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Automatic Heart Sounds Detection and Systolic Murmur Characterization Using Wavelet Transform and AR Modeling

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Abstract— **This paper describes a signal processing procedure that identifies the first and the second heart sounds (S_1 and S_2), extracts the systole from the diastole, detects and characterizes the systolic murmur found within. The identification of heart sounds was facilitated by discrete wavelet transform (DWT) approximation using the Coiflet wavelet and followed by using indicators that quantify signal activity and strength. The systole was isolated and divided into smaller short segments where the signal activity measure and absolute amplitude were computed. S_1 and S_2, and the onset and duration of a systolic murmur were marked. Using the indices derived from AR modeling, a systolic murmur can be characterized by its timing, duration, pitch, and shape either as crescendo, decrescendo, crescendo-decrescendo, or plateau. The performance of the proposed procedure was evaluated and proved with clinically recorded systolic murmur episodes.**

I. INTRODUCTION

Heart disease is the number one cause for adult death in many countries. To date, the stethoscope, invented almost two hundred years ago, still remains as the primary bedside diagnostic tool. The effectiveness of cardiac auscultation, however, heavily depends on an individual physician's experience and skill. As a result of the involved complexity and subjective judgment in cardiac auscultation, many patients who have been referred to cardiologists for further medical examinations turn out to be normal. Some of these unnecessary examinations could have been prevented to save the cost associated with extra examinations and to avoid the waste of valuable medical resources if cardiac auscultation were more accurate and objective [1], [4]-[5].

With the advantage of modern computers and signal processing developments, computer-based digital cardiac auscultation presents a natural path of pursuit [12] for improvement. The underlying paper extends our previous studies [1],[10]-[11] and presents a computer based identification and scoring system with little or no human supervision. The main goal of the computer-aided auscultation approach is to provide consistent and reliable characterization of heart murmurs to assist physicians in evaluating cardiovascular conditions and identifying signs of abnormal alternations or heart diseases [4], [12]. More specifically, the suggested approach provides quantitative descriptions of heart murmurs that delineate clinical features such as murmur timing, duration, pitch and shape configuration [10]-[12].

When the heart sounds are analyzed with the ECG, the first heart sound S_1 (snap sounds caused by the closure of mitral and tricuspid valves) can be immediately identified after the QRS complex, while S_2 (the closure of aortic and pulmonary valves) occurs following the T-wave in ECG [12]. In a situation where the ECG is not available, the challenge of a computer based heart sound and murmur analysis becomes more complex. To clarify, in our study, we focus on systolic murmurs with an assumption that the diastole cycle is longer than the systole cycle in order to differentiate S_1 from S_2. Once S_1 and S_2 are marked, systole cycles can be extracted from the complete cardiac cycles for further analysis.

To effectively assist cardiac auscultation, important heart sound and murmur features must be accurately provided with clinical interpretation. Accordingly, our approach is to generate heart murmur features of timing, duration, pitch, and shape. To achieve these goals, we employed several signal dependent indices and known signal processing algorithms including discrete wavelet transform (DWT) [6]-[7] and autoregressive (AR) modeling [9].

The proposed signal processing consists of two major steps: (i) detecting heart sounds (S_1, S_2) and extracting the systole from consecutive cardiac cycles, and (ii) examining the systole and characterizing the systolic murmur using clinical descriptors. The two steps are explained below in Section II and Section III, respectively. The detected murmur will be marked by its onset and duration; the murmur pitch frequency is estimated as the averaged pitch frequency between the onset and the end of a murmur; and murmur configuration/shape is delineated either as crescendo, decrescendo, crescendo-decrescendo, or plateau.

The performance of our scoring system has been tested using three types of systolic murmur episodes from patients with documented heart problems [8] such as early-systolic, mid-systolic, late-systolic murmurs in Fig.1, where the early systolic murmur has a decrescendo shape, mid-systolic a crescendo-decrescendo shape, and late-systolic murmur the decrescendo shape. Results are discussed and summarized in Section IV.

