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Phonocardiogram Signal Segmentation and Classification Using Variance Fractal Dimension

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Abstract – This paper presents an algorithm for S1 and S2 heart sound segmentation using variance fractal dimension. Heart sounds analysis can provide lots of information about heart condition whether it is normal or abnormal. Heart sounds signals are time-varying signals. We explore the performance of applying fractal coding on heart sound data. Some conventional fractal coding problems have been studied with heart sound data to provide an overview on this subject. Heart sound is assumed as a non-stationary signal embedding two main sounds S1 and S2, murmurs and eventually unusual ambient sound. The variance fractal dimension is applied to adaptively identify the boundaries of sound lobes. S1 components are detected using QRS synchronization while for S2 components a non-supervised classification approach is applied, based on temporal features of the lobes. Some preliminary results are presented using recorded heart sounds.

Keywords – Heart Sound Segmentation, Variance Fractal Dimension, Clustering.

I. INTRODUCTION

Heart disorders are the primary cause of death in industrialized countries. The solution to this health problem is believed to be changing the focus from curative healthcare to preventive healthcare, i.e., controlling costs (social and economical) by reducing preventable healthcare conditions. In this sense long term tele-monitoring is a promising tool to achieve the aforementioned goal. In order to be cost effective and usable for long time periods, these tools require intelligent systems to be able to autonomously perform diagnostic functions and to support users in solving problems, hence requiring low computational algorithms that could be run in real time. The technique of phonocardiography has evolved continuously to grab an important role in the proper and accurate diagnosis of the defects of the heart. This technique, though seemingly quite reliable, but it is quite difficult to master.

Although PCG and ultrasonic examination are widely used in cardio logical diagnosis, the old-age art of the heart sound analysis by auscultation is first performed by physicians to evaluate the functional state of the heart. However, the diagnosis is seldom based on the auscultation alone due to the fact that the auscultation is subjective and depends highly on the skills of the interpreter. Still a simple initial examination should be done by the ordinary doctors using effective and objective means before the suspected patient might be sent to the cardiologist for further examinations. In auscultation the observer tries to listen and analyze the heart sounds components separately, and then synthesize the heard features. The important components of a cardiac cycle which should be identified are: the first heart sound (Sl), the systolic period, the second heart sound (S2), and the diastolic period in this sequence in time. The important features, which should be quantified, are: the rhythm, the timing instants and relative intensity of the heart sound components, the splitting of S2, the existence of murmurs or other extra sounds, and the timing, intensity and quality of the murmurs and extra sounds. Although plenty of qualitative descriptions of different sounds are available, it is difficult only by listening them to quantify their properties. It might be concluded that objective and effective methods based on the quantified features of the heart sound components are needed to make reliable diagnosis [1].

A. Phonocardiography – Technique:

The auscultation of the heart gives valuable information to the physician about the functional integrity of the heart. The technique of phonocardiography has evolved continuously to grab an important role in the proper and accurate diagnosis of the defects of the heart. This technique, through seemingly quite reliable, is quite difficult to master. As with the stethoscope, it requires highly educated professionals to read the phonocardiograph. Thus, there arises the necessity of developing a device which would make the process of auscultation and diagnosis of heart defects much simpler. Such is the main objective of this paper [1].

The auscultation of the heart gives the clinician valuable information about the functional integrity of the heart. Additional detail can be gathered when the temporal relationships between the heart sounds and the electrical and mechanical events of the cardiac cycle are compared. This approach to the analysis of heart sounds using a study of the frequency spectra is known as phonocardiography. The phonocardiogram is a device capable of obtaining heart sounds and displaying the obtained signals in the form of a graph drawn with the signal amplitude in one axis and with time in the other.

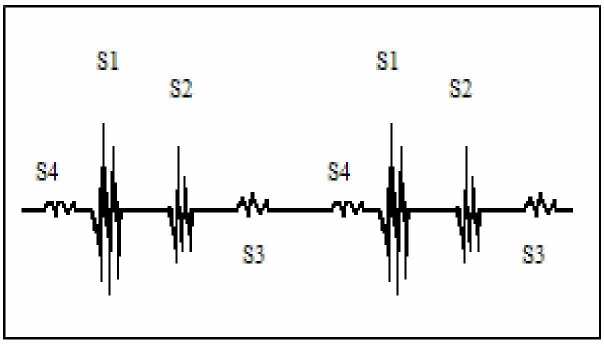

Figure 1: Heart Sound Components

II. SEGMENTATION OF HEART SOUND INTO LOBES

The main stages of the proposed segmentation algorithm for sound lobes identification are depicted in Figure 1. After heart sound acquisition and quality assessment, the signal is first high-passed to eliminate inaudible components, which may be induced by slow movements, such as chest and muscle movements, during sound recording.

