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Delineation of Systolic and Diastolic Heart Murmurs via Wavelet Transform and Autoregressive Modeling

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Abstract. This paper describes a signal processing algorithm that utilizes wavelet transform and autoregressive modeling to identify heart sounds and to generate clinical features that characterize systolic and diastolic heart murmurs. A wavelet transform (WT) based on the Daubechies wavelet was adopted to facilitate the identification of the first and second heart sounds (S_1 and S_2) and to isolate systole and diastole periods without referring to the ECG waveform. Quantitative descriptors of heart murmur features such as the pitch frequency and configuration (crescendo, decrescendo, or plateau) were derived from either the systole or the diastole period where the murmur resides using a second order autoregressive (AR) whitening filters. The performance of this combined WT and AR modeling signal analysis was evaluated and demonstrated on selected systolic and diastolic murmurs and the results are presented in this paper.

Keywords: Heart Sounds; Heart Murmurs; Wavelet Transform; Autoregressive Modeling.

1. Introduction

Modern medical diagnostic tools for heart diseases have been emerging rapidly due to technological advancements in many fields such as CAT scans, MRIs, and ultrasounds. However, the traditional bedside diagnostic tool—the stethoscope—is still the first and most often applied instrument to detect any anatomical alternations of the human cardiovascular system. Even though the outcomes derived from computer-aided electronic auscultatory devices have not yet established their clinical value with consistent and supporting statistics, computer-aided electronic auscultatory devices that are able to record and to identify clinically important heart sounds, including S_1, S_2, and suspected murmurs, can be effectively utilized to provide support to physicians in evaluating heart sounds and identifying signs of potential heart diseases [Freeman and Levin, 1933; Mason, 2000].

To develop an effective signal processing algorithm that can add more functionality to computer-aided cardiac auscultatory devices, a basic understanding of the cardiac cycle is in order. The heart pumps blood through the cardiovascular system by contracting (systole) and relaxing (diastole), where systole takes place after the first heart sound S_1 and diastole follows the second heart sound S_2. The first heart sound S_1 is caused by the closure of the tricuspid and mitral valves, where the closure of the mitral valve slightly precedes that of the tricuspid valve; the second heart sound S_2 is caused by the closure of the aortic and pulmonary valves, with the closure of the aortic valve preceding that of the pulmonary valve.

When the heart sound and murmur is studied in association with the ECG waveform, the timing of S_1 occurrence can be identified immediately after the QRS complex and that of S_2 occurrence follows the T-wave. A useful clue in differentiating systole from diastole without referring to the ECG waveform is the fact that the duration of systole is usually shorter than that of diastole. Furthermore, the pitches (frequencies) of S_1 and S_2 are generally lower than those of murmurs [Mason, 2000; Atanasov and Ning, 2007].

When the first and second heart sounds (S_1 and S_2) are heard through auscultatory instruments by human ears, they appear as crisp and snapped. Heart murmurs, on the other hand, are noise-like. They are caused by the turbulence of blood flowing through the cardiovascular system; the cause of turbulent flow can be attributed to many possible anatomical alternations [Akay et al., 1993; Akay et al., 1994].

The auscultatory information reveals a unique aspect of the operation of hearts not available via other diagnostic devices. Therefore, amid emerging diagnostic tools, cardiac auscultation remains a vital investigative process for physicians to reveal crucial information regarding the well-being and abnormal alternations of the cardiovascular system.

One common limitation of cardiac auscultation diagnosis based on human audition is that the result is heavily influenced by the subjective judgment of an individual, rather than objective assessment. Other parameters, such as a physician's clinical experience and quality of hearing instruments, also have influence. The constant challenge for human auscultation is to provide a complete description of heart murmur features, including timing, duration, quality, pitch, intensity, and configuration, by listening to sounds in time frames that are less than a second.

