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Automatic Classification of Phonocardiogram

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ABSTRACT: This paper presents a novel method of automatic classification of phonocardiogram. The noisy phonocardiogram is segmented to form noisy datasets of one heart cycle. The dataset is created for murmur and normal sounds. The datasets are LMS filtered to produce two new datasets to form the filtered datasets. The test sound which is a noisy phonocardiogram is taken, segmented and each segment of one cycle duration is checked for normal and murmur segments. The test sound is LMS filtered and re-segmented. The segments are checked for normal and murmur sounds and the results are compared with the previously obtained results.

KEYWORDS: Phonocardiogram, Homomorphic filtering, LMS filtering, K-means clustering.

I. INTRODUCTION

Phonocardiography is the study of heart sounds. The acquisition of phonocardiogram is done in hospitals using stethoscopes. Very often this acquisition is affected by the presence of the ambient background noise. So detection of murmurs becomes difficult. So removal of the noise becomes utmost important for the early diagnosis of the diseases. Filtering is one such method used to remove the noise. There are many filtering techniques used and adaptive filtering is one of them. This paper discusses the use of LMS filter to remove the noise in the raw phonocardiogram. LMS filtering techniques are known for their fast convergence rate.

This paper discusses the three very important aspects of phonocardiogram signal processing namely segmentation by homo-morphic filtering, filtering by LMS techniques and classification by k-means clustering. The dataset for our purpose was obtained from Peter Bentley's website mentioned in [1] containing mostly noisy sounds.

The whole system was built up in Matlab R2010 environment and the simulations and comparisons were done to assess the results of all the three phonocardiogram signal processing techniques.

II. METHODOLOGY

2.1 Creation of raw datasets :

The phonocardiogram obtained from [1] is used to create a raw dataset of impure heart sounds. The dataset is created for separate abnormal and normal heart sounds. The dataset is created by taking a sample phonocardiogram, segmenting it and storing the sounds containing individual heart cycles in a separate folder called Abnormal (for abnormal sounds) and normal (for normal sounds) in matlab workspace in the form of wav files. Both the folders contain 200 sounds each of normal and pathological sounds. All sounds are of same length and sampling rate. The segmentation is automated by writing a matlab code for homo-morphic filtering to generate the sounds as mentioned in [2].

2.2 Creation of Filtered datasets:

The raw dataset of impure heart sounds is then further LMS filtered to produce filtered datasets. The filtered dataset consists of filtered normal and abnormal heart sounds to be separately stored in nfilt (normal sounds) and afilt (abnormal sounds) folders in matlab workspace in the form of wav files. Both the folders contain 200 sounds each of normal and pathological sounds. All sounds are of same length and sampling rate.

2.3 Implementation of algorithms:

The procedure for implementation is explained with the help of flow chart as is shown in figure 1. The sounds in filtered and raw datasets are used for training purpose. A test sound is taken in raw form and loaded into matlab workspace. The raw sound is segmented using homo-morphic filtering and each heart cycle is then individually classified as murmur or normal heart sound using k-means clustering. The test sound is now LMS filtered to remove the inherent noise. The filtered test sound is now again subjected to segmentation using homo-morphic filtering. The

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segmented sounds representing the individual heart cycles is classified as murmur or normal sound using k-means clustering for the same set of parameters.