In the current implementation of the algorithm a fourth order Butterworth filter with a cut-off frequency of 25Hz is utilized for this Purpose. In the second stage the variance fractal dimension of the filtered signal is computed using several scale resolutions. It should be noted that significant sound lobs should exhibit persistency at fine and coarse detail scales. This observation will be one of the criteria applied during the lob validation stage. After low pass filtering, the variance fractal dimension is applied to identify sound lobe boundaries. Finally, some criteria are then applied to reject false sound lobes.

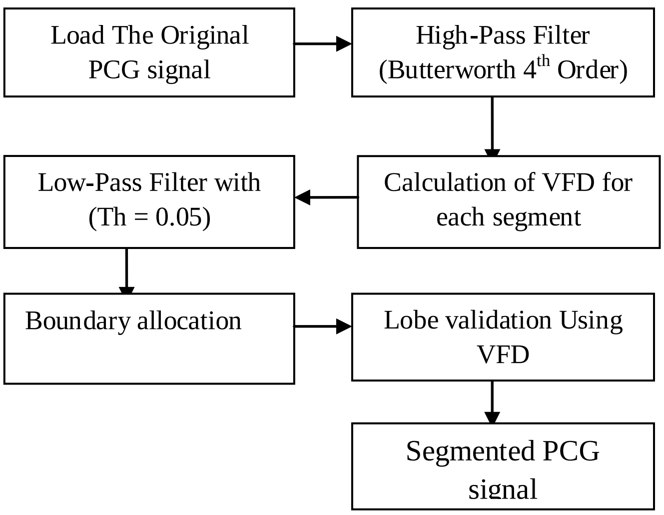

Figure 2: Block Diagram of the proposed algorithm.

A. Variance Fractal Dimension:

Heart sounds exhibit a set of properties which suggest they are fractal in nature [2]. First, these signals do not self-cross. Second, these signals exhibit quasi-periodicity, since they emerge from natural biological processes, i.e., heart beats. Furthermore, they are self-affine, since, in order to scale them, a different scaling factor is required for each axis [16]. This suggests that fractal dimension can be utilized to properly characterize and analyze these signals. Fractal dimension quantifies the complexity of a pattern or the information embodied in the pattern in terms of morphology, entropy, spectra or variance [10]. In this work the variance fractal dimension is utilised, since it enables real time computation. VFD has found several applications in signal analysis. For instance, in [8] VFD is used to locate heart sounds in lung sound recordings, Lazareck and Moussavi [14] have developed an algorithm based on VFD for swallowing sound segmentation, whereas Yap and Moussavi [15] applied the same analysis tool for respiratory onset detection. In another field of application, Hall et al. [9] utilize VFD for the detection of transient in radio frequency fingerprinting. In deriving the variance fractal dimension, the Hurst exponent is computed based on the power law relation which exists between the variance of the signal's amplitude increments over time increments [8][10].

$$\mathrm{var}(\Delta x_{\Delta t}) \approx \Delta t^{2H} \qquad (1)$$

Using the result from equation (1) it is observed that the Hurst exponent may be obtained from

$$H = \lim_{\Delta t \to 0} \frac{1}{2} \frac{\log(\mathrm{var}(\Delta x_{\Delta t}))}{\log(\Delta t)} \qquad (2)$$

In the above equations, x and t represent, respectively the signal and time, whereas Δstands for increment, i.e.,

$$\Delta t = t_{i+1} - t_i \qquad (3)$$

$$\Delta x_{\Delta t} = x(t_{i+1}) - x(t_i) \qquad (4)$$

From the above equations it is observed that the variance dimension is a measurement calculated by analyzing the spread of the increments in the signal amplitude in the time domain. This spread is indicative of the multifractal richness in the signal, e.g., a unifractal object yields a flat line. The VFD (Dσ) for a process with embedding Euclidian dimension E is computed as in equation (5),

$$D\sigma = E + 1 - H \qquad (5)$$

Since it is known that the variance in heart sound lobes and Channel noise differ significantly, heart sound boundaries should be clearly marked by accentuated changes in variance. Therefore, these boundaries should be captured from the Variance fractal dimension. To accentuate this effect, in this Work the variance fractal dimension is determined from the Energy of x rather from x itself, i.e., from $x \leftarrow x^2$.

