signal to form a residue signal that will be decomposed in the subsequent iterations [8].

2.2. K-Means Clustering

We next analyzed all the TF atoms decomposed from different beats of a subject's PCG to group the atoms into a finite number of clusters, that each cluster contains atoms with similar parameters. Clustering of the atoms was carried out by the K-means method. K-means attempts to find a user-specified number of clusters (K), which are represented by their centroids. One of the common initialization methods for the K-means algorithm can be performed by determining the local maxima of the joint probability density function (PDF) of the samples and placing a cluster centroid at each peak [9]. After detecting these maxima, their locations were used as the initial centroids for the K-means clustering. For each cluster, a representative TF atom was created by merging all the atoms of that cluster.

2.3. MP-Based TF Decomposition (MPTFD)

A MPTFD was obtained by taking the WVD of the representative TF atoms of the previous stage by

$$W(t,\omega)=\sum_{k=1}^{K}\left|a_k\right|^2 W_{g\text{representative}_k}(t,\omega) \tag{3}$$

where $W_{g\text{representative}_k}(t,\omega)$ is the WVD of the kth representative atom, a_k is its coefficient, and K is the number of clusters. This cross-term-free decomposition has very good readability and is appropriate for analysis of nonstationary, multicomponent signals [10].

2.4. Feature Extraction

The four TF parameters of the MPTFD are the energy parameter (EP), energy spread parameter (ESP), frequency parameter (FP) and frequency spread parameter FSP, as described by (4)-(7), respectively

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$$EP(t)=\frac{\sum_{\omega=0}^{\omega_m} W(t,\omega)}{\omega_m} \tag{4}$$

$$ESP(t)=\left[\frac{\sum_{\omega=0}^{\omega_m} \left|W(t,\omega)-EP(t)\right|^2}{\omega_m}\right]^{1/2} \tag{5}$$

$$FP(t)=\frac{\sum_{\omega=0}^{\omega_m} \omega W(t,\omega)}{\sum_{\omega=0}^{\omega_m} W(t,\omega)} \tag{6}$$

$$FSP(t)=\left[\frac{\sum_{\omega=0}^{\omega_m} \left|\omega-FP(t)\right|^2 W(t,\omega)}{\sum_{\omega=0}^{\omega_m} W(t,\omega)}\right]^{1/2} \tag{7}$$

where ω_m is the maximum frequency present in the signal [10]. The average (m*EP* , m*ESP* , m*FP* , m*FSP*) and standard deviation values (s*EP* , s*ESP* , s*FP* , s*FSP*) of each parameter, described above, were used as the features of the input vector for the classifier.

2.5. Data Collection and Preprocessing

Heart sound and ECG data of 70 patients have been collected under the supervision of Dr. Sepehri's group. From 70 PCGs, 35 signals are from children with pathological murmurs. The remaining 35 signals are from children with normal heart valves. The PCG signals in this data set have been labeled by a cardiologist using echocardiography. All PCG and ECG signals have been recorded over a time-interval of 10 seconds. For data acquisition, a WelchAllyn Meditron stethoscope, the ECG, and a 1.8 GHz ACER notebook with a 16 bit stereo soundcard and sampling rate of 44.1 kHz have been used.

Preprocessing of the heart sound recordings is necessary to withhold unrepresentative data and separate individual heart beats. First, an 8th-order Butterworth low-pass IIR filter (at 1 kHz) was used to remove the high frequency noise from the PCG signal. Then, down sampling to 2 kHz was performed prior to any processing block. Segmentation of the raw PCG into intervals corresponding to different cardiac beats is done to perform the analysis on each of the individual beats. S1 occurs shortly before R peak in ECG, thus detecting properly the R peaks one can pick up the beginning and end points of every heart beat. Therefore, the automatic segmentation of a recording PCG into separate heart beats was carried out by means of ECG's R peaks and a method similar to what was proposed in [1]. A sample segmented normal PCG and an abnormal PCG with systolic murmur (SM) are shown in **Figure 2**. Synchronization of PCG and ECG is obvious.

3. Results and Discussions

For the sake of illustration, the mentioned PCG with SM is considered here. We applied the MP algorithm to decompose each individual beat of this PCG. The MP algorithm was allowed to proceed until the iteration reached a preset number M as a stopping criterion. For the application in hand, M was set to 50, because the selected atoms after this iteration have negligible correlation with the original signal. At this stage, the MP algorithm has selected 50 Gabor atoms from the dictionary for decomposing each of 11 beats of the analyzed PCG.

