Heart Sound Signal Modeling and Segmentation based on Improved Shannon Energy Envelogram using Adaptive Windows

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Abstract

Various segmentation algorithms have been proposed for better classification of the highly nonstationary heart sounds. This paper proposes an improved segmentation technique based on Shannon Energy calculation of the phonocardiogram using adaptive windows. The major focus of the research has been on a simple yet comprehensive signal representation as well as on extracting most information from the Shannon energy envelogram. Earlier algorithms had a major disadvantage of losing the temporal resolution of the signal which can sometimes lead to ausculations unnoticed.

First of all sinusoidal modeling of the filtered PCG is done. Zero crossings of the signal are detected and window size for the Shannon Energy calculation is formulated. With variable window size, Shannon Energy envelopes are computed. Sequence analysis is then performed on various features of envelopes and zero segments for simple classification, though aim of the paper is not the classifier design. The algorithm proves to extract details of the signal with high precision.

Keywords: Phonocardiogram (PCG), envelogram, envelopes, lobes, zero segments

1. Introduction

Phonocardiography is routinely performed by physicians during physical examination. It is the oldest yet simplest and standardized technique for estimating heart sounds, their characteristics and any malfunctioning. However, the low frequency, low intensity and short duration of the heart sounds and vibrations make the analysis by human ear/hands very difficult and diagnosis by auscultation highly depends on the skills and experience of the listener [1]. Automatic analysis of the PCG requires signal to be appropriately segmented to reveal its essential characteristics.

The two major audible heart sounds in a normal cardiac cycle are the first and second heart sounds, S1 and S2 respectively. S1 occurs at the onset of the ventricular contraction during the closure of the AV-valves. It contains a series of low-frequency vibrations, and is usually the longest and loudest heart sound. S2 is heard at the end of the ventricular systole, during the closure of the semilunar valves. Typically, its frequency is higher than S1, and its duration is shorter. A normal cardiac period thus comprises of S1**,** the systolic period, S2 and the diastolic period in this sequence in time. Pathological conditions and abnormalities may add other sounds such as S3, S4, opening snaps, ejection clicks, splits, murmurs or stenosis into the normal cycle. S3, a third low-frequency sound (*ventricular gallop*) may be heard at the beginning of the diastole, during the rapid filling of the ventricles. S4, the fourth heart sound (*atrial gallop*) may be heard in late diastole during atrial contraction. Opening snaps of the mitral valve or ejection sound of the blood in the aorta may be heard in case of valve disease (stenosis, regurgitation). Murmurs are high-frequency, noise-like sounds that are heard between the two major heart sounds during systole or diastole. They can be innocent, but can also indicate certain cardiovascular defects [2].

Detection of each of the components of a PCG usually requires a reference signal such as an electrocardiogram. It makes classification easier by demarcating the boundaries of each of the component but it increases system/apparatus complexity. Therefore, no reference signal has been used.

In this paper sinusoidal modeling of the heart sound signal is done which simplifies the signal the same way as low pass filtering removes noise, however the major focus was not to remove noise but to simplify the signal for further analysis. Therefore, algorithm is optimized not to lose any meaningful information from the signal. Envelopes of the PCG are computed using adoptive windows where size of the window is determined from the size of every half cycle of the signal. The objective of the research has been on simplifying the PCG for analysis and using uncomplicated procedures to extract every bit of significant information. Algorithms are computed in MATLAB. Results obtained are very impressive especially because high temporal resolution is achieved and abnormalities in the PCG are highlighted. These aberrations could not be clarified by simple Shannon Energy Envelogram algorithms [1] or wavelet transform techniques [3] or time frequency analysis [4] of the signal.

2. Database

The database of normal and various pathologies of heart sounds have been taken from "e- general medical". The sampling frequency is 11025Hz. Since normal and abnormal heart sounds lies inside a frequency range of 50 to 700 Hz, signal is low pass filtered out using Chebyshev (type 1) filter with a cutoff frequency of 882 Hz [1]. Frequency components higher than this cutoff value are usually associated with noise.