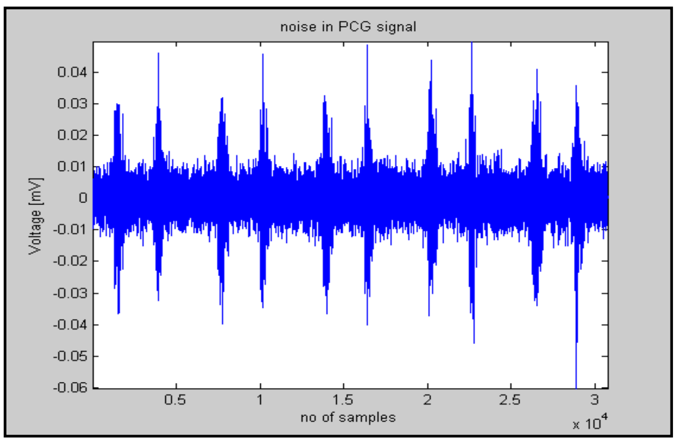

Figure 3: Normal heart sound signal.

Let N_T be the size of the sliding analysis window. For each window, VFD is computed for time increments equation (3). The value k represents an integer Chosen such that each window contains a number of

$$N_k = int\left(\frac{N_T}{k}\right) \qquad (6)$$

In practice k is selected such that there is a reasonable separation between data samples for Δt_k and, on the other hand, N_k is sufficiently large for variance calculation. To obtain each VFD the previous analysis window is shifted by $P_{shift} \leq N_T$, and the VFD is calculated for this new window and set of samples. It should be noted that the effect of N_T is similar to scale in multi-scale analysis. In fact, as N_T increases it is observed that features tend to be blurred [8][10].

As in multi-scale analysis it is observed that for coarser scales features tend to be shifted, leading to less accurate localization. Furthermore, for small windows VFD tends to oscillate due to redundant calculations [8]. To avoid these effects, in this work a low-pass filter is applied for finer scales, enabling the elimination of high frequency variations in VFD, i.e., the elimination of spurious features and VFD oscillation, while keeping localization of relevant ones.

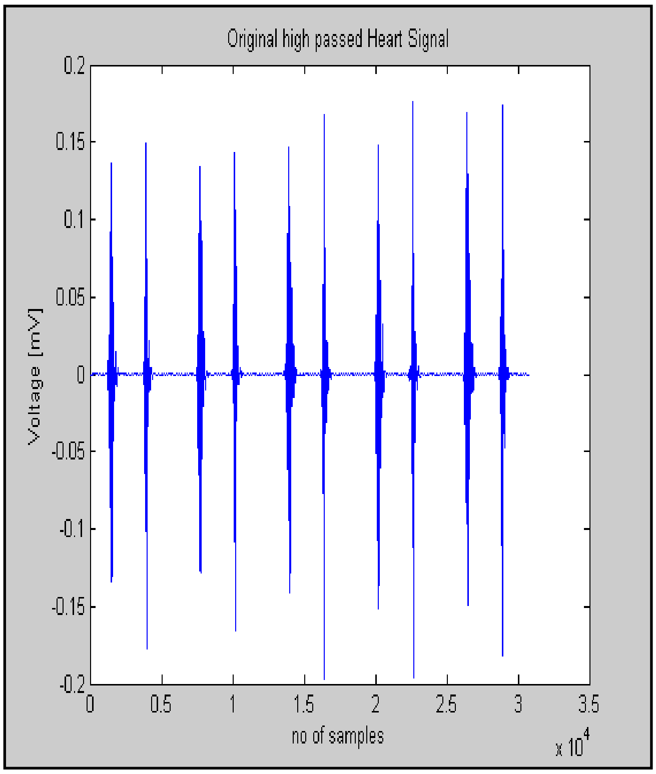

Figure 4: De-noised and high passed PCG signal.

B. *Finding heart sound boundaries using VFD:*

To identify boundaries in the significant heart sound Segments VFD is computed using two distinct scales N_T^C (coarse scale) and N_T^f (fine scale), being

$$N_T^f = \frac{N_T^C}{10}$$

N_T^C it is defined based on the observed average duration of S1, S2 and murmur sound segments, and the average distance between the first and second heart sounds is typically 200ms≤ N_T^C ≤400ms . While the duration of S1 and S2 is usually around 100*ms*. For sound signals sampled with a 44.1 kHz sampling frequency it was experimentally determined that 64 ≤ k ≤128. In each iteration the P_{shift} was selected such that the sliding window exhibits a 50 percent overlap, i.e.

