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Classification of Heart Sound Signals Using Discrete Wavelet Analysis

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Abstract: Heart auscultation which is the interpretation of sounds produced by the heart is a fundamental tool in the diagnosis of heart disease. It is the most commonly used technique for screening and diagnosis in primary health care. The efficiency of this diagnosis can be improved considerably by using modern digital signal processing techniques. This study utilizes the discrete wavelet transforms to identify the first heart sound S1, second heart sound S2 and murmurs. An algorithm was developed with the aim of classifying phonocardiogram signals into three categories: signal with systolic murmur, signal with diastolic murmur, or normal signal.

Key words: Heart sounds, heart auscultation, classification of phonocardiogram signals, discrete wavelet

INTRODUCTION

Heart auscultation which is the interpretation of sounds produced by the heart is a fundamental tool in the diagnosis of heart disease[1]. It can provide valuable information concerning the integrity and function of the heart valves and several hemodynamic mechanisms. It is the most commonly used technique for screening and diagnosis in primary health care. In some circumstances, particularly in remote areas or developing countries, auscultation may be the only method available[2]. However, detecting relevant symptoms and forming a diagnosis based on sounds heard through a stethoscope is a skill that can take years to acquire and refine. It has been reported that a disturbing percentage of medical school graduates cannot properly use a stethoscope for diagnosing common heart conditions[3]. Furthermore, many physicians rely heavily on Electrocardiogram (ECG) specialists, leading to higher health care costs and a general decline in stethoscope skills[4]. It would be very advantageous if the benefits of auscultation could be obtained with a reduced learning period, using equipment that is low-cost, robust and easy to use. A computer-aided diagnosis can help considerably in the heart sound analysis and quantitative characterization of abnormalities, thereby improving the overall efficiency of the diagnosis. This can be achieved by analyzing the Phonocardiogram (PCG), which is a recording of the acoustical waves produced by mechanical action of the heart, by modern digital signal processing techniques. Hence, more accurate and valuable information can be acquired about the heart condition.

A research study has been started in Hashemite University in Jordan with the aim of developing a new method for automated classification of PCG signals. The method is based on the clinical observations of cardiologists and uses wavelet analysis with classification techniques to analyse, quantify and classify different aspects of heart sounds of different pathologies. The first step of this study, which is the primary objective of this study, is to develop an efficient algorithm for the automatic segmentation of the heart sound into separate cycles followed by the classification of the signals. Each cycle is divided into four parts: the first heart sound S1, the systolic period, the second heart sound S2 and the diastolic period. The signals are classified as having systolic murmur, diastolic murmur, or being normal.

Heart sounds: Heart plays a vital role in the circulation of blood and life in their vein. The heart is divided into four chambers. The upper chambers are called atria and the lower chambers are called ventricles. The heart muscle squeezes blood from chamber to chamber. At each squeeze, the valves open to let blood through to the next chamber. Then the valves close to stop blood from moving backward. In this way, the valves keep blood moving as efficiently as possible through the heart and out to the body[4]. The heart sounds result from the interplay of dynamic events associated with the contraction and relaxation of the atria and ventricles, the

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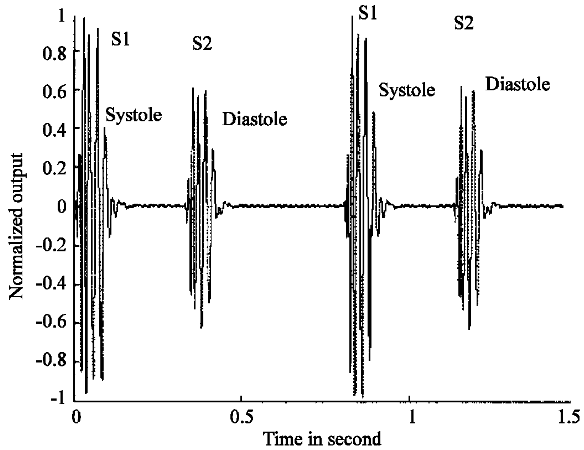

Fig. 1: Typical heart sounds for a normal heart beat

valve movements and blood flow[1]. The heart sounds consist of normal heart sounds and murmurs.

