HEART DISEASES DIAGNOSIS USING HMM

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ABSTRACT

The bare ear and the stethoscope were until recently of great help in classifying most of heart diseases especially those who are related to valves problems. The newely developed electronic stethoscope and phonocardiography represent useful tools for recording heart sound signals. In this paper a diagnostic technique for heart diseases using heart sounds is suggested. Wavelet decomposition and mel cepstrum are used for feature extraction. Classification of the different heart diseases is then done using Hidden Markov Models (HMM). Three different techniques have been used and compared. The obtained recognition Rates (RR) were 97.3%, 98.2%, and 99.1%.

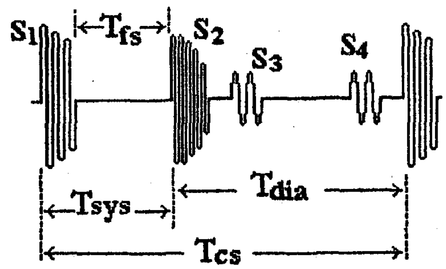
Keywords: heart sounds, Wavelet decomposition and reconstruction, mel cepstrum, Hidden Markov Models, decimation.

1. INTRODUCTION

Non-invasive diagnostic methods of heart diseases, such as Phonocardiography (PCG) [5] and Electrocardiogram (ECG) are useful means for judging the proper function of the heart. In auscultation, the listener tries to analyze the heart sound components separately and then synthesize the heart features. Heart sounds analysis by auscultation highly depends on the skills and experience of the listener. Therefore, the recording of the heart sounds and analyzing them by a computerized and objective way would be highly desirable. The sound material consists of records of heart sounds that are recorded at 16-bit accuracy and 11025 Hz sampling frequency using the traditional stethoscope [4]. A total of 330 periods of PCG ware used to train and test the proposed classifier.

2. HEART SOUND COMPONENTS

Heart sound is a repetitive wave that consists of four sounds representing the sequence of events in a cardiac cycle. Fig.1 illustrates the shape and relative location of the sounds of one cycle [8].



S_1= First Heart Sound.
S_2=Second Heart Sound.
S_3=Third Heart Sound.
S_4=Fourth Heart Sound.
T_{sys}=Systolic Period.
T_{dia}=Diastolic Period.
T_{cs}=Cardiac Cycle Duration.
T_{fs}= The Time Separation between S_1 and S_2.

Figure 2.1 The Heart Sounds.

The first heart sound (S1) is a low-pitched dull sound that precedes the systole. It is formed mainly by closure of the Atrioventricular (A-V) valves (Mitral before Tricuspid) at the start of ventricular contraction. The mitral and tricuspid valves closures may be incompletely fused so that splitting may be audible [8]. It could be best heard at the apex and lower sternum S1 lasts approximately for 150 ms and has frequency components in range of 50-140 Hz [3].

The second heart sound (S2) is sharper in quality than S1 and can be heard all over the precordium. It is caused by closure of the semilunar valves (Aortic before pulmonary). The duration of ejection of the left ventricle is shorter than that of the right ventricle, therefore, the systemic pressure is higher than the pulmonary pressure, and the aortic component (A2) is heard before the pulmonary component (P2). The intensity of each component depends upon the closing pressure in the corresponding valve therefore A2 is louder than P2 [8]. S2 has frequency components in the range of 80-200 Hz [3].

The third heart sound (S3) results from the sudden halt of the movement of the ventricle in response to filling in early diastole after the A-V valves. It is normally heard in children and young adults [8].

The fourth heart sound (S4) is caused by the sudden halt of the ventricle in response to filling in presystole as a result of atrial contraction. It is usually inaudible and is added to S1 [8].

Any deformation or additional sounds in the heart sound signal is called murmurs. Murmurs are sounds caused by turbulent blood flow, which is associated with improperly functioning valves. Valves that do not open all the way (stenosed) or valves that do not close all the way (regurgitated). Murmurs have relatively higher frequency contents (up to 600 Hz) compared to the other heart sounds [3].

3. PREPROCESSING OF HEART SOUNDS

Recorded heart sounds on a PC are usually noisy, therefore, they should be denoised before a single heart beat is isolated [4]. Denoising is achieved through a six-stages wavelet decomposition, thresholding and then reconstruction. Segmentation is done by normalizing to the absolute maximum of the signal according to equation (1).

$$X_{norm}(k) = \frac{X(k)}{\max\left(\left|X(i)\right|\right)} \tag{3.1}$$

A threshold is then set to calculate the duration of S1, S2, and their separation [4].

4. FEATURE EXTRACTION

In this paper, three different feature extraction methods have been used and compared.