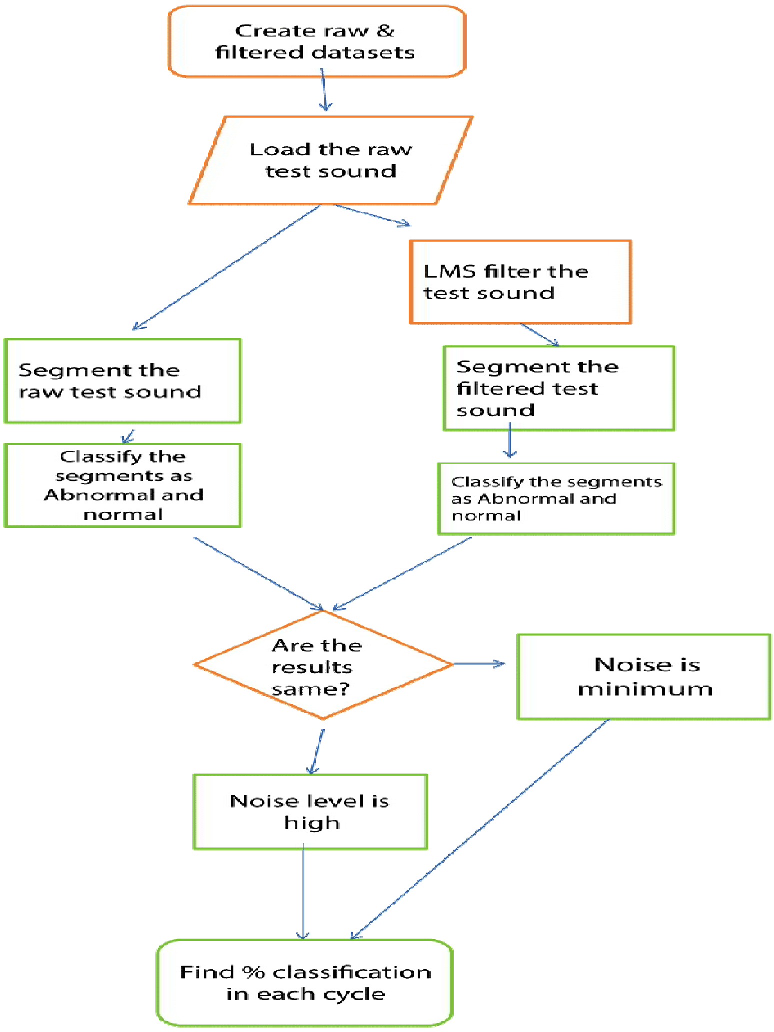

Figure 1: Flow chart showing implementation of algorithms.

The results of clustering are compared and assessed. If same results are obtained then it could be concluded that amount of noise in heart sound is very less and does not hinder murmur detection. If the results are different then it could be concluded that amount of noise in heart sound is very high and does affect murmur detection. The classification percentage is then calculated based on the amount of murmur present in the heart sound, if any.

III. RESULTS AND DISCUSSION

The result of the automatic classification of phonocardiogram is a consequence of 3 major processes namely, segmentation by homo-morphic filtering; noise suppression by adaptive filtering using LMS algorithm; and classification of sounds by k-means clustering. The first process is the segmentation by homo-morphic filtering which includes the following steps. The figure below shows steps in segmentation procedure.

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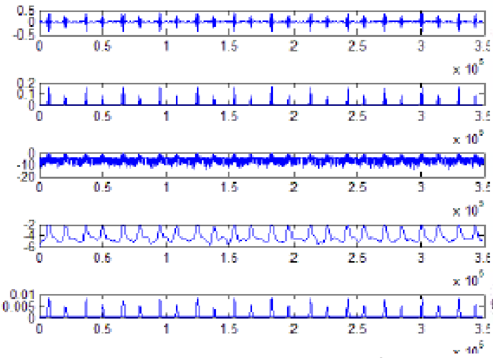

Figure 2: Segmentation steps for the raw heart sound 201108011118.wav.

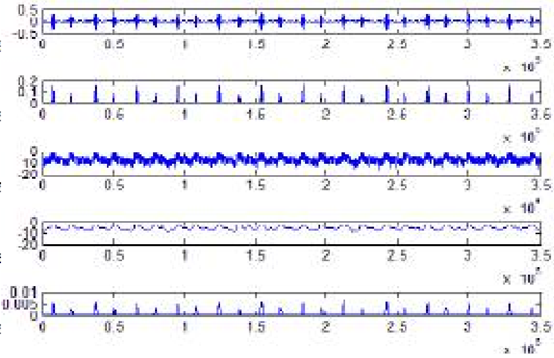

Figure 3: Segmentation steps for the filtered heart sound 201108011118.wav.