3. Methods

3.1 Signal Modeling

PCG is a running sequence of crests and troughs with multiple frequencies inside every half cycle. The objective is to smoothen out these crests and troughs in a way that every individual half cycle carries only one fundamental frequency and no other multiple frequencies. This is done by first calculating the zero crossings of the signal. Two adjacent zero crossings contain either a crest or a trough. From this crest/trough of duration'd', a complete sinusoidal period of duration '2d' is constructed by adding the original half cycle with a phase shifted version of its negative half cycle. Then its Fourier transform is taken and fundamental frequency 'f_o' of the sinusoidal period is known. Multiple other frequencies show the deformation of the sinusoidal envelope due to extra, often irrelevant to analysis, information contained in PCG. These multiple frequencies are nullified and sinusoid is reconstructed from the fundamental frequency 'f_o'. The appropriate half cycle, either crest or trough is cut out and the original half cycle is replaced by it. This process is repeated for the complete duration of PCG until the entire signal is reconstructed. In order to remove discontinuities at the ends of half cycles the complete signal is again passed through the same low pass Chebyshev Type 1 filter with a cutoff frequency of 882Hz as before.

Reconstructing half cycles rather than complete cycles is done so as not to lose the characteristics of the signal since nonstationary nature of PCG implies usually variable amplitudes and durations of adjacent crests and troughs. Figure 1(a) shows the actual phonocardiogram while Figure 1(b) shows the resulting sinusoidal modeling of the signal. As evident no clear distinction can be made between the two due to the resolution of the signal which clearly implies no lose of significant information from the signal. In order to elucidate the effect of modeling, a small segment of PCG is shown in Figure 2(a) and its modeled version in Figure 2(b). Here signal smoothing effect in each of the crests and troughs is evident, without any compromise on their amplitudes and durations.

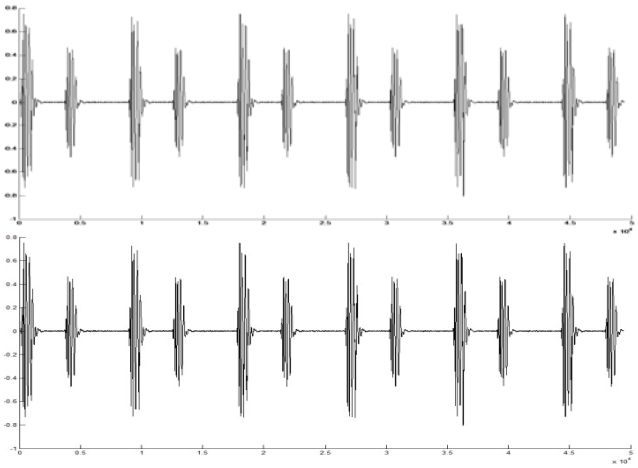

Figure 1. (a) Actual Heart Sound; (b) Sinosoidally Modeled Heart Sound

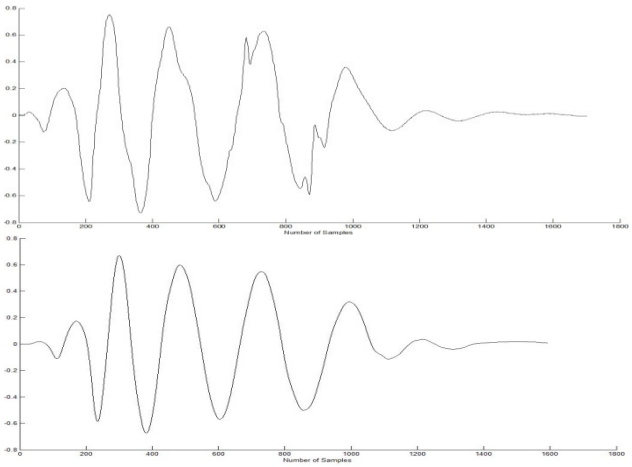

Figure 2. (a) Original PCG segment indicationg S1; (b) Sinosoidal Modelling of S1 segment