Since frequency selective filters cannot effectively separate S_1 and S_2 from heart murmurs, we used wavelet transform to isolate the heart sounds S_1 and S_2 to divide the signal into systole and diastole. WT analysis has been shown to be effective in analyzing heart sounds to identify S_1, S_2, and murmurs [Kumar et al., 2006; Atanasov and Ning, 2008; Delgado-Trejos et al., 2009] and AR modeling is effective in spectral analysis [Ning and Bronzino, 1990; Ning and Hsieh, 1995; Atanasov and Ning, 2007]. Our goal in this endeavor is to develop an effective signal processing algorithm to analyze heart sounds and murmurs and to extract the aforementioned features with objective (quantitative) measures. In WT analysis, the choice of a mother wavelet that resembles S_1 and S_2 and has a center frequency different from that of heart murmurs is crucial to effectively identifying S_1 and S_2 and performing other tasks that follow. We found and confirmed through our extensive analysis that the Daubechies wavelet (*db6*) is the most effective mother wavelet for this purpose [Kumar et al., 2006; Atanasov and Ning, 2008].

By identifying S_1 and S_2, the murmur embedded within systole and/or the diastole can be singled out for further analysis, which was performed by dividing the identified murmur (in systole or diastole) into short segments and using a second order AR model for each short segment to extract the dominant pitch frequency and other features of the heart murmur. The AR model coefficients were estimated using Burg's algorithm. The performance of this combined WT and AR modeling signal processing approach was evaluated by tests on a set of heart sound episodes that include systolic and diastolic murmurs. The results of processing a systolic murmur with aortic regurgitation and an Austin Flint murmur with mid-diastolic murmur are presented in this paper.

2. Method

2.1. Wavelet Transform

A wavelet transform (WT) is a way of approximating signals through a linear combination of scaled versions of a mother wavelet. WT differs from Fourier transform in that a mother wavelet, instead of sinusoids, is used as the basic function to span the signal space. An individual wavelet is localized in space, whereas a sinusoid is not. This localization is particularly useful because the frequency in a heart sound signal changes with time. WT is able give both time-resolution and frequency-resolution information [Unser and Aldroubi, 1996; Qian and Chen, 1996; Lang and Forinash, 1998; Mallat, 1999].

For a given signal $x(t)$, the continuous-time wavelet transform (CWT) [Lang and Forinash, 1998] is shown by the equation:

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

where $h^*((t-\tau)/a)$ represents the scaled and shifted version of the mother wavelet. Since WT uses short data windows for high frequency components and long data windows for low frequency components, WT can be used to separate heart sounds from heart murmurs. S_1 and S_2 both have lower frequency sounds (below 60-80 Hz) than do typical murmurs (above 125 Hz). For a complete cardiac cycle, a lower resolution signal can be derived by filtering with a half-band low-pass filter, where two outputs, details and approximations, are separated into higher and lower frequency components, respectively [Kumar et al., 2006; Atanasov and Ning, 2008]. The mother wavelet has a center frequency, and the frequency band of the retained signal decreases as its scale $\boldsymbol{a}$ increases. There is a pseudo-frequency for the wavelet component at scale $\boldsymbol{a}$.

One of the most commonly referred to murmur feature is the loudness level. For more than 70 years, the Levine scale has been used in clinical practice. This scale classifies heart murmur intensity to six levels. The intensity of sound is defined as power over unit area (e.g. watt/cm^2). In our analysis, we divided the digitized heart sound signal into many short segments and an energy index based on the mean-squared value of a short segment of data was used to measure the sound intensity:

$$ENGY = \frac{1}{N}\sum_{k=1}^{N}(x(k) - \mu_k)^2 \tag{2}$$

where

μ = mean value of the data segment.

The measure is the variance estimate in statistics and is valuable in categorizing loudness level of heart murmurs.