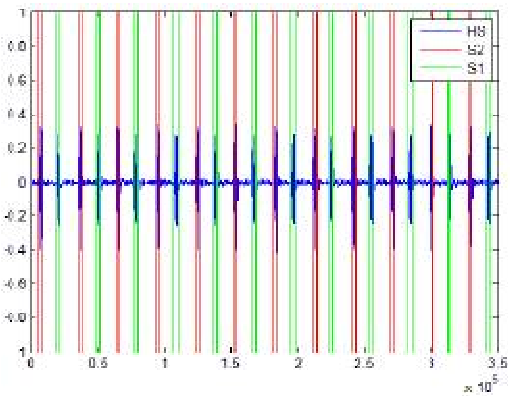

Figure 4: Segmentation of the raw heart sound 201108011118.wav.

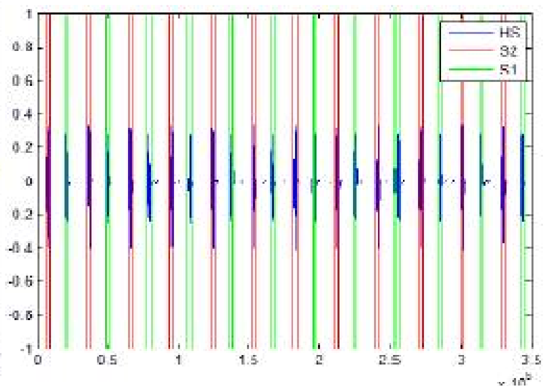

Figure 5: Segmentation of the filtered heart sound 201108011118.wav.

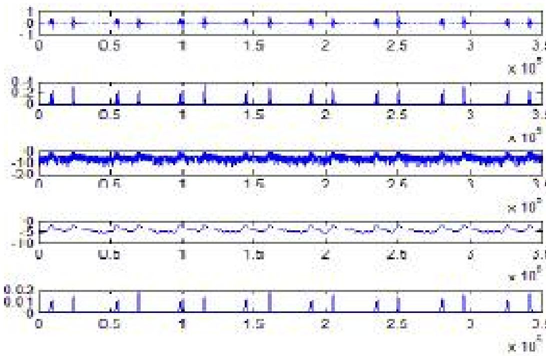

Figure 6: Segmentation steps for the raw heart sound 201108222258.wav.

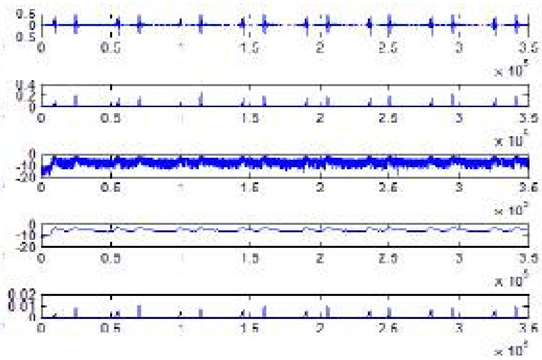

Figure 7: Segmentation steps for the filtered heart sound 201108222258.wav.

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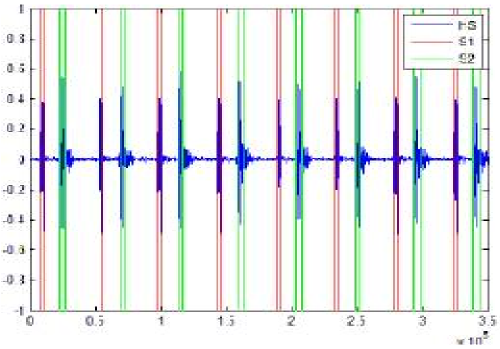

Figure 8: Segmentation of the raw heart sound 201108222258.wav.

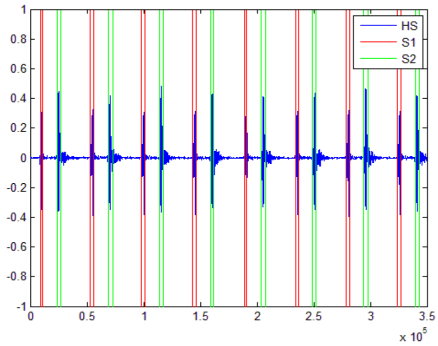

Figure 9: Segmentation of the filtered heart sound 201108222258.wav.