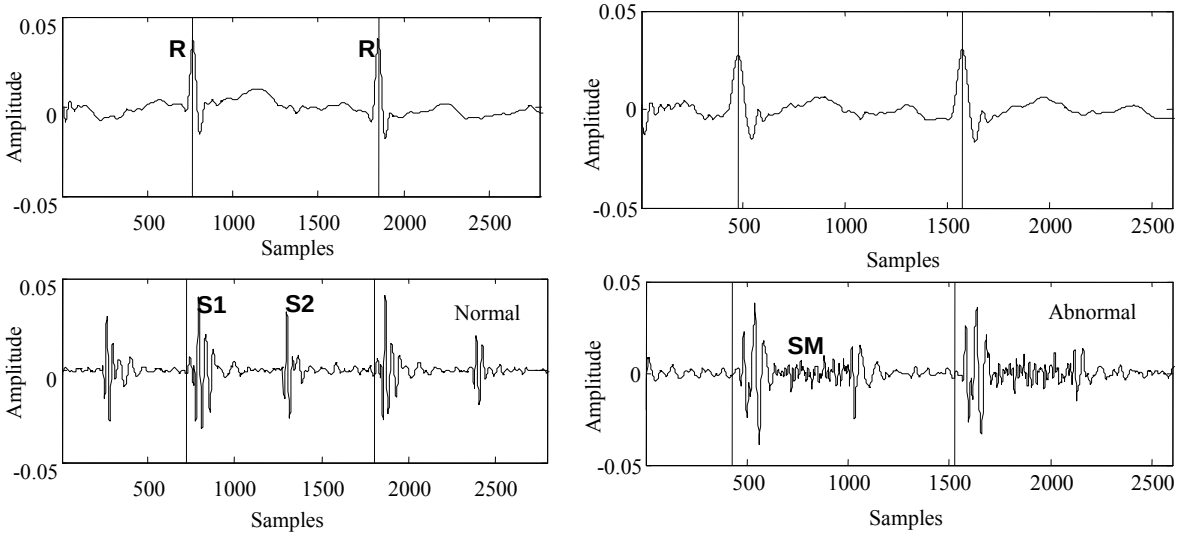

Figure 2. Segmented ECG & PCG of a normal subject & an abnormal subject with systolic murmur (SM).

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Therefore, a total of 550 TF atoms were selected for further clustering and analysis. Each Gabor atom is characterized by a 5-D parameter vector $u=\left[p, f, a, s, \phi\right]^T$. Since clustering in a 5-D space was difficult, principle component analysis (PCA) was applied to reduce the dimension of the parameter vectors to three ($v=\left[PC1, PC2, PC3\right]^T$). The joint PDF of the new parameter vectors in the $PC1-PC2-PC3$ space was used to obtain initial points of clusters. The local peaks of PDF with values larger than 50% of the maximum PDF value were selected as initial centroids of clusters which were 20 peaks. After the clustering procedure, the 550 TF atoms were categorized into twenty clusters, named as $C1, C2, \cdots, C20$. We examined statistical properties of the parameters including their mean and standard deviation for each cluster, which are illustrated in **Table 1**. Based on the mean values of parameters, a representative atom was created for each cluster and by synthesizing these atoms a prototypical beat was constructed (**Figure 3(a)**). This prototypical beat provides a robust, compact representation of the PCG signal. The MPTFD of the representative atoms is shown in **Figure 3(b)**. High-frequency activates have been represented with good TF localization in this distribution. The EP, ESP, FP, and FSP waveforms were obtained from the MPTFD and their mean and standard deviation were calculated to form feature vectors.

The classification of PCGs as normal or pathological was achieved using a three-layer feed-forward multilayer perceptron (MLP). The input layer consisted of 8 nodes indicating the input feature vectors. After some preliminary simulations, it turned out that 11 nodes in the hidden layer showed a satisfactory performance. A tan-sigmoid transfer function was applied to each neuron of the hidden layer. The output layer consisted of one neuron with a linear transfer function in which 0 represented a normal case and 1 represented a pathological case. The neural network was trained using back propagation error method and its training was conducted until the maximum iteration limit of 30 was reached. The classification accuracy was estimated using the leave-one-out method, which one sample is excluded from the dataset and the classifier is trained with the remaining samples. Then the excluded signal is used as the test data and the classification accuracy is determined. This is repeated for all samples of the dataset and the performance was calculated averaging the classification results.