4.1 The Traditional Method

In this method, the following operations are performed:

a) Windowing using a 25 ms Hamming window that is shifted each 10 ms to extract the frames.

b) For each frame, mel-cepstral coefficients [9] were calculated using 26 triangular bandpass filters equally spaced on the mel scale [2]. A raised sine lifter of length 22 is used to rescale the coefficients. The first 12 cepstral coefficients consisted the observation vector which is the input for the HMM [7].

4.2 The Decimation Method

The heart sounds are wavelet transformed into two-level Daubechies 6 (db6) transform where they are down sampled by a factor of 4 (frequency decimation), i.e. from a sampling frequency of 11050 Hz to 2763 Hz. Murmurs having frequencies higher than the normal sounds (up to 600 Hz) are not affected since they are still below the new sampling frequency (2763 Hz) such that any useful events of the heart are not missed. Wavelet transform can be used to down sample [3].

Only the approximation (a_2) of the second level was considered where it is normalized and windowed as before. The mel-cepstrum is then taken for each frame. The first 12 coefficients of each frame are concatenated to furnish the input to the HMM.

4.3 The Wavelet Method

After denoising and normalizing the sound signal, a four-level wavelet transform is applied as before. The 4th level approximation together with the details of the 3rd and 4th levels were considered. The frequency bands of the details and approximations are

3rd-level details (d_3): 1382 to 2763 Hz;
4th-level details (d_4): 691 to 1382 Hz;
4th-level approximation (a_4): 0 to 691 Hz;

These outputs after being normalized are then concatenated to form the vector (S) [3]:

$$S = d3 + d4 + a4$$

Which is applied to a Hamming window. The mel cepstrum is then taken where the first 12 coefficients are used to feed the HMM.

5. HIDDEN MARKOV MODELS (HMMs)

In HMM based sound recognition, it is assumed that the sequence of observed vectors (i.e. vectors of mel cepstral coefficients) corresponding to each signal is generated by a Markov model as shown in Fig. 2.

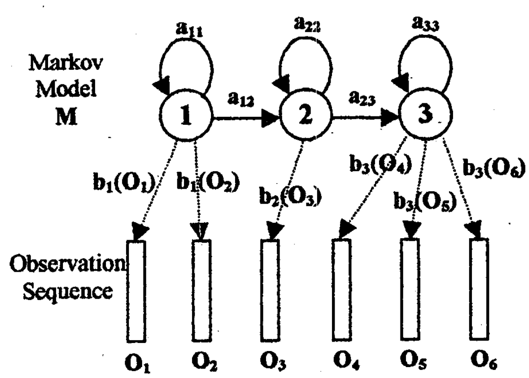


Figure 5.1 The Markov Generation Model

A Markov model is a finite state machine which changes state once every time unit and each time t that a state j is entered, an observation vector o_t is generated from the probability $b_j(o_t)$. Also, the transition from state i to state j is given by the probability a_{ij}.

The HMM uses a Viterbi algorithm to uncover the the best state sequence that maximizes the probaility of generation of the observation sequence O by the model M, P(O/M). P(O/M) depends on the parameters $\{a_{ij}\}$ and $\{b_j(o_t)\}$ which can be calculated very efficiently using a set of training examples for each model. Each state can be modeled by a number of Gaussian mixture densities (GM) to provide an efficient estimation of $\{b_j(o_t)\}$.

In this paper, the HMM Toolkit (HTK) is used for the classification of 11 different heart diseases. A separate HMM is trained on each disease. Input data to the HTK should be denoised, normalized and then processed, before being classified, to get what is called the observation sequences [7].

6. RESULTS

A data set of 330 different heartbeats covering 11 valve-related heart diseases. 220 heartbeats were used to train the HMMs while 110 are left for testing. Using the traditional method an average RR of 96.4% have been obtained with one GM for each state which was raised to 97.3% considering five GM's. Applying the decimation method on the other hand, considering five GM's of each state have yielded an average RR of 98.2%. An excellent RR of 99.1% was obtained using the wavelet method also with five GM's. The results are summarized in table (1) below.

Table(6.1): Summary of the results

Technique	Size of testing data set	Correct Recognition	RR %
Traditional method (1GM)	110	106	96.4
Traditional method (5GM)	110	107	97.3
Decimation method (5GM)	110	108	98.2
Wavelet method (5GM)	110	109	99.1

7. CONCLUSION

HMM has proven to be a useful tool for classifying heart diseases through heart sound analysis. It provided much better results compared to neural network classifier that have been obtained RR of 95.7% [1]. Main reason of such improvement is the fact that HMM consider each frame as being a stationary signal. Results have shown that the number of GM's is crucial in determining the obtainable RR's. An improvement of from 96.4% for one GM to 97.3% for 5 GM's has been achieved. Also processing of the signals is essential to get true and representative features. Recognition rates ranging from 98.2% to 99.1%. have been achieved.

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