Figure 1 shows a typical heart sounds for a normal heart beat. There are two heart sounds called S1 and S2. The first heart sound S1 occurs at the onset of ventricular contraction during the closure of the mitral and the tricuspid valves. It indicates the beginning of a ventricular systole. The second heart sound S2 marks the end of ventricular systole and the beginning of diastole. This second sound is created by the closing of the aortic and pulmonic valves as blood exits the heart to the body and lungs[4]. For young person, it is normal to detect a third (S3) and fourth heart (S4) sounds. However, S3 and S4 are regarded as pathological in older adults[5].

A heart murmur is an abnormal, extra sound during the heartbeat cycle made by blood moving through the heart and its valves[6]. These sounds are generated primarily by the turbulent flow of blood in the heart which are characteristic of cardiac disease such as aortic stenosis, or valve defects. If a valve does not fully open, there will be less blood circulation. On the other hand, if a valve does not close properly, blood may leak backward or regurgitate. In either case, the faulty valve causes turbulence thus producing murmurs. Murmurs can occur in either systole or diastole[4] in Fig. 2.

For the diagnosis of the heart condition, it is important to identify the types of murmurs. According to Lee[5], the murmurs can be classified as pre-systolic murmur, early systolic murmur, late systolic murmur, early diastolic murmur, late diastolic murmur and continuous murmur according to their occurring time. In this preliminary study, the classification will be done based on three categories: Normal (NO), Systolic Murmur (SM) and Diastolic Murmur (DM). Since it is generally difficult to distinguish between these types of murmurs by just relying on the human hearing capabilities, it is crucial to

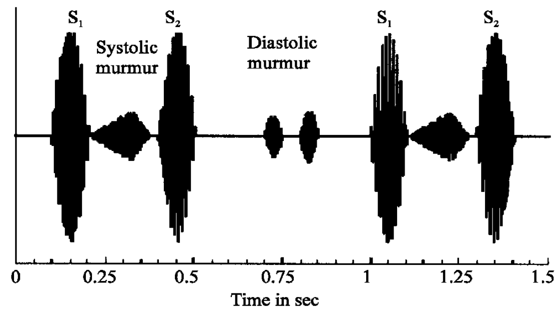

Fig. 2: Typical heart sounds for a heart with both systolic and diastolic murmurs[4]

use signal processing techniques as an aid for such type of identification. Next section will discuss the use of signal processing for heart sound analysis and identification.

Signal processing for heart sound: The complex and highly nonstationary nature of PCG signals can make them challenging to analyze in an automated way. However, recent technological developments have made extremely powerful digital signal processing techniques both widely accessible and practical. Wavelet transforms have become well known as useful tools for various signal processing applications[1,7-10]. Khadra *et al.* were the first to suggest that the wavelet transform can provide a useful tool for the time frequency analysis and characterisation of the primary heart sounds[9]. Its adequacy for this particular application was further confirmed by many researchers[10]. Using wavelet analysis, many methods have been applied to study the correlation between these sounds and various heart defects[9,11-16]. In this study, discrete wavelet analysis with signal detection is used to segment the heart sound data into separate cycles. A brief review about wavelet transform is presented in the next paragraph.

The wavelet transform was developed as a method to obtain simultaneous high resolution in time and frequency domain. It can provide detailed information on the time-frequency content of the PCG signal during the whole cardiac cycle. Wavelet transform can be continuous or discrete. The continuous wavelet transform reveals more details about a signal but its computational time is enormous. For most applications, however, the goal of signal processing is to represent the signal efficiently with fewer parameters and less computation time. The Discrete Wavelet Transform (DWT) can satisfy these requirements[17]. The DWT calculates the wavelet coefficients at discrete intervals of time and scales. The DWT coefficients can be used to form a set of features that unambiguously characterize different types of