For comparison purposes, another method which performs beat-to-beat detection of murmur was also executed. Unlike our proposed framework that simply examines the prototypical beat, the second technique investigates each individual beat of the PCG and classifies the subject as having murmur if the majority of the beats are

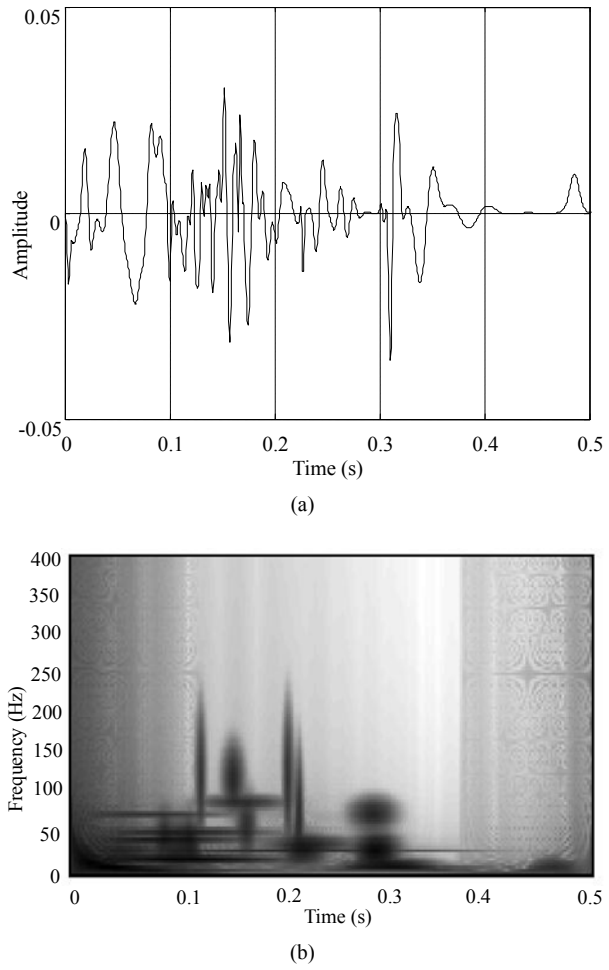

Figure 3. (a) Prototypical beat (b) MPTFD of the prototypical beat.

labeled as showing murmur. First, each beat of the PCG was decomposed into a series of atoms by the MP algorithm. Then, the TF features corresponding to that beat were extracted from the WVD of the selected atoms. Next, presence of murmur was diagnosed by applying the features into the MLP classifier. Finally, identification of subject as normal or abnormal was done based on the labels of majority of beats.

Results are shown in **Tables 2** and **3** in the form of a confusion matrix with percentage classification accuracy. The use of prototypical beat results higher classification accuracy of 95.71% compared to the beat-to-beat classification accuracy of 90.01%. From the table it can be seen that out of 35 normal signals, 34 were correctly classified as normal, and 1 was misclassified as pathological. Similarly, out of 35 pathological signals, 33 were correctly classified as pathological and 2 were misclassified as normal. The misclassified signals were analyzed in detail, and we observed that they were perceptually

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Table 1. Statistical values of parameters of first five clusters (mean ± SD).

Cluster	C1	C2	C3	C4	C5
Amplitude	0.182 ± 0.1	0.124 ± 0.075	0.117 ± 0.062	0.088 ± 0.043	0.075 ± 0.032
Time position (ms)	29.45 ± 9.12	301 ± 4.55	297 ± 2.93	127.5 ± 12.41	159 ± 8.26
Scale (ms)	51.5 ± 10.73	36 ± 6.41	60 ± 4.33	14 ± 8.92	25 ± 4.27
Frequency (Hz)	21.65 ± 4.27	33.46 ± 7.77	78.74 ± 12.23	147.6 ± 6.54	139.8 ± 5.43
Phase (rad)	0.6792 ± 0.281	–1.9342 ± 0.961	–1.2938 ± 0.629	–2.0339 ± 0.876	0.777 ± 0.265

Table 2. Classification results of prototypical beat in identification of valvular disorders. Cross-validation: MLP with leave-one-out method, %: Percentage of classification.

Method	Groups	Normal	Pathological	Total
Cross-validation	Normal	34	1	35
	Pathological	2	33	35
%	Normal	**97.14**	2.86	100
	Pathological	5.71	**94.29**	100

Table 3. Classification results of individual beats in identification of valvular disorders. Cross-validation: MLP with leave-one-out method, %: Percentage of classification.

Method	Groups	Normal	Pathological	Total
Cross-validation	Normal	32	3	35
	Pathological	4	31	35
%	Normal	**91.43**	8.57	100
	Pathological	11.40	**88.60**	100

similar to normal and that they could be hardly classified as pathological by an untrained listener.

4. Conclusions

In this paper, the TF features of PCG signal were extracted by using the MP algorithm, K-means clustering method, and WVD for detection of murmurs. The MP algorithm first decomposed signal into a set of TF atoms, and a clustering was followed to group these atoms into several clusters. The representative atom for each cluster was calculated and MPTFD was obtained by taking the WVD of these atoms. The TF features of PCG were extracted from MPTFD followed by classification using a MLP-based classifier. The proposed method showed good potential for the noninvasive diagnosis of murmurs.

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