Quantitative Delineation of Heart Murmurs Using Features Derived from Autoregressive Modeling

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Abstract – In this paper, the focus is on systolic heart murmurs of clinical significance. Quantitative features characterizing the murmurs are derived by dividing the systole into many short non-overlapping segments and using second order autoregressive (AR) models. Features thus derived can provide a quantitative delineation of the murmur with respect to the onset, duration, intensity and pitch (frequency). We applied the said approach to examine several systolic murmurs and obtained rather accurate descriptions that parallel closely to published clinical documentation.

Keywords: heart murmurs, AR modeling, classification

I. INTRODUCTION

Heart sounds and murmurs acquired from the stethoscope carry unique information of the anatomy and physiology of the cardiovascular system. Systematic approaches for cardiac auscultation have been adopted to examine parameters such as location, timing, intensity, duration, pitch, and quality of heart murmurs. These parameters can be used to detect and estimate the severity of possible cardiovascular abnormalities [3].

In this paper, quantitative features obtained based on AR modeling were extracted to examine different systolic murmurs, including atrial septal defect (ASD), ventricular septal defect (VSD), Still's murmur, and mitral valve prolapse (MVP). A systolic murmur starts with or after the first heart sound (S1) and terminates before or with the second heart sound (S2) [5]. The systole waveform was partitioned into consecutive, short and non-overlapped segments and for each segment, quantitative features, which correlate with the main features in medical practice, were estimated. These quantitative features provide an objective approach to alleviate differences in opinions and human errors and to better classify heart murmurs [1].

II. METHODS

AR models are widely utilized in diverse applications, mostly because of its ease of computation and effectiveness in modeling. A set of N data samples {x(n) n=1,…N} from a stationary process can be considered as the output of an p^{th} order AR model driven by white noise {e(n)}, i.e.,

$$e(n) = \sum_{i=0}^{p} a_i x(n-i) \qquad (1)$$

where $\{a_i\}$ are AR coefficients. Many AR modeling algorithms have been developed, each with documented advantages and drawbacks under certain simulation scenarios. Among them, Burg's method has enjoyed more acceptance than others and is the method of choice in this study [4].

Using a 2^{nd} AR model, the frequency of a data segment can be estimated by

$$frq = \tan^{-1}\left(\frac{\sqrt{4a_2 - a_1^2}}{a_1}\right). \qquad (2)$$

The equation in (2) provides a very efficient way to estimate the dominant frequency of a short data sequence. It avoids the computation of power spectrum normally required to determine energy distribution in the frequency domain [2].

A prediction error (*pde*) normalized by adjusted sample length can be also obtained by (3).

$$pde = \frac{1}{N-p} \sum_{k=p+1}^{N} e^2(n). \qquad (3)$$

The *pde* parameter can be interpreted at large as a measure of randomness or unpredictability of the underlying data segment. To underscore the intensity of murmurs, the energy of a mean-removed data segment can be computed using (4).

$$engy = \frac{1}{N} \sum_{n=1}^{N} (x(n) - \mu_x)^2. \qquad (4)$$

III. RESULTS AND DISCUSSION

The systole of each murmur was isolated from the digitized heart sound and divided into short segments, i.e., ***140*** samples/segment or ***28.0*** ms, to better satisfy the condition of piece-wise stationarity. Fig.1 shows an example waveform of a mid-systolic murmur, atrial septal defect (ASD).

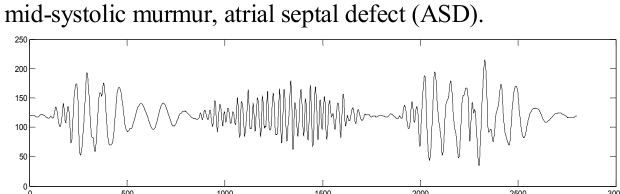

Fig. 1: Murmur of atrial septal defect (ASD)

Our results have shown that the features suggested in this paper can provide an effective and accurate delineation of systolic murmurs listed in the Introduction Section and correlate closely to clinical descriptions documented in the medical literature. Using the features in (2), (3) and (4), ASD shown in Fig.1 is delineated in Fig.2 below.

