Classification of Phonocardiogram using an Adaptive Fuzzy Inference System

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Abstract - *This paper proposes a novel approach for the classification of phonocardiograms based on statistical properties of the PCG signal energy envelograms using fuzzy inference system. Fuzzification of features is done to remove absolute boundaries and assign a degree of association to every segment of the signal with the corresponding heart sound. Since heart sound signals are highly nonstationary, characteristic features of the signal segments are usually fuzzified. Developed Mamdani-type fuzzy inference classifier, helps distinguish between different heart sounds and fuzzy features with great accuracy.*

First of all, sequences of different features of the envelogram are computed which are then statistically manipulated and used as input to the inference system. Rules for the classification are created and output is computed. Crisp results represent degree of association with the correct heart sound. The developed algorithm is tested on standard databases. Results indicate 97% average accuracy to identify different segments of the PCG signal.

Keywords: Phonocardiogram (PCG), Biomedical Signal Processing, Segmentation of heart sounds, Fuzzy Inference system.

1 Introduction

In digital phonocardiography, correct automatic identification and classification of heart sounds is still a complex and difficult task due to highly nonstationary nature of the heart sounds and its variability from person to person [1, 2]. Two major audible heart sounds in a normal cardiac cycle are the first and second heart sounds, S1 and S2 respectively. 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.

Feature extraction of PCG initiates from envelogram computation, i.e. segmenting the PCG into envelopes and zero segments. Various methods for envelogram computation have been reported in literature such as mean Shannon Energy, AM demodulation, Hilbertz Transform, Wavelet decomposition, rectification and low pass filtering of the PCG. Thresholds are set in order to limit noise and clarify zero segments as well as envelope boundaries. In our work we have computed envelogram from average Shannon Energy of the signal. After an efficient segmentation of the PCG, characteristic features of the envelogram are analyzed namely: amplitude, duration, mean frequency and average energy of envelopes as well as duration of zero segments. These features form a set of sequences which are used as inputs for the fuzzy inference system. Fuzzy Inference System is based on general properties of various heart sounds such as: usual intensity and duration of S1 is greater than that of S2 and etcetera. The crisp output of the system gives degree of association of the inspected segment with the theoretical one. Based on this association, classification is done. Murmurs, on the other hand, can occur anywhere in the cardiac cycle. If a murmur is classified, it is again fed to another fuzzy system which classifies it as innocent, pathological or highly pathological. Final classification however is performed by comparing the sequence classified by the fuzzy system with the actual cardiac cycle. Here, it is tested that no same segments (except murmurs) are classified adjacent to each other (e.g. after S1 there should be S2). If classifier identifies the next lobe again as S1, then either the first or second lobe is misclassified or a split is indicated. This case usually occurs in split sound pathologies, and correct identification is made at this stage. The objective of the final stage is simply to filter out the sequence of events classified by the fuzzy system by a more astringent criterion.

2 Database

Database of normal and various cardiac abnormalities of heart sounds was taken from "e-general medical" [3]. The data is sampled at 11025Hz and low pass filtered out using Chebyshev (type I) filter with a cutoff frequency of 882 Hz [1]. Frequency components higher than this cutoff value are usually associated with noise.

3 Signal Processing

3.1 Envelogram Computation

Average Shannon Energy of the signal is computed as

$$E_{avg} = -\frac{1}{N}\sum_{t=1}^{N}[signal^2(t) * \log(signal^2(t))]$$

where N is window size and is taken to be duration between two zero crossings of the signal. This variable window size rather than fixed window size as in [1] enhances signal characteristics by computing distinct envelograms for major heart sounds and murmurs which results in classification based on envelogram features. Figure 1(a) shows PCG of a normal subject while Figure 1 (b) gives Shannon Energy envelogram computed using adaptive windows. Here the horizontal axis is changed from total number of windows to the total sample size of the signal and it is assumed that every sample of the window has a constant energy equal to the energy of respective window. This representation makes feature extraction simpler and data from the envelograms easy to manipulate.