II. HEART SOUNDS IDENTIFICATION

To set the tone, the signal processing procedure suggested herein will first divide a cardiac cycle into major segments in sequence: first heart sound (S_1), systole, second heart

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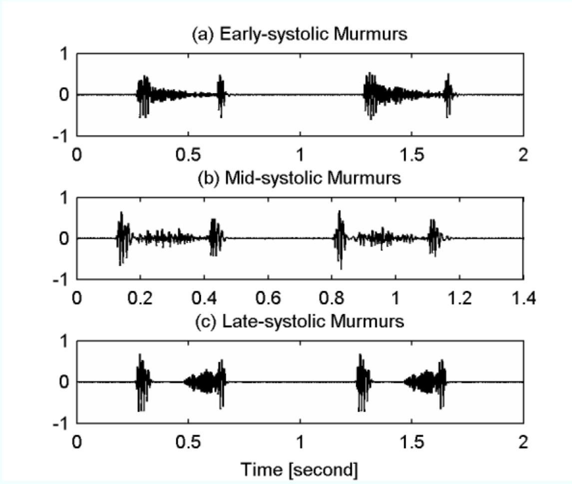

Figure 1. Three different types of systolic murmurs

sound (S_2), and diastole. Quantitative measures that resemble clinical diagnosis parameters are extracted afterwards using customized algorithms to be explained in the following. Without loss of generality, multiple cardiac cycles with systolic heart murmurs shown in Fig.1 are used to exemplify the underlying approach.

A. *Activity Index Function*

Since S_1 and S_2 can be identified by their distinctly larger amplitude, a cardiac cycle can be divided into many short segments of equal length and computed an energy index function for each short segment to delineate its relative amplitude. With the suggested *Activity Index*, the larger amplitudes of S_1 and S_2 in a cardiac cycle can be identified.

$$ACTY_n = \frac{1}{N}\sum_{k=1}^{N}(x(k)-\mu_n)^2 \qquad (1)$$

where μ_n is the mean value of the n^{th} segment short segment data $\{x(k)\}$.

B. *Discrete Wavelet Transform (DWT)*

The Wavelet Transform (WT) [3] has enjoyed a wide popularity in research for examining, in particular, non-stationary signals or signals with transient phenomena of interest. The WT uses a joint time-scale representation of the signal of interest. In addition, the time-resolution of WT can be traded for better scale-resolution and vice versa. The flexibility in resolution has earned WT the reputation for being useful in exploring non-stationary signals with sudden transients [3],[7]. Since most biomedical signals have frequency contents that change over time, a joint time-scale representation is at times appropriate.

The WT uses short data windows at high frequencies and long ones at low frequencies. In the current study of heart sounds and murmurs, it will facilitate the separation of the heart sounds S1 and S2 which are generally low frequency and murmurs, which generally exhibit higher frequency contents. Using the WT with a carefully determined level of *approximation*, one can retain mostly only the characteristic S1 and S2 sounds and expedite the identification of the heart sounds and the isolation of systole. For a given signal

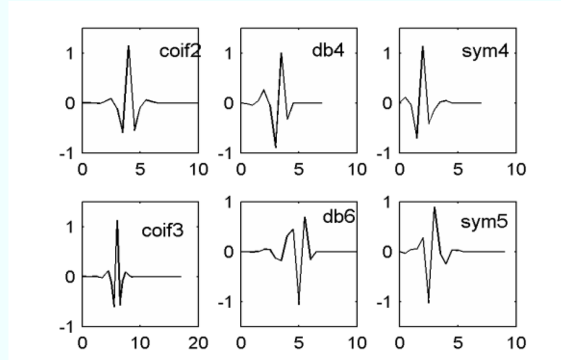

Figure 2. Six different mother wavelets

x(t),The Continuous Wavelet Transform (CWT) is given below [4].

$$CWT_x(\tau,a) = \frac{1}{\sqrt{a}}\int x(t)h^*\left(\frac{t-\tau}{a}\right)dt \qquad (2)$$

where *h(t-τ/a)* is a scaled, shifted version of a mother wavelet.