2.2. Autoregressive Modeling

Autoregressive (AR) models are of particular interest for many applications mainly because AR model coefficients can be efficiently computed. The estimated AR model coefficients can be used not only for power spectrum estimation, but also can be used to derive quantitative characteristics of the underlying time series, e.g., the dominant frequency [Ning and Bronzino, 1990]. For this reason, a second order AR model was used and the AR model coefficients of the heart sound $x(n)$ were estimated by the Burg algorithm. The Burg algorithm calculates the AR coefficients (a_1,a_2) by minimizing the combined forward and backward prediction errors:

$$\begin{aligned} e_f(k) &= x(k) - a_1 x(k-1) - a_2(k-2) \\ e_b(k) &= x(k) - a_1(k+1) - a_2 x(k+2) \end{aligned} \tag{3}$$

As mentioned earlier, the AR model coefficients can be used for many purposes. The poles of the characteristic equation formed from the AR models were used in [Ning and Bronzino, 1990] to quantify the hippocampal EEG frequency during REM sleep and in [Ning and Hsieh, 1995] to detect the sounds associated with turbulent blood flow. Since it is of clinical interest to physicians during cardiac auscultation to describe a murmur's pitch and configuration, a second order AR model was used in this paper. The AR model coefficients (a_1,a_2) were estimated for each segment and utilized to estimate the pitch frequency as follows:

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

where

f_s = data sampling frequency in hertz.

The frequency estimate is valid only when the poles derived from the AR polynomial are a pair of complex conjugate poles [Ning and Bronzino, 1990]. In addition to the estimated frequency derived from the angle of the poles, the magnitude of the pair of complex conjugate poles (varying between 0 and 1 when estimated via the Burg algorithm) also serves as a good indicator with regard to the frequency bandwidth. For example, poles having a magnitude near the unit circle result in a sharp peak in the power spectrum, i.e., a narrow-band energy concentration such as a pure sine wave, while smaller pole magnitudes behave otherwise [Ning and Hsieh, 1995; Atanasov and Ning, 2007].

Using a second order AR model, the mean linear prediction error (LPE) described below can also be used as a quantitative measure for murmur classification.

$$LPE = \sum_k e_f(k)^2 + e_b(k)^2 \tag{5}$$

The signal analysis procedure is briefly described below. WT was applied first to help identify the S_1 and S_2 heart sounds; systole and diastole were separated from a complete cardiac cycle. For example, if the energy index in (2) exceeds 25% of the mean energy of S_1 and S_2 in the segment that immediately follows S_1 (or S_2), then the murmur can be classified as a systolic (or diastolic) murmur. The pitch and LPE were computed by segments. By examining the average rate of change in ENGY (2) and LPE (5), one can delineate the detected murmur as having a crescendo, decrescendo, or plateau.

3. Results

To show the results of the underlying approach, samples encompassing two complete cardiac cycles were selected from each heart murmur scenario. Heart murmurs of different types were examined. Without loss of generality, we showed one example of a systolic murmur and another one of a diastolic murmur. The heart sounds and murmur signals analyzed in this paper were selected from [Mason, 2000] with a sampling frequency of 4.41 kHz and a 16-bit quantization.

The first example is a systolic murmur with aortic regurgitation (Fig. 1a). Using WT with the *db6* wavelet, the filtered signal is shown in Fig. 1b, and the calculated energy index is displayed in Fig. 1c. The heart sounds S_1 and S_2 can be easily identified in Fig. 1c. Usually, decomposition at levels four or five of the Daubechies wavelet is adequate in WT to separate heart sounds S_1 and S_2 from murmurs.

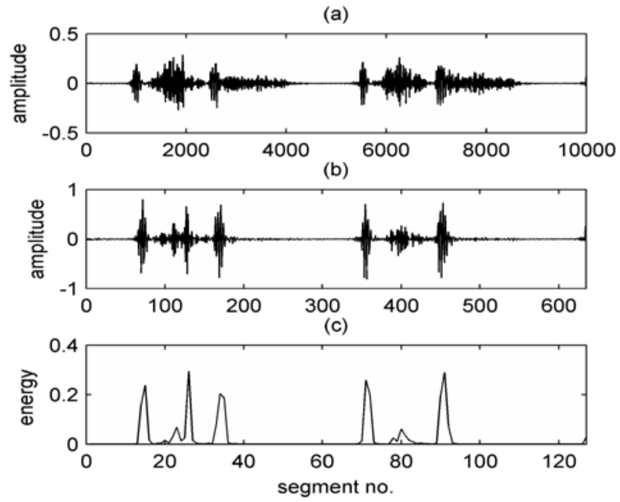

Figure 1. *Systolic murmur with aortic regurgitation: (a) heart sounds and murmurs, (b) filtered signal with db6 wavelet (4th level of decomposition), and (c) energy index.*