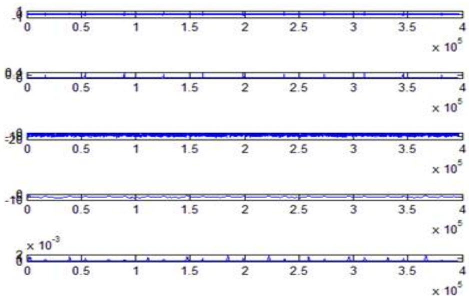

Figure 10: Segmentation steps for the raw heart sound 201106221450.wav.

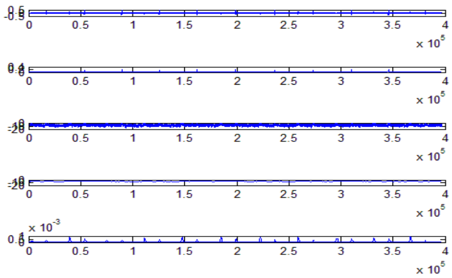

Figure 11: Segmentation steps for the filtered heart sound 201106221450.wav.

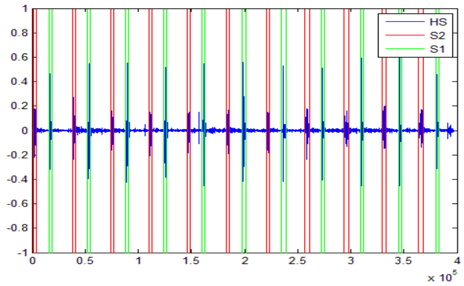

Figure 12: Segmentation of the raw heart sound 201106221450.wav.

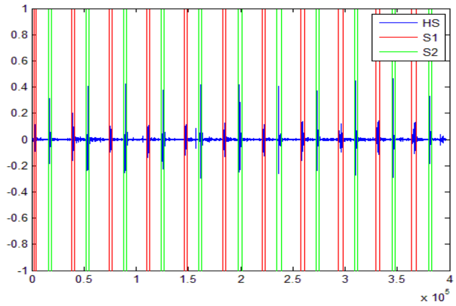

Figure 13: Segmentation of the filtered heart sound 201106221450.wav.

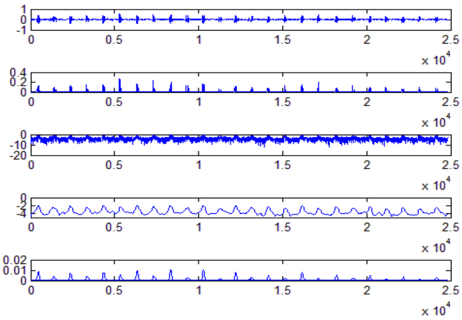

Figure 14: Segmentation steps for the raw heart sound 103_1305031931979_B.wav.

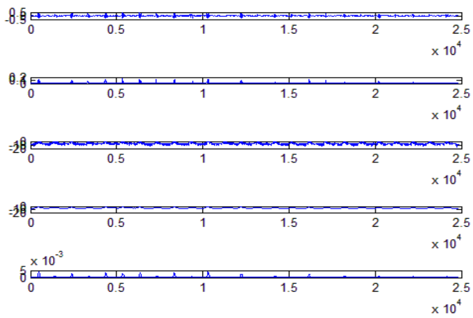

Figure 15: Segmentation steps for the filtered heart sound 103_1305031931979_B.wav.

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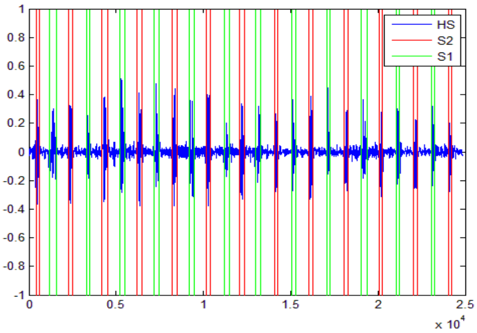

Figure 16: Segmentation of the raw heart sound 103_1305031931979_B.wav.