$$P_{shift} = \frac{N_T}{2}.$$

The scaled VFD values determined with N_T^C and N_T^f respectively. As can be observed, sound segment boundaries are clearly identified by the slope and slope change of VFD and could readily be identified using a threshold procedure. However, it was observed that for heart sounds, significant segments exhibit around 50% of the overall area of VFD if a sufficiently large window is applied. Hence, sound segment boundaries are identified by the zero crossings of y , where (<> average operator)

$$y \equiv VFD - th_{segment} \qquad (7)$$

$$th_{segment}^{m} = \alpha\langle VFD^m\rangle + (1-\alpha)th_{segment}^{m-1} \qquad (8)$$

$$th_{segment}^{1} = \langle VFD^1\rangle \qquad (9)$$

As can be observed from equations (8) and (9), a convex combination is applied in order to update the threshold for each contiguous sound window m identified during noise suppression. In the current implementation α = 0.9. Significant sound segments are characterized by higher VFD, since their variance is greater than the variance of the channel's noise. Hence $y > 0$.

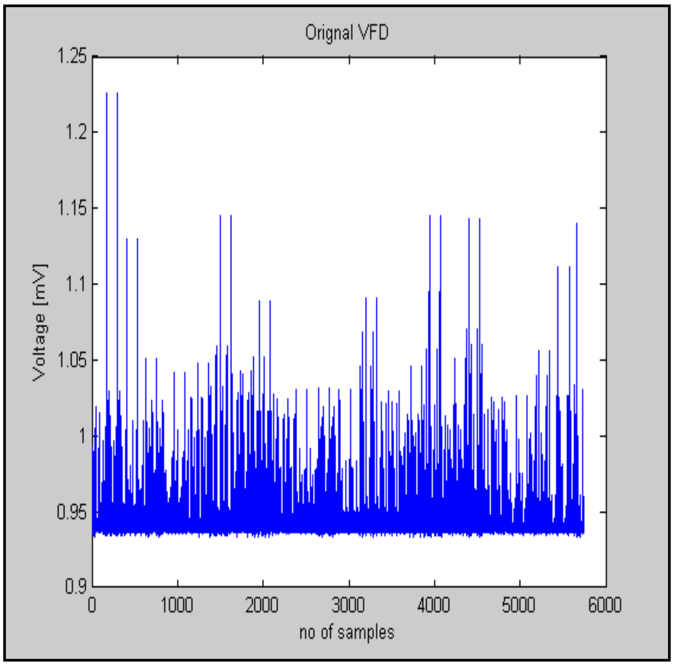

Figure 5: VFD of complete PCG signal

C. *Sound segment validation:*

As mentioned above S1, S2 and murmur sound segments exhibit characteristic durations. Furthermore, significant sound segments should be persistently identified for different analysis scales. This is an useful observation to discriminate between valid and non-valid murmur segments. In fact, in many situations murmur segments highly resemble channel noise. Using these principles the following criteria are applied to each of the identified sound segments for validation. Let

$$j = n_i^{start}, \ldots . n_i^{stop} \qquad (10)$$

Be the identified sound segment. Segment S_i is considered a valid heart sound segment if the following criteria are verified:

a. Duration limits:

$$t_{min} \leq t_s(n_i^{stop} - n_i^{start}) \leq t_{\max} \qquad (11)$$

b. Fine-coarse scale support:

$$\exists j \epsilon \{n_i^{start} - n_i^{stop}\}: VFD(N_T^C, j) - \langle VFD(N_T^C)\rangle \geq O \ (12)$$

In equation (12) $VFD(N_T^C, j)$ stands for the VFD value computed for point j using the coarse scale analysis window, While $\langle VFD\ (N_T^C)\rangle$ represents the average VFD value. In the current implementation of the algorithm t_{min} = 10*ms* and t_{max} = 300*ms* (average value of the S1-S2 between times).