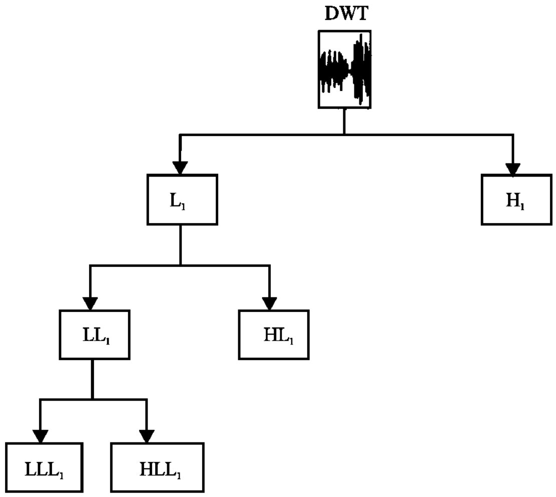

Fig. 3: Filter bank representation of the DWT decompositions into lower frequency components (L_1, LL_1 and LLL_1) and higher frequency components (H_1, HL_1, HLL_1)

signals[18]. The dilation function of the DWT can be represented as a tree of low and high pass filters, with each step transforming the low pass filter into further lower and higher frequency components as shown in Fig. 3. The original signal is successively decomposed into components of lower resolution, while the high frequency components are not analysed any further. The low-frequency components of the signal are called approximations, while the high-frequency components are called details.

Data description: Representation of murmurs from pathologic and non-pathologic subjects has been acquired from 14 patients with aortic stenosis and with different degrees of valve competence and 7 healthy persons. All data has been collected over a number of years from patients at the Brighton and Sussex University Hospital using digital stethoscopes built at the University of Sussex. The PCG data is collected at a sampling frequency of 4096 Hz. The data has noise and it is cleaned by high-pass Butterworth filter. Another cardiac auscultation of heart murmurs database of sixty one samples were obtained from[19]. The data was classified and it includes one normal heart sound, 28 signals with diastolic murmurs and 32 signals with systolic murmurs. Depending on the signal, the sampling rate varies from 8000 Hz to 22050 Hz.

MATERIALS AND METHODS

The first step in the identification of types of murmur is to delineate the systolic and diastolic phases. This process is called segmentation. The true segmentation based solely on the PCG data is not an easy task since in many pathological cases the distinction of S1 and S2 may not be obvious from the time domain representation or the frequency domain representation of the signal. However, this task might become easier if the time-frequency analysis is considered. In this study, DWT time-frequency analysis along with the common properties of S1 and S2 are used to locate S1, S2, systolic and diastolic periods. Then the results are used to classify the PCG signals into one of three categories: normal, systolic murmur or diastolic murmur.

RESULTS AND DISCUSSION

In order to identify S1 and S2 correctly, we need to consider its main features in time and frequency domains. First, it has been noted from the available data and from previous studies[20] that the longest time interval between two adjacent peaks is the diastolic period which extends from the end of S2 to the beginning of S1. Fig. 1 and 2 confirm these observations.

Second, as heart rate increases the duration of the diastolic period decreases while the systolic period which extends from the end of S1 to the beginning of S2 is relatively constant[4]. From the available data with normal heart beat, it has been observed that the systolic period varies between 0.14 to 0.18 second while the diastolic period varies between 0.24 to 0.44 sec.

Third, in many cases, it has been observed that the peak of S1 is higher than that of S2. However, many pathological signals have shown that S1 is either smaller or has similar magnitude as S2. In addition, earlier studies using FFT have shown that the frequency spectrum of S1 is generally dominant in the low frequency range (10-80 Hz), while the frequency spectrum of S2 becomes significant at medium frequency range (50-140 Hz)[21]. The combination of time and frequency properties is quite valuable in the identification of S1 and S2[20]. Figure 4 shows a PCG signal with selected approximation a_6 and details d_6, d_5 and d_4. The signal has a sampling frequency of 8000Hz and a_6, d_6, d_5 and d_4 corresponds to different frequency bands and were obtained from the DWT decomposition and reconstruction of the signal using wavelet base Daubechies ‘db6’. The sixth level approximation, a_6, corresponds to a frequency band 0 to 62.5 Hz. The 6^{th} level detail, d_6, corresponds to a frequency band 62.5 to 125 Hz. While the 5th and 4th level details d_5 and d_4 correspond to the respective frequency bands 125 to 250 Hz and 250 to 500 Hz. In the time domain, the signal shows the presence of S1, S2 and murmurs. From this plot, it is quite difficult to decide which of the peaks represent