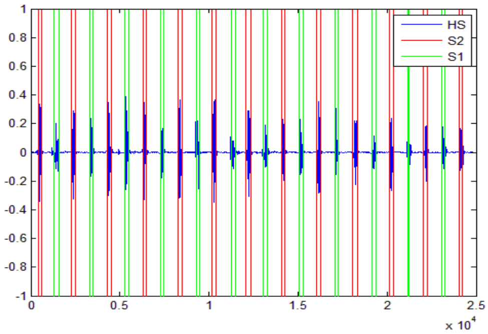

Figure 17: Segmentation of the filtered heart sound 103_1305031931979_B.wav.

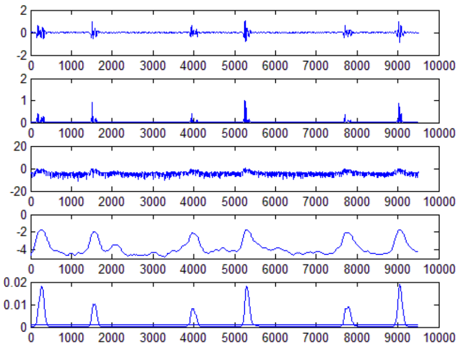

Figure 18: Segmentation steps for the raw heart Sound106_1306776721273_C2.wav.

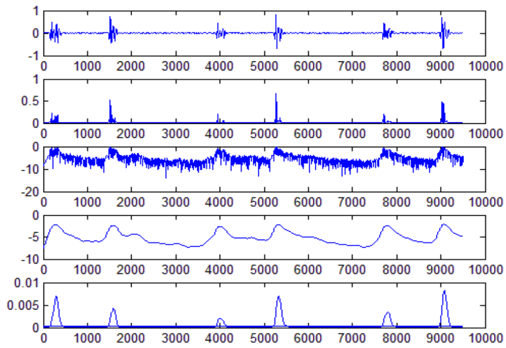

Figure 19: Segmentation steps for the filtered heart sound 106_1306776721273_C2.wav.

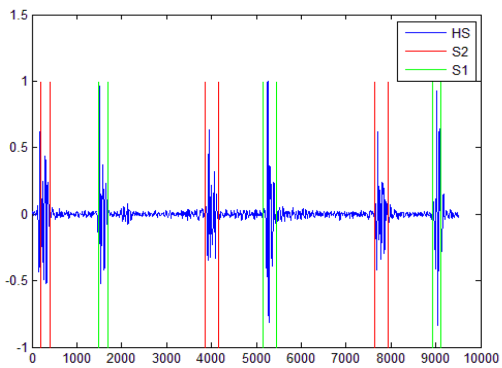

Figure 20: Segmentation of the raw heart sound 106_1306776721273_C2.wav.

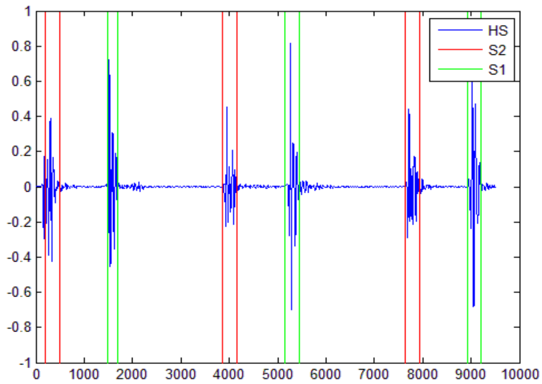

Figure 21: Segmentation of the filtered heart sound 106_1306776721273_C2.wav.