After identification of S_1 and S_2, the onset and duration of systole and diastole can be marked. Figure 2 displays the systolic murmur and the calculated energy index values by short segments. The evolution of the energy index in time (Fig. 2b) captures the crescendo configuration of the murmur. The chosen segment length will affect the calculation of the energy index and, therefore, the configuration profile. Various segment lengths were tested and we found that a segment length of 50 samples is appropriate for this study.

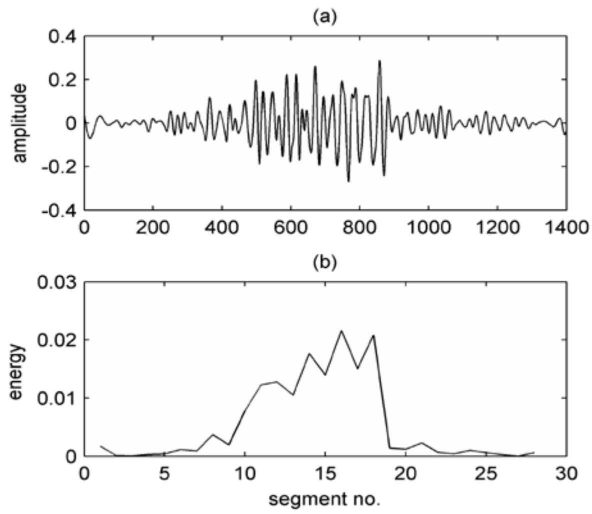

Figure 2. *(a) Systolic murmur and (b) energy index by segments.*

AR model coefficients were estimated for each segment. Features thus generated by AR modeling are summarized in Fig. 3. The pitch frequency of the murmur varies between 118-294 Hz (Fig. 3b) and the pitch frequencies are narrow-band for the pole magnitudes near the unit circle, varying between 0.99 and 1.00 throughout the systole. The LPE profile (Fig. 3c) quantifies, in addition to the crescendo configuration of the energy index at the beginning, the transient behavior demonstrated in Fig. 2a.

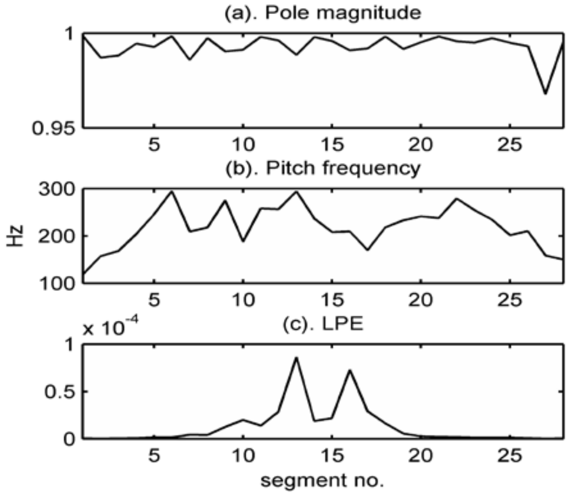

Figure 3. *AR model based heart murmur features: (a) pole magnitude, (b) segment pitch frequency, and (c) linear prediction errors.*

Another example examined here is an Austin Flint murmur. It is a mid-diastolic mitral murmur simulating that of mitral stenosis (Fig. 4a). The Austin Flint murmurs were processed by WT using the fourth-level decomposition. The pitch frequency of the mid-diastolic murmur varies between 120-216 Hz (Fig. 5c). The pole magnitudes are between 0.94 and 1.00 throughout the diastole, showing narrow-band energy concentration. The energy index (Fig. 5b) delineates the murmur configuration, i.e., crescendo at the start of the murmur and a sharp decrescendo near the end. The LPE does not follow the crescendo and decrescendo of the energy index; rather, it depicts the changing of waveform patterns.