The WT based multi-resolution signal decomposition proposed by Mallat [6] has been used to identify the heart sound (S_1, S_2) boundaries. The Mallat algorithm uses dyadic (based on powers of two) scales and positions to make the analysis much more efficient without losing accuracy. Given a sequence representing a cardiac signal, a lower resolution signal is derived by low-pass filtering with a half-band low-pass filter. The scale in the analysis can be doubled by sub-sampling by two according to the Nyquist's rule. The success of deriving a good approximation depends greatly on the choice of the mother wavelet and the decomposition level. Figure 2 shows the wavelets being tested in the current study. With the derived approximation, the identification of S_1 and S_2 becomes obvious. An example of approximation is shown in Fig.3.

C. *Dissecting Systole and Diastole*

Once heart sounds S_1 and S_2 are identified and labeled, systole and diastole can be segmented between borders of S_1 and S_2. Durations of S_1 and S_2 lie between 55 to 65 milliseconds in general. Without loss of generality, we simplified the delineation of the S_1 and S_2 boundary within

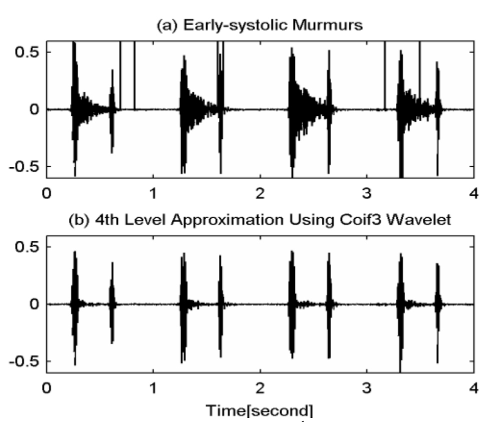

Figure 3. Approximation at the 5^{th} level using coif3 wavelet

30-msec of the signal before the marked peaks in this energy index and 30-msec that follows the peak, or when the ACTY index drops to less than 10% of the marked peak value.

The locations of S_1 and S_2 for the cardiac cycles of the early systolic murmur shown in Fig.3 can be immediately marked using the activity index in (1). Through comparison of the distances between marks, S_1 and S_2 can be correctly labeled. In certain heart sound and murmur episodes where S_1 is louder than S_2, the labeling process can be easier and more accurate by incorporating this fact. The process of identification and labeling S_1 and S_2 remains unchanged with the knowledge that S_2 is louder than S_1.

III. Heart Murmur Characterization

To characterize the systolic heart murmurs, we will use quantitative measures derived from the methods described below.

A. *Murmur Pitch*

Murmur pitch is usually described as high or low. The pitch frequency of a heart murmur is calculated in this study with second-order AR model in (3) without referring to the spectrum estimation and Fourier transform. The second-order AR model is sufficient for capturing the dominant frequency of the target signal of interest [9].

$$e_k = x(k) - a_1 x(k-1) - a_2 x(k-2) \tag{3}$$

The AR model coefficients $\{a_1, a_2\}$ are estimated using the Burg's time series analysis algorithm [9]. The murmur pitch frequency is calculated by the following

$$pitch = \frac{f_s}{2\pi}\tan^{-1}\left(\frac{\sqrt{4a_2 - a_1^2}}{a_1}\right) \tag{4}$$

where f_s is the sampling frequency. The isolated systole cycle is divided into short segments and the pitch frequency of each segment is calculated to provide a profile of the change during systole.