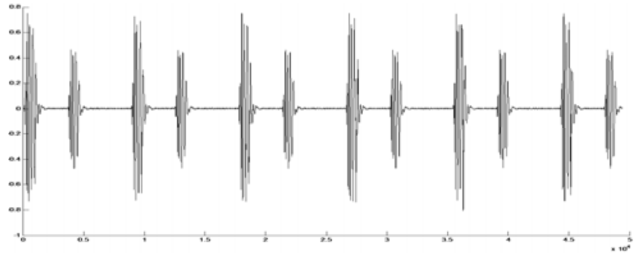


Figure 1 (a) Original PCG of a normal subject

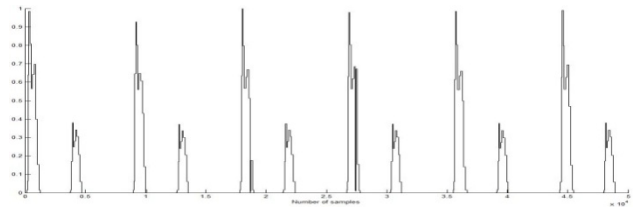


Figure 1(b) Shannon energy envelogram of the PCG

3.2 Feature Extraction

Envelogram features are the physical characteristics of the envelogram. These characteristics help in categorizing heart sounds and indentifying pathologies. Following features are used as inputs for the fuzzy system.

3.2.1 Amplitude of Envelopes

Amplitude of envelopes corresponds to the intensity of heart sounds. Usually S1 has highest intensity followed by S2, S3 and S4. Envelopes of innocent murmurs and some cases of mild aortic stenosis have least intensity. This criterion is used as one of the inputs to the fuzzy classifier to separate out major heart sounds from the minor ones. A sequence of amplitudes of all the envelopes of an envelogram is formulated and fed as an argument to the fuzzy classifier.

3.2.2 Energy of Envelopes

Total Shannon Energy of the individual envelopes gives a fair clue for the identification of different heart sounds. The best thing about taking total energies of the envelopes is that it clearly differentiates every heart sound. However, in cases of sound splits total energy of the envelope may not be a useful feature. For example if there is a split in S1 sound, S1 is detected in the form of two envelopes in the envelogram. Here total energy of S1 is divided into two halves and energy computed from a single envelope is in fact a fraction of the total energy of S1. In such cases ratio of total energy of individual envelopes to the duration of respective envelopes is a useful argument for classification. This ratio however blurs boundaries between S2, S3 and murmurs.

3.2.3 Duration of Envelopes

Duration of envelopes is an indirect measure of frequency content of the envelopes. In typical cases S1 has longest duration followed by S2, S3/S4 and finally murmurs, which have highest frequency content. This feature is very helpful in the identification of murmurs and stenosis, since intensity of a murmur may be close to major sounds but its duration would never be.

3.2.4 Duration of zero segment

Zero segments are parts of the envelogram where energy of the signal is nearly zero. In noisy conditions a threshold is often set, below which energy of the envelopes is forced to zero; hence rejecting extra envelopes. Durations of zero segments correspond to systolic (zero segment following S1) and diastolic (zero segment following S2) periods. Generally diastolic period is much greater than systole; therefore they are used as reference indicators for S1 and S2. However in cases where diastole contains S3/S4 and abnormalities like severe stenosis, correct differentiation between systole and diastole is difficult to make. In such cases, S1s and S2s are used as reference indicators for systole and diastole.

4 Fuzzy Classifier

Figure 2 shows schematic of the fuzzy inference system based on Mamdani's method [4]. Inputs to the system are the features discussed in section 3.2 namely amplitude of the envelopes, duration of the envelopes, energy of envelopes and ratio of energy to the duration of the envelopes. For each of these inputs, rules are formulated through which output is inferred. These inputs are sufficient to differentiate between S1, S2, S3 and murmurs/stenosis.