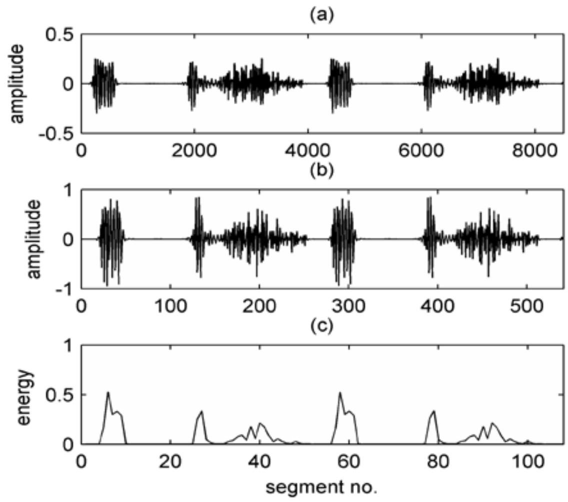

Figure 4. *Austin Flint murmur: (a) heart sounds and murmurs, (b) filtered signal with db6 wavelet (4^{th} level of decomposition), and (c) energy index.*

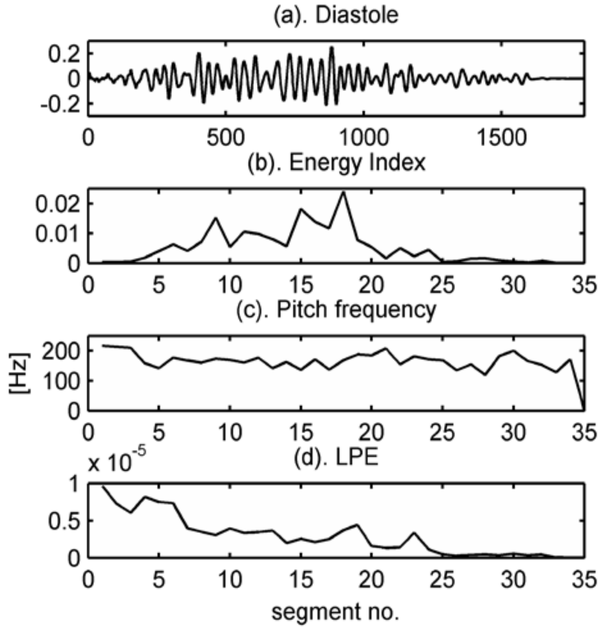

Figure 5. *AR features of Austin Flint murmur: (a) diastole, (b) energy index, (c) segment pitch frequency, and (d) LPE.*

4. Discussion

The Daubecies (*db6*) wavelet effectively separated the heart sounds from the heart murmurs in most cases. In the case of continuous and loud murmurs (where the signal appears to be one continuous murmur), WT was unable to separate S_1 and S_2. In all other cases, however, WT was able to make S_1 and S_2 easily identifiable at either the fourth or fifth levels of decomposition. The energy index of the signal further made the precise onset of S_1 and S_2 easy to see. The results of the AR modeling reported frequencies in a range higher than that of heart sounds, which is expected for heart murmurs. Pole magnitudes are also high (near the unit circle). The LPE feature provides useful information in some cases. There are other mother wavelets that can also perform the task of identification of S_1 and S_2 and obtain similar results. The dominant frequency can be estimated by other methods, but we found the second order AR model the most efficient in computation and ease of implementation.

5. Conclusions

A signal processing approach based on WT and AR modeling was implemented and evaluated to examine its performance for potential in computer-aided cardiac auscultation. The proposed signal processing approach is capable of identifying the first and second heart sounds and to generate quantitative features of heart murmurs in regards to the murmur energy (loudness), pitch frequency, and murmur configuration. These quantified features are valuable and may be intelligently utilized in computer-aided cardiac auscultation. Preliminary results on analyzing heart episodes that include systolic and diastolic murmurs have shown a promising future.

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