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	Nameofsegment (seg)	SNR Before LMS	SNR After LMS
201108011118.wav	Seg 1	9.8918	10.7072
	Seg 2	9.995	10.7381
	Seg 3	9.8897	10.6044
	Seg 4	9.4978	10.2643
	Seg 5	9.6345	10.4446
	Seg 6	9.7449	10.5955
	Seg 7	9.724	10.3986
	Seg 8	9.7134	10.5342
	Seg 9	9.5802	10.5235
	Seg10	9.7608	10.5252
	Seg11	9.6925	10.473
201108222258.wav	Seg1	13.0258	13.6127
	Seg2	14.9012	15.5216
	Seg3	15.669	16.102
	Seg4	15.8739	16.3168
	Seg5	15.7966	16.2142
	Seg6	14.9906	15.7146
	Seg7	15.5339	16.057
201106221450.wav	Seg1	10.479	10.9796
	Seg2	13.5019	13.5073
	Seg3	12.5922	13.0246
	Seg4	13.4389	13.4435
	Seg5	13.2626	13.6019
	Seg6	13.3013	13.4519
	Seg7	13.4235	13.6796
	Seg8	13.2032	13.1967
	Seg9	12.9923	13.2406
	Seg10	13.5785	13.7664
103_1305031931979_B.wav	Seg1	1.0074	2.0011
	Seg2	0.85361	1.2119
	Seg3	0.73026	0.54173
	Seg4	0.72377	0.83007
	Seg5	0.84982	1.0803
	Seg6	1.4503	2.121
	Seg7	0.65694	1.8496
	Seg8	0.90006	0.8452
	Seg9	1.3787	0.90407
	Seg10	2.2954	1.327
	Seg11	1.5564	2.4287
106_1306776721273_C2.wav	Seg1	1.2706	1.7075
	Seg2	-0.24437	1.1495

Table 1: shows SNR of heart sound segments before and after LMS.

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Sound	Name of segment (seg)	Before	After LMS	Doctor’s
201108011118.wav	Seg 1	Normal	Normal	Normal
	Seg 2	Normal	Normal	Normal
	Seg 3	Normal	Normal	Normal
	Seg 4	Normal	Normal	Normal
	Seg 5	Normal	Normal	Normal
	Seg 6	Normal	Normal	Normal
	Seg 7	Normal	Normal	Normal
	Seg 8	Normal	Normal	Normal
	Seg 9	Normal	Normal	Normal
	Seg10	Normal	Normal	Normal
	Seg11	Normal	Normal	Normal
201108222221.wav	Seg1	Abnormal	Abnormal	Abnormal
	Seg2	Abnormal	Abnormal	Abnormal
	Seg3	Abnormal	Abnormal	Abnormal
	Seg4	Abnormal	Abnormal	Abnormal
	Seg5	Abnormal	Abnormal	Abnormal
	Seg6	Abnormal	Abnormal	Abnormal
	Seg7	Abnormal	Abnormal	Abnormal
201106221450.wav	Seg1	Abnormal	Normal	Normal
	Seg2	Normal	Normal	Normal
	Seg3	Normal	Normal	Normal
	Seg4	Normal	Normal	Normal
	Seg5	Normal	Normal	Normal
	Seg6	Normal	Normal	Normal
	Seg7	Normal	Normal	Normal
	Seg8	Normal	Normal	Normal
	Seg9	Normal	Normal	Normal
	Seg10	Abnormal	Normal	Normal
103_1305031931979_B.wav	Seg1	Normal	Normal	Normal
	Seg2	Abnormal	Normal	Normal
	Seg3	Abnormal	Normal	Normal
	Seg4	Abnormal	Normal	Normal
	Seg5	Abnormal	Normal	Normal
	Seg6	Normal	Normal	Normal
	Seg7	Normal	Normal	Normal
	Seg8	Normal	Normal	Normal
	Seg9	Abnormal	Normal	Normal
	Seg10	Normal	Normal	Normal
	Seg11	Normal	Normal	Normal
106_1306776721273_C2.wav	Seg1	Abnormal	Normal	Normal
	Seg2	Abnormal	Normal	Normal

Table 2: shows the abnormality of heart sound segments along with doctor’s views.