Fig. 2A Dominant Frequency of ASD Waveform

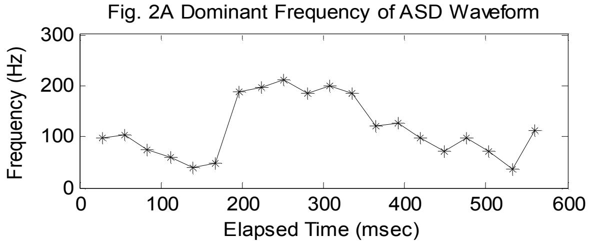

Fig.2B Variance of ASD Waveform

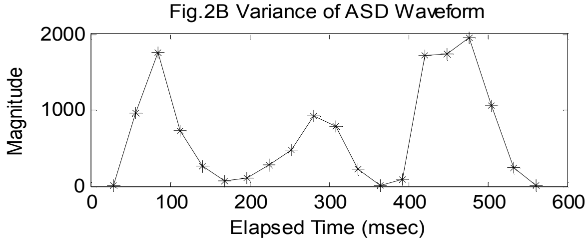

Fig. 2C Prediction Error of ASD Waveform

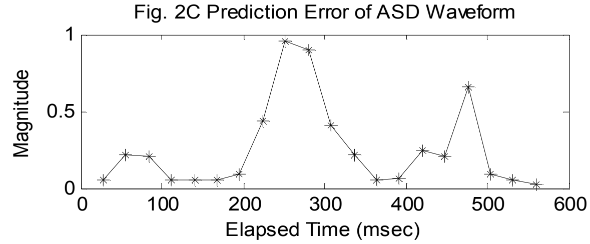

Fig.2A describes the progressive change of signal frequency by segment during systole and captures the relative high pitch of the murmur. Fig.2B and Fig.2C display similar patterns. Both correctly indicate the differences between the mid-systole murmur and S_1 and S_2 sounds.

Similar analysis was performed on the waveform of a ventricular septal defect (VSD) shown in Fig. 3.

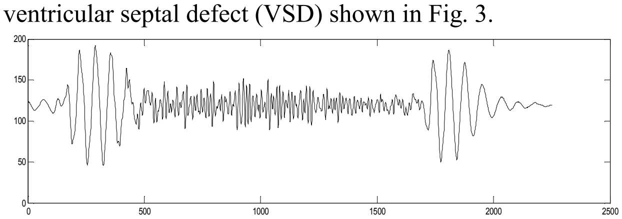

Fig. 3: Murmur of ventricular septal defect (VSD)

The systole of the VSD murmur was isolated from the digitized heart sound and divided into short segments, i.e., **113** samples/segment or **22.6** ms and the features in (2), (3), and (4) were used again to delineate the murmur as shown if Fig.4 below.

Fig. 4A Dominant Frequency of VSD Waveform

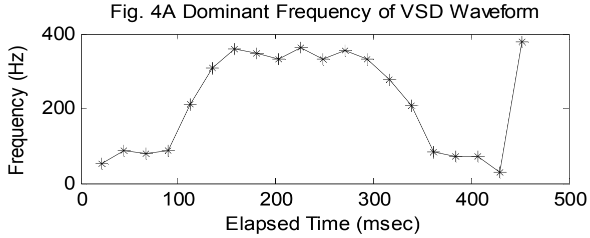

Fig. 4B Variance of VSD Waveform

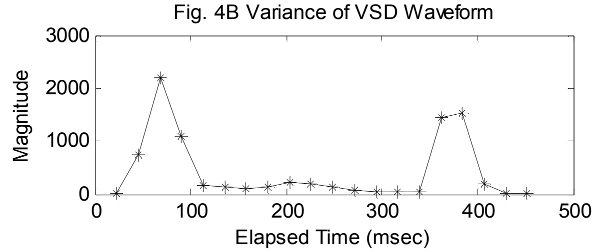

Fig. 4C Prediction Error of VSD Waveform

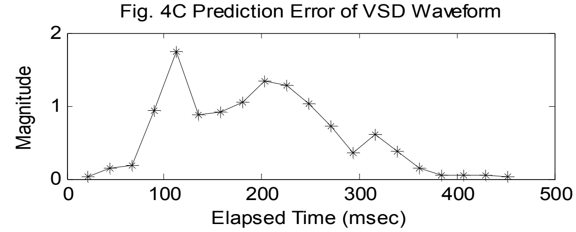

Fig. 4A correctly captures the high pitch of the VSD murmur. Fig. 4B shows the relatively low but non-zero energy of the murmur through-out the whole systole, which correctly describes the pan-systolic identity of the VSD murmur. Fig. 4C serves to indicate the difference between the pan-systole VSD murmur and S_1 and S_2 sounds.

IV. CONCLUSIONS

The abovementioned features, extracted using a second order autoregressive model, provide the possibility to correctly classify systolic heart murmurs. Quantitative description of the important heart murmur parameters such as timing, intensity, duration, and pitch can be obtained from the analysis. This accurate information can be used to minimize human error, alleviate differences in individual opinions and to aid the classification of heart murmurs.

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