3.2 Segmentation using Shannon Energy Envelograms

Various strategies such as homomorphic filtering, AM demodulation, wavelet decomposition and etcetera have been reported in literature in order to compute envelogram of the phonocardiograms, however the uniqueness of Shannon Energy in computing envelopes lies in the fact that the Shannon Energy emphasizes the medium intensity signal and attenuates the effect of low intensity signal much more than that of high intensity signal [1]. Therefore, Shannon Energy is used as a calculation method for computing envelopes; however, this computation is done by adaptive windows in an innovative way.

Instantaneous Shannon Energy is calculated as:

Shannon Energy (t) $= -signal^2(\mathrm{t}) * \log(signal^2(t))$

However, in order to evaluate envelopes average Shannon Energy is calculated in some time duration.

$$E_{avg} = -\frac{1}{N}\sum_{t=1}^{N} \text{Shannon Energy}(t)$$

where 'N' is the window size in number of samples. [1] has taken continuous 0.02 seconds window with 0.01 seconds segment overlapping. In our research we have taken window size equal to the length of every half cycle encountered during sinusoidal modeling of the PCG. This approach calculates average Shannon Energy of every crest or trough encountered throughout the signal which reveals more information about the shape and boundaries of envelopes. In order to limit noise a threshold may be set below which energy is set to zero. PCG we used, had a very good SNR therefore we selected a threshold value of only 0.032 on a scale of 0—1. However this threshold may be set as a variable for the clinicians to optimize the algorithm under different circumstances and noise conditions.

Figure 3(a) shows the actual PCG of a normal subject. Figure 3(b) calculates the Shannon Energy envelopes using fixed sized windows (t=0.02s) while Figure 3(c) shows the envelopes extracted using adaptive windows which clearly shows extra envelope adjacent to fifth and seventh lobe. This however is not a pathological case since this extra lobe is not found throughout the signal and scrutinizing the signal classifies them as innocent murmurs. Capabilities of using adoptive windows are thus acknowledged in revealing more information from the signal. These murmurs went unnoticed as illustrated in Figure 3(b). This effect is even more profound in pathological cases. Extra information revealed, however leaves a tougher job for the classifier to categorize these lobes accurately but sequence analysis, as performed later, makes this job reasonably simple too. Figure 3(d) shows another version of improved envelogram technique. Here the horizontal scale is changed from number of windows to the number of samples and every half cycle is assumed to have a constant energy equal to the Shannon Energy of the respective window. Advantage of displaying information in this form is that it gives a rough idea about the duration of the windows i.e. by noticing the energy at some instance, one can observe the duration of that energy. It will give a rough idea of the fundamental frequency of that window since frequency is inversely proportional to the Time period; smaller window sizes will correspond to higher frequencies and vice versa. This would be a very helpful computation for analysis since smaller window sizes may imply murmurs and other pathologies. Furthermore this quantizing effect also helps in visualizing the correct boundaries of the envelopes, enabling classifier for better classification of duration of lobes and zero segments. Figure 3(d) is also a dc biased version so that the minimum value is set to zero.