B. *Murmur Timing and Duration*

In this study, a heart murmur is identified when the activity index (1) is larger than an empirically determined threshold tied to the activity level of S_2. The murmur onset is marked when the activity index of the systole being examined segment by segment rises above the threshold for a few consecutive segments. The end of the murmur is marked in a similar but reverse approach, i.e., as soon as the activity index drops below the threshold for more than two segments. The murmur *timing* is calculated as the time between the waning side of S_1 to the onset of murmur. Murmur *duration* was determined as the time between the murmur onset and its end.

C. *Murmur Configuration*

The murmur configuration is commonly recognized as crescendo, decrescendo, crescendo-decrescendo, or plateau. A useful measure to score the murmur amplitude level is the average absolute value of a segment.

$$ABV_n = \frac{1}{N}\sum_{k=1}^{N} | x(k) - \mu_n |, \tag{5}$$

where μ_n represents the mean value of the n^{th} segment. The *ABV* index is easily calculated and serves as a good indicator to describe the murmur shape. We have found in our study that both ACTY and ABV indices are equally effective in identifying S_1 and S_2 and delineating murmur shape. Using either index in (1) or (5), the shape of a murmur can be captured by the slope that best fits the changing ABV indices by segments. The slope can be estimated by finding the best linear fit in (6) using the minimum mean squared errors.

$$ABV_n = c + slope * n, \tag{6}$$

IV. Results and Discussion

Systolic murmurs examined in this paper are clinical data collected in [8]. The choice of the mother wavelet is crucial to approximation of S_1 and S_2. We compared six different mother wavelets shown with varying levels of approximation to process the three types of systolic murmurs. Figure 4 exemplifies the results using Daubechies (*db6*) wavelet on cardiac cycles with early-systolic murmurs. One can immediately observe that the 4^{th} level approximation leads the best manifestation of S_1 and S_2. The choice of the best DWT approximation levels, admittedly, is subject to debate. Here, we consider the best level as the one that leads to best manifestation of S_1 and S_2. It's worth mentioning that approximations from high levels do not necessarily lead to better results. For a comparison of differences in mother wavelets and approximation levels, the results are summarized in Table I.

Mother Wavelets and the Most Accurate Approximation Level

Murmur type	*coif2*	*coif3*	*db4*	*db6*	*sym4*	*sym5*
Early-systolic	4	4	4	4	4	4
Mid-systolic	5	5	5	5	5	6
Late-systolic	4	4	4	4	4	4