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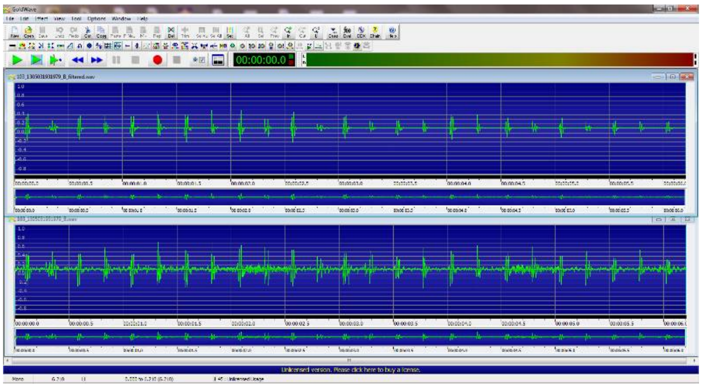

Figure 22: shows filtered and raw sounds viewed in Gold-wave software by the doctor.

Five test sound analysis of the phonocardiogram are shown as listed in table 1 and 2. The first step in the analysis of segmentation includes homo morphic filtering. The energy of a heart sound signal is obtained as a squared amplitude of the signal. A logarithm of the squared amplitude for a test heart sound is taken. It is then filtered using a low-pass filter with a cut-off frequency of 10 Hz in order to remove murmurs that hinder the segmentation. The exponential of the resulting output of the filter is calculated which is then threshold to 0.8 times the mean value as per [2]. The sounds above the threshold are considered heart sounds while the remaining is discarded. The steps for segmentation are shown in figures 2, 6, 10, 14 and 18. The heart sounds are time marked as sounds S1 (small amplitude shown by green lines) and S2 (larger amplitude shown by red lines). It is clear from figures 4, 8, 12, 16, 20. The segmented heart sounds usually designated by y, are compared with the dataset of normal and abnormal raw heart sounds segment-wise. Each segment of the raw test sound is then classified as normal or abnormal depending on the result of the k-means clustering algorithm.

The k-means clustering algorithm is implemented for the resulting segments of raw heart sounds. A minimum value of k=3 is arbitrarily fixed. The features used here are the mean value of each segment, the standard deviation and the variance. Using these features, a k-means algorithm first calculates the Euclidean distance between the segments of the raw test heart sound and the heart sound segments of the training dataset of normal and abnormal heart sounds. Smaller the value of Euclidean distance more normal is the heart sound. The result is displayed in the command window as normal or abnormal.

The second part of the automatic classification is the classification of the LMS filtered heart sound obtained by adaptive filtering of raw test heart sound. The LMS algorithm is used to generate the filtered training dataset consisting of normal and abnormal heart sounds. The parameters of the algorithm are set so as to remove the noise and retain the murmur portion of the heart sound along with S1 and S2 sounds. The parameters are fixed as follows:

The step size μ=0.1;

The filter length M=10;

The leakage factor =0.1;

The delay=10 samples.

The LMS algorithm is used with the same parameters to create a filtered training dataset and to filter the raw test sound. The raw test sounds are LMS filtered and designated as ylms. The LMS filtered sounds are then further segmented using the same homo morphic filtering method discussed above. The steps for segmentation are shown in figures 3, 7, 11, 15 and 19. The segmented heart sounds are shown in figures 5, 9, 13, 17 and 21. The figures show that most of the noise present in the heart sound had been filtered out.

The segmental signal to noise ratio is also calculated for the test sound segments both filtered and raw. It is given by equations (1) and (2) as, overall_SNR_raw and overall_SNR_filtered

Overall SNR_raw = 10*log10 (sum (*y*. ^2)/sum ((y-ylms). ^2));(1)

Overall SNR_raw = 10*log10 (sum (*y*-ylms. ^2)/sum ((y-ylms). ^2));(2)

Table 1 shows the segmental SNR of each segment of raw sound before LMS filtering and that of filtered sound after LMS filtering. The table reveals an important fact that SNR has improved considerably on application of LMS algorithm.