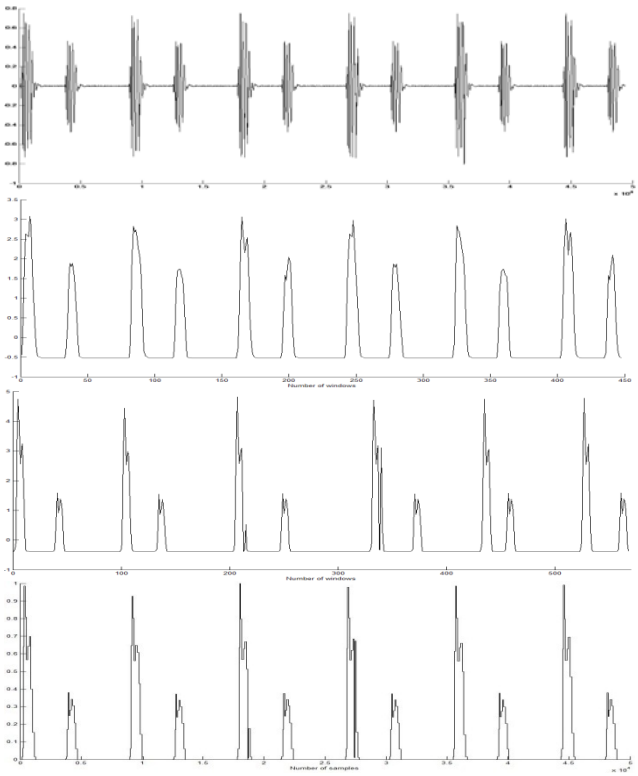

Figure 3. (a)Actual Heart Sound; (b) Shannon Energy Envelogram using fixed window size; (c) Shannon Energy Envelogram using adaptive windows; (d) Quantized version of Shannon Energy Envelogram

Moving on to pathological cases, Figure 4(a) shows a case of Systolic Split in S1 (one single priod is shown). Comparing the results of using fixed windows as in Figure 4(b) and that of adoptive windows, Figure 4(c), a clear split with zero segment is prominent in later. This clarity allows us to magnify signal details further and hence better classification can be made.

Opening Snaps following second heart sound, are often mixed with S2 during analysis. Figure 5 shows such a case where Figure 5(a) shows the actual PCG containg opening snap. Figure 5(b) shows envelogram calculated using fixed windows while Figure 5(c) shows envelogram computed using adaptive windows. Figure 5(c) clearly demarcates S2 and opening snap boundries. Though Figure 5(b) does show two peaked S2 lobes but Figure 5(c) actually seperates that lobe out of S2. Zooming in enables us see an actual zero segment between S2 and opening snap sound. Morever Figure 5(c) also gives a rough clue about the frequency content of the opening snap. Again zooming in would enable us actually visualize that, opening snap is not just an envelope like S2's envelope in Figure 5(b) but infact it's enegy and frequency content is highly nonstationary. This would be an additional useful information for the classifier.

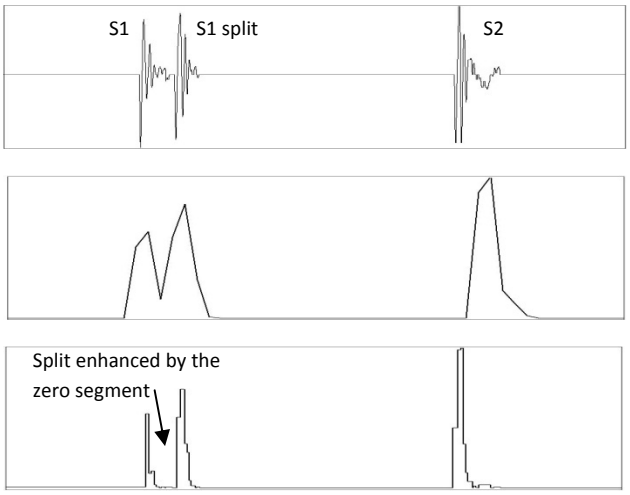

Figure 4 (a) Systolic Split in S1; (b) Shannon Energy envelogram using fixed windows; (c) Shannon Energy Envelogram using adotive windows.