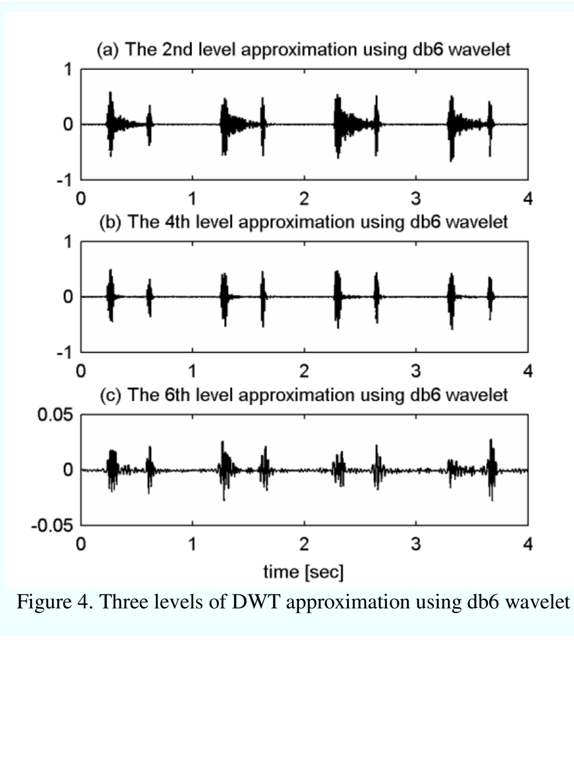

Figure 4. Three levels of DWT approximation using db6 wavelet

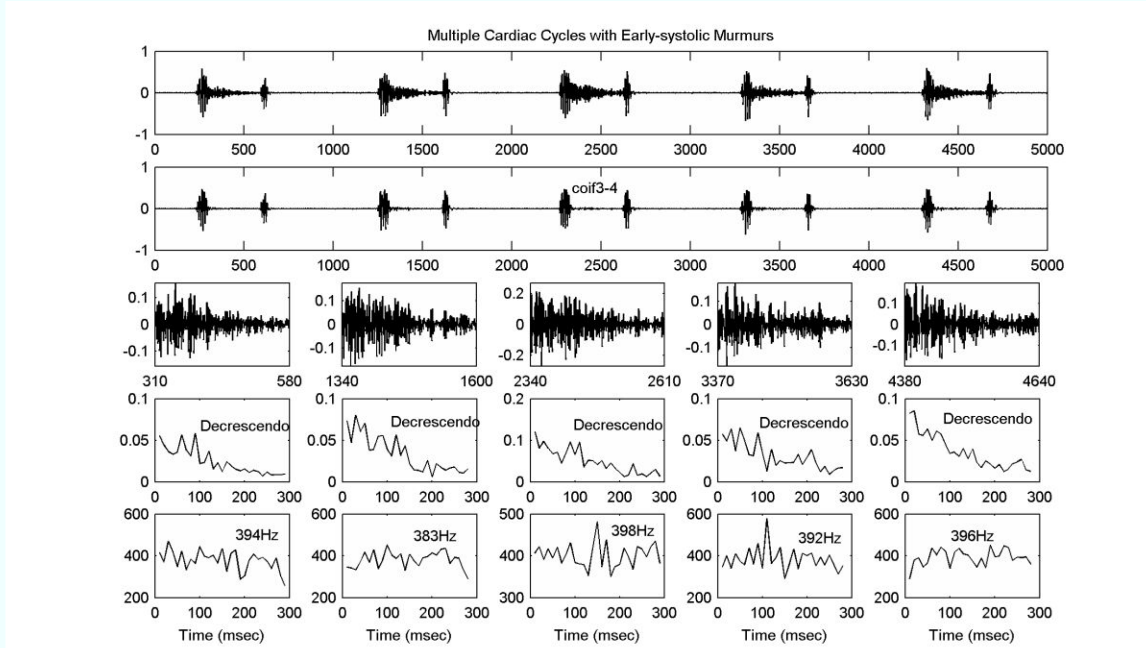

Figure 5. Five cardiac cycles of early-systolic murmurs: the first row shows the raw data; the second row displays the DWT approximation at the 4th level using coif3 wavelet; the third row shows the systolic murmur being extracted from the systole cycle with the onset and end indicated; the fourth row represents the murmur configuration (shape) determined by the slope of ABV indices; the bottom row shows the average pitch frequency of the each early-systolic murmur.

In this paper, we adopted the Coiflet (*coif3*) as the mother wavelet and chose the 4th level approximation to facilitate the identification of heart sounds. After DWT approximation, the auscultation signal was divided into short segments of 10 milliseconds. S_1 and S_2 were identified by the peaks of ACTY and their boundaries were marked when the ACTY index dropped below 10% or 30 milliseconds from the peak.

With an isolated systole marked between S_1 and S_2, a murmur was called when two successive segments displayed ACTY indices more than 20% of the average S_2 value. Murmur pitch and was estimated by (4) and shape configuration delineated by (6). Test results of five cardiac cycles are exemplified in Fig.5. The second row displays the DWT approximation at the 4th level using *coif3* wavelet. The third row shows the systolic murmur extracted from each cycle from the onset to the end. Similar results were obtained when processing mid-systolic and late-systolic murmurs in [8]. It should be noted that choice of thresholds in identifying heart sounds and marking boundaries will affect the overall results. To validate the observed performance and to examine the performance sensitivity to selected thresholds, extensive tests on heart murmur databases are planned.

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