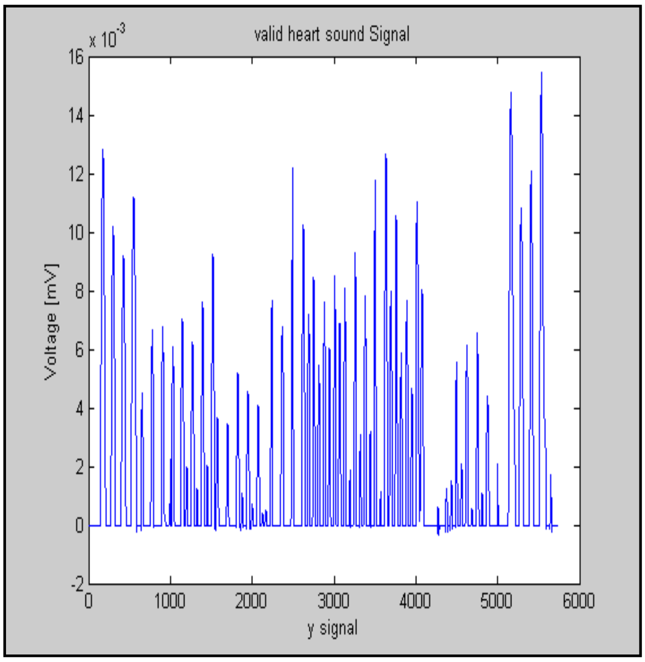

Figure 6: valid heart sound lobes.

D. Classification of Heart Sound Components :

Having successfully figured out the boundaries of sound lobes of types S1 and S2 as well as major murmurs and noisy segments, the next step is to classify these segments accordingly to a predefined set of classes, i.e., S1, S2 and murmur or noise, if present.

Classification of segmented lobes is done based on their features and ECG QRS complexes. Having successfully figured out the boundaries of sound lobes of type S1, S2 as well as major murmurs, the next step to classify these segments and here S1 segments are identified using ECG Q component synchronization i.e., the lobe closer to each Q component of the ECG is assumed to be a S1 lobe, systole occur during this time period, S2 segments are identified using T components, diasystole occur during this time period and S4 by P-wave.

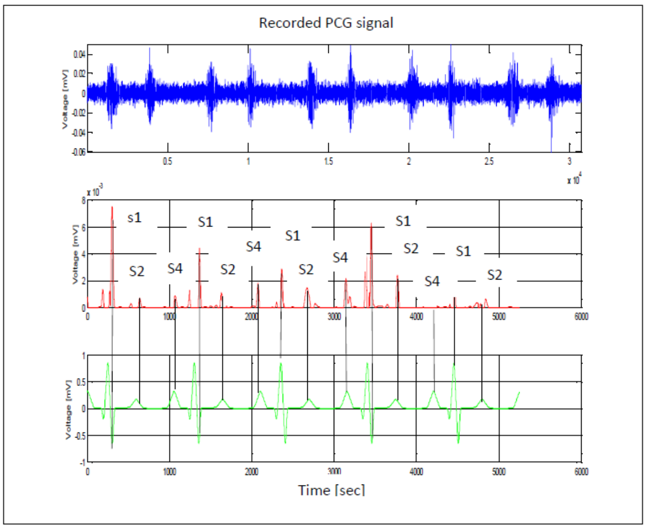

Figure 7: Waveform of (a) Recorded Normal Heart Sound (b) Segmented Heart Sound signal (c) Classified PCG Signal

III. RESULT

In this paper we are proposing a method for the generation of the entire required graph for the heart sound segmentation which exhibits excellent ability to explain physician about heart related problem.

Patient exhibits non constant heart rhythm. Nevertheless, as can be observed, the S1-S2 interval is relatively regular. It should be noted that these conditions are quite common for patients with heart diseases, namely patients with prosthetic valve implants. This is also a function of heart sound acquisition locations. Furthermore, these patients frequently exhibit or tend to develop atrial or ventricular arrhythmias, which induce heart sounds of different characteristics. These sounds can interfere in diagnosis algorithms based on heart sound.

IV. CONCLUSIONS

Phonocardiogram signal is very a complex signal. PCG signal contains numerous non stationary or transitory characteristics - timing of heart sound, their components, location in cardiac cycle. Specially, the PCG signals are characterized by transient and fast change in frequency as time progress. To find these characteristics, the time frequency analysis technique can provide better diagnostic. This paper presents a quick overview on fractal coding of heart sound. We review fractal coding development through the main literature on this subject. The trajectories produced using the variance fractal dimension offer potential for increasing performance in study of heart sound signal.

The problem of heart sound segmentation and classification using low complexity methodologies was addressed in this paper. The variance fractal dimension, which is a measure of signal complexity, is here applied in the segmentation of heart sounds. In order to clearly detect the boundaries of segments two distinct time scales are considered, which are based on the observed average time duration of relevant heart sound segments.

Some aspects of fractal have been practiced through studies on various heart sound sequences. In this paper, our purpose is to carry out this research on fractal coding is an attempt to extend fractal coding to heart sound data &

explore how the fractal system performs under its heart sound model. Our study tries to contribute to future fractal heart sound coding research with result & evidence.

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