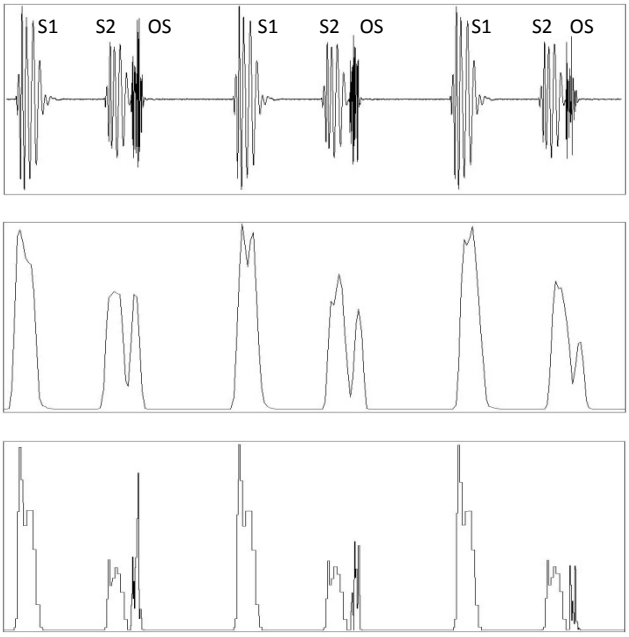

Figure 5 (a) PCG indicating opening snap; (b) Shannon Energy envelogram using fixed window size; (b) Shannon Energy quantized envelogram using adoptive windows

3.3 Sequence Analysis

Sequence analysis is the data representation of different sets of information extracted by improved PCG envelograms. Various aspects such as amplitude of lobes, length of lobes, duration of zero segments, frequency content of lobes and etcetera, of each PCG analyzed, are formulated into separate sequences and the result is displayed for examination and further classification. Note, however, that this is not the classifier but the display of data fed to classifier and the sequence analysis is performed inorder to reveal various features revealed by our algorithm.

Figure 6(a) shows a normal PCG along with its envelogram as shown earlier. Normally intensity of S1 is greater than that of S2. This aspect is analyzed in Figure 6(b) which shows sequence of maximum amplitudes of each of the lobes/envelopes of the normal PCG. Based on this reasoning S1s and S2s are marked. Note that sixth lobe having least amplitude of all is an aberration. Classification of this lobe may be interpretted from the zero segment duration of the Envelogram. Zero segments represent systole and diastole in normal cases however deviations may represent splits and clicks, where the deviant lobe is part of the adjacent S1 or S2 or they may represent murmurs or stenosis. Diastolic period is usually greater than the systole. This fact is utilized in identifying correct periods in Figure 6(c). Stem plot of each of the zero segments reveals an ongoing sequence of systole and diastole. Note that duration of fifth segment is virtually zero which indicates that proceeding 6th lobe is a part of the nearest envelope, S1 (5th lobe) in this case. Gap caused between them is due to a murmur, however it is not a split since a split causes a larger gap duration.