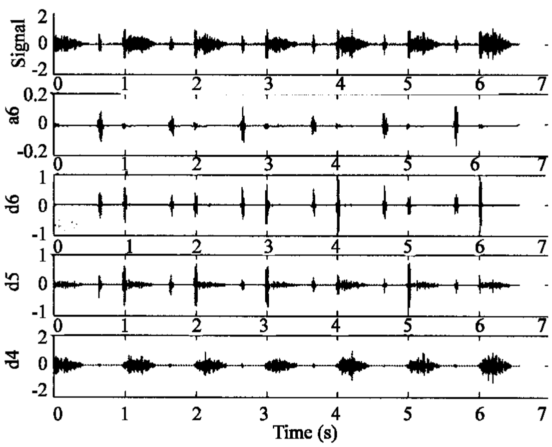

Fig. 4: An original signal with its approximation a_6 and details d_6, d_5 and d_4

S1 or S2. However, when the plot of a_6 is considered, we can easily observe a peak which corresponds to S1 since it is dominant in this frequency band. The appearance of the peaks corresponding to S2 is evident in the plot of d6. The presence of murmurs is clearer in the plot of d5 and d4. In conclusion, the DWT decomposition and reconstruction of the PCG signal at selected level can be very useful in the identification of S1 and S2.

Taking into consideration the previous discussion, the classification algorithm used in this study follows seven major steps.

- The PCG signal is normalised, then it is decomposed using DWT decomposition for selected approximation and details using wavelet base Daubechies 'db6'. The level is selected so that the corresponding approximation and detail cover the low frequency range. In the previous example, the selected level is 6; the approximation a_6 and detail d_6 cover the frequency range from 0 to 62.5 Hz and from 62.5 to 125 Hz, respectively. Lower details is also considered for better distinction of S1 and S2 from the murmurs.
- Determine the envelope of the PCG signal and the reconstructed coefficients. If x(n) represents one of the data, its envelope can be determined using the following expression

$$y(k) = \sum_{i=1}^{N} \text{mean}\left|x(i + k\,N)\right| \qquad (1)$$

where x(n) is divided into intervals of 0.01 second and the average value is assigned to its envelope y(k). N presents the number of points in 0.01 second.

- Detect the peak values from the envelope of the reconstructed approximation coefficient. The peak values mostly belong to S1 and its duration is determined using a threshold that depends on the minimum value of each interval.
- Detect the peak values of the suspected S2 from the envelope of the reconstructed detail approximations and estimate its duration.
- Identify the correct S1 and S2 and their durations.
- Estimate the systolic and the diastolic periods.
- Calculate the energy of the PCG signal within the systolic and the diastolic period. If the energy exceeds a specified threshold in each interval, then the PCG signal is classified as having SM or DM. Otherwise, the signal is classified as normal.

Table 1: Accuracy of the classification results

	Normal	Systolic	Diastolic
Accuracy	100%	88%	89%

Twenty one signals are used for training the algorithm to get the appropriate threshold values. The remaining signals are used to test the performance of the proposed algorithm. The test results produce the classification accuracy shown in Table 1.

In most studies, the algorithm was able to segment the heart sounds into periodic cycle successfully. The classification accuracy is close to 90% for systolic and diastolic cases. The main factor that contributes to the reduction of the classification accuracy is the presence of large intensity murmurs overlapped with S1 or S2. The analysis of such cases is quite complex and will be investigated in future study. Another factor that contributes to the errors is the presence of high level interfering noise in some of the available data.

CONCLUSION

This study presents an algorithm which uses discrete wavelet transform in the automatic identification of S1, S2 and classifies the signal into three categories: normal, systolic murmur and diastolic murmur. The classification results are close to 90%. Most errors are due to the large intensity murmurs overlapped with S1 and S2. This case is quite complex and will be investigated further in future study.

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