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Table 2 shows the classification of heart sound segments of the test sound before and after LMS filtering. Table 2 reveals that the sound 201108011118.wav had all its segments normal before and after LMS filtering. There were eleven segments. The sound 201108222221.wav had all its segments abnormal before and after LMS filtering. There were seven segments. In sound 201106221450.wav segment 1 and 10 were abnormal before LMS filtering but became normal after LMS filtering. This is inherent due to presence of noise that got cancelled with the filtering. Remaining segments were normal in both instances. There were 10 segments in all. In the sound103_1305031931979_B.wav same results were observed. Segments 2, 3, 4 and 9 which were abnormal in the first case turned out to be normal in the latter case. Other segments remained normal. There were 11 segments in all. In sound 106_1306776721273_C2.wav all segments were abnormal before LMS and became normal after LMS. There were only two segments in all.
All the test sounds were tested in consultation with the cardiologists. The heart sounds both raw and filtered were analysed using Gold-wave software. Gold-wave aids a cardiologists in revealing information about the presence of noise or murmur in the heart sound. The audio-visual interpretation of the presence of noise, murmur and heart sounds were given by the cardiologists and the detailed analysis is listed in tables 1 and 2. The cardiologists' feedback reveals that all sounds classified under LMS filtered matched the cardiologists' results. Figure 22 shows the screenshot of a Gold-wave software showing LMS filtered and raw sounds.
The feedback of the cardiologists along with the automatic classification algorithm results reveals a great deal of information about the nature of heart sounds. In sound 201108011118.wav noise did not affect the classification or in other words there was minimal noise. Classification yielded a normal sound with 100% accuracy. In sound 201108222221.wav too noise did not affect the classification or in other words there was minimal noise. Classification yielded an abnormal sound with 100% accuracy. In sound 201106221450.wav noise did affect classification. The classification accuracy was 80% before filtering and 100% after filtering. In sound 103_1305031931979_B.wav sound affected classification. Before filtering the accuracy was 55% normal and 100% accuracy of normalcy was obtained after filtering. In sound 106_1306776721273_C2.wav noise completely misclassified the sound. Before filtering the accuracy was 0% normalcy and after filtering the accuracy was 100%.

IV. CONCLUSION

Automatic classification of phonocardiogram involves quick and easy classification of heart sound. Usually the recording of phonocardiogram is done in noisy environments. As the doctors require quick and urgent analysis of heart sounds a concrete platform is necessary. Since noisy phonocardiogram yield inaccurate results, automatic classification of phonocardiogram could yield a much needed platform for early diagnosis of diseases. This work utilises a simple but robust method of segmentation called segmentation by homo-morphic filtering. The segmentation of the heart sound utilised in this work will be helpful for the doctors to gauge different vital parameters of heart sound and ailments. For example segmentation could be used to calculate the heart rate, which itself is a vital parameter for determining the condition of heart.
Since phonocardiogram is a nonlinear signal it is often difficult to remove the background noise. So LMS algorithm will prove to be a vital tool in removing such noises which is a part of this work. Removing the noise has the advantage that SNR will be greatly improved and the clarity of the sound both in terms of audio and visual will be improved.
The work also focusses on k-means clustering algorithm for classification purpose. It utilises Euclidian distance as a measure of calculating the normality or abnormality of heart sound. Since it requires very less computational requirements performs at high speed and more accurately even in noisy environments it has been discussed in this work.
All together the combination of all three algorithms along with cardiologists' feedback has provided a great opportunity to build a system with high accuracy that is capable of providing good and reliable results.

V. FUTURE SCOPE

Phonocardiography has a bright future. Especially it is very convenient for early and fast detection of diseases for a doctor using the principles, methods and practises of phonocardiography. This works entitles for non-real time acquisition of phonocardiogram and its classification in noisy and noiseless environments.
The future scope would be to build a system that acquires a real-time phonocardiogram, filters its, segments it and classifies it. It would be a novel idea to build such a system that would provide automatic classification of phonocardiogram in real time noisy environments.

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REFERENCES

1. P Bentley et al.Classifying Heart Sounds Challenge. The PASCAL (2011).
2. P Ramaswamy and Ventus, Biological Signal Analysis. Publishing ApS, ISBN (2010).
3. MSVishwanath, et al. Phonocardiography–the future of cardiac Auscultation, International Journal of Scientific & Engineering Research(2011)2: 2229-5518.