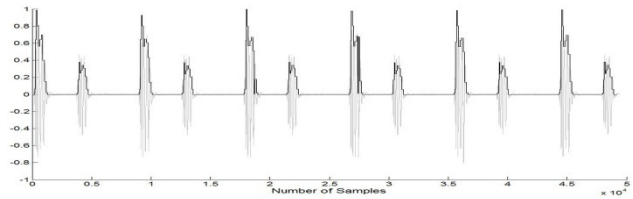

Figure 6 (a) Normal PCG and its Shannon Energy Envelogram

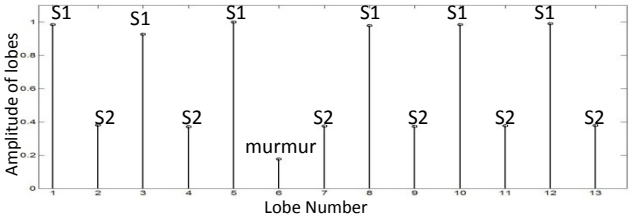

Figure 6 (b) Maximum height of each of the lobes

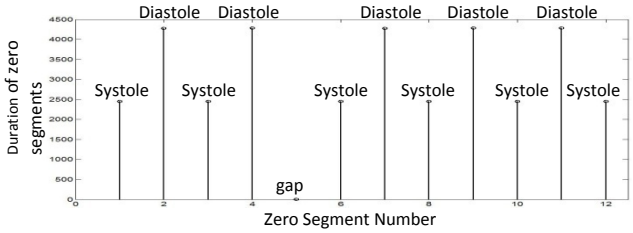

Figure 6 (c) Duration of zero segments

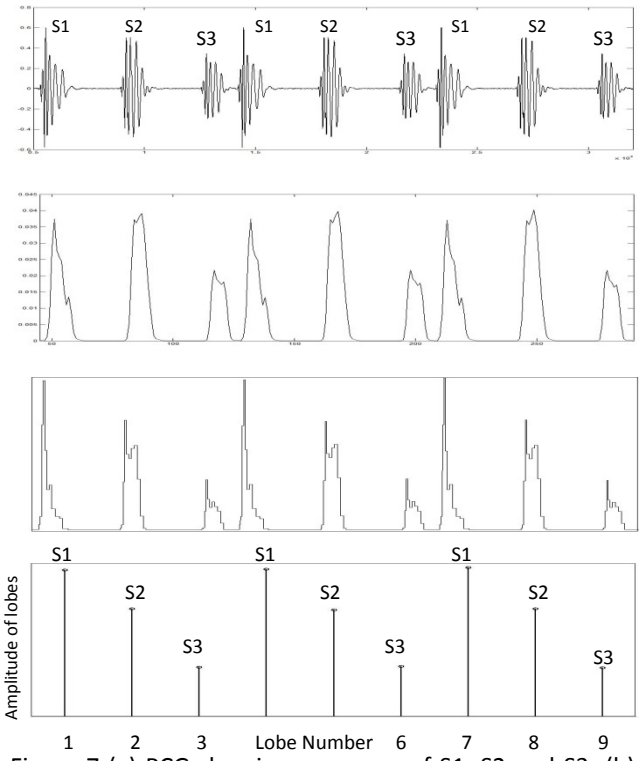

Figure 7 (a) PCG showing sequence of S1, S2 and S3; (b) Envelogram calculated using fixed sized windows; (c) Envelogram computed using adoptive windows; (d) Sequence showing maximum height of each of the envelopes detected in (c). S1s, S2s and S3s are easily classifiable.

Figure 7(a) shows PCG containg sequence of S1, S2 and S3 heart sounds while 7(d) plots magnitude of maximum height of envelopes calculated using adoptive windows. Sequence in 7(d) is sufficient to judge a series of S1, S2 and S3; on the other hand, this classification would have been very difficult if maximum amplitude of Figure 7(b) was used instead which shows nearly equal amplitude levels for S1 and S2.

This technique proves very useful in enhancing signal details and can generally be applied on any pathological case. As a final example a case of early aortic stenosis which indicates stenosis or murmurs in early systolic period, is presented for analysis. Figure 8(a) shows three cardiac cycles of the PCG indicating early systolic murmurs. Figure 8(b) shows S1 magnified, indicating the complexity of the wave. Figure 8(c) is sinusoidal model of S1 segment shown in Fig. 8(b). Note the complexity of the wave is reduced considerably. If envelope of this segment was computed using fix window size, only the shape of the envelope would have given a little clue about the pathology however the variable window size actually splits these murmurs into separate small envelopes as indicated in figure 8(d), where Shannon Energy envelogram using variable window size is computed. A point to clarify here is that Shannon Energy is computed within the windows given by sinusoidal model but energy in this duration is calculated from the original signal so as not to miss or hide any signal detail.

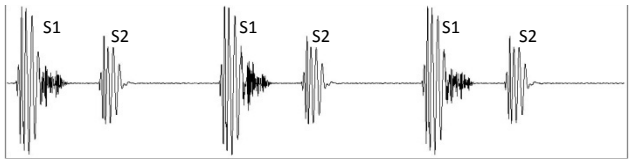

Figure 8 (a) PCG showing late systolic murmurs

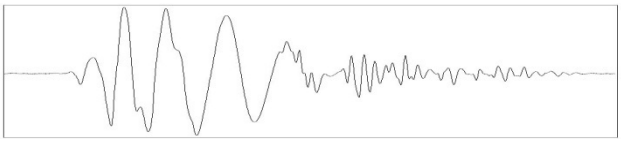

Figure 8 (b) S1 magnified

Figure 8 (c) Sinusoidal model of S1 shown in 10b

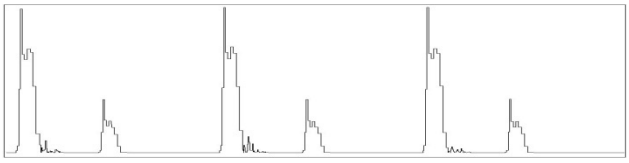

Figure 8 (d) Shannon Energy envelogram computed using adoptive windows

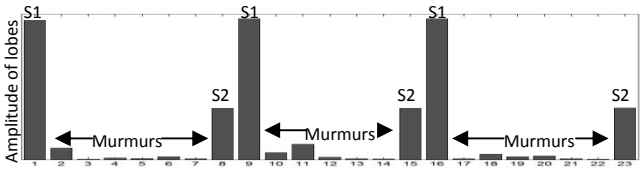

Figure 8 (e) Maximum amplitude of each of the lobes

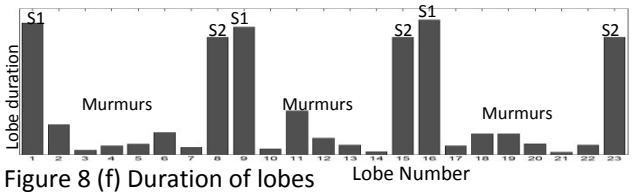

Figure 8 (f) Duration of lobes

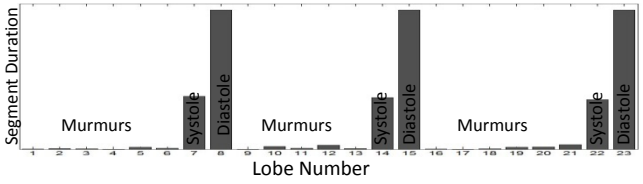

Figure 8 (g) Duration of zero segments

Figure 8(e) shows a bar plot of maximum amplitudes of each of the distinct envelopes/lobes detected in Figure 8(d). Lobes 1, 8, 9, 15, 16 and 23 have relatively higher amplitudes and are thus classified as S1s and S2s respectively according to the usual assumption that intensity of S1 is higher than S2. Rest of the lobes either have very low amplitudes or their amplitude content is virtually zero, that is why they are classified as murmurs. Figure 8(f) shows duration of each of the lobes/ envelopes computed. This indirectly correspond to the frequency content of the lobes. Note that lobes 1, 8, 9, 15,16 and 23 again have discriminatingly larger lobe duration which implies low frequency content, that of S1s and S2s. On the other hand the remaining lobes with smaller lobe durations correspond to lobes containing high frequency content and they can correctly be classified as murmurs. Figure 8(g) plots the duration of zero segments in the PCG i.e. the segments where no envelope was detected (gaps). These segments give information about 1) systole and diastole periods; 2) verify murmur classification comparing earlier results and 3) the relative position of murmurs with reference to systole and diastole. Diastolic and systolic periods are evident in Figure 8(g) however figure also indicates that these murmurs precede every Systolic period and hence they are a part of S1 sounds. From this clue, the case of early aortic stenosis can easily be classified. The ability to magnify signal details is obvious from these figures and confirmed by plotting these sequences for analysis and classification.

4. Conclusion

Simplification of the highly nonstationary heart sounds without information loss was the basis of research. The main objective of the research, however, was to extract every significant detail, either obvious or minute, from the signal and highlight the abnormalities in it. Computation of envelograms for classification is not a new technique, however the information given by the envelopes was never sufficient for the classifiers for correct classification. This technique of using adaptive windows to compute Shannon Energy envelopes, overcomes these limitations and is able to enhance signal details and presents us with more signal characteristics. It not only gives obvious signal details but amplifies signal abnormalities as aimed. Sequence analysis as performed later justifies our argument.

5. References

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