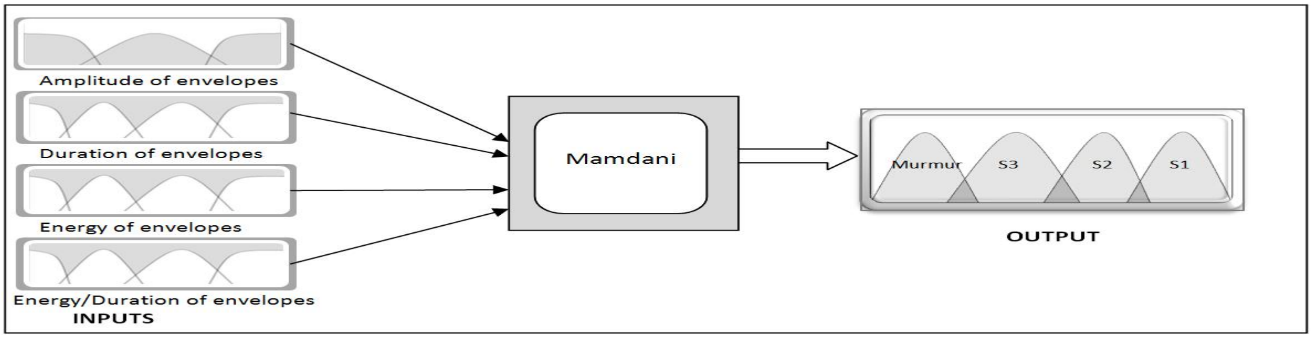


Figure 2. Complete Fuzzy inference system with four distinct inputs, i) Maximum amplitude of each of the envelopes; ii) Duration of envelopes; iii) Total energy of envelopes; iv) Ratio of energy of envelopes to the duration of envelopes. Four outputs extracted from the output of the fuzzy classifier are S1, S2, S3 and murmur/Stenosis.

4.1 Membership Functions

Membership functions of all the inputs are described by asymmetric curves to map input space to resulting membership value. Leftmost membership functions of each of the inputs are polynomial based Z curves which are open to the right while the rightmost are sigmoidal membership functions, open to the left. Membership functions between leftmost and rightmost functions need to be asymmetric and closed in nature and are thus modeled by product of two sigmoidal curves. Overlapping of these curves depend upon the extent of clustering of the input values. Note that our algorithm changes the shape of these membership functions with every new input depending upon the statistical nature of the input data. Overlapping, smoothness and duration of these membership functions is governed by distribution of the data and is therefore unique for every case. Our algorithm is therefore adaptive and proves very efficient for different cases. All four input membership functions for the normal case are shown in Figure 3(e).

Output membership functions are all Gaussian in nature with approximately 20 percent overlapping on each side. Rarely an output lies in the overlapping region which implies that envelope under inspection has a degree of both the sound types and it may need further analysis.

4.2 Clustering

Figure 3(a) shows PCG of a normal subject along with its envelogram. Figure 3(b) plots maximum amplitude of each of the envelopes. At this stage inference can be made about S1, S2 and one murmur found in envelope number 6. However there are cases where this distinction is difficult to make. In order to pass arguments to fuzzy system, data clustering is done. Figure 3(c) shows a histogram of the sequence of maximum amplitudes shown in Figure 3(b). Histogram makes three clusters of the data. These clusters show that six envelopes have highest amplitude levels (which correspond to S1), six have medium amplitude levels (corresponding to S2) and only one has lowest amplitude (corresponding to an innocent murmur). Ranges of amplitude levels (upper and lower bounds of each of the bar) indicated on the horizontal axis determine input arguments for the membership function curves, which are duration and intersecting points of the curves. Data clustering is done for all the inputs. Generally, three data clusters are formed but for cases where more than three clusters are made, manipulation of the histogram is done in such a way that data is sectioned into three clusters. This manipulation is not only based on the relative distance of each bar from the other in histogram, but is based on the fact that number of S1s, S2s and S3s should be equal (with plus minus 1 deviation, if a cycle is not complete). This manipulation helped in forming distinct clusters for the data. Figure 3(d) shows this clustering effect of maximum amplitude levels in order to compute upper and lower bounds for each of the membership function curves of the fuzzy system.

A case of interest is where S3 and murmurs occur in the same PCG. In such a case, four clusters each for S1, S2, S3 and murmurs would initially be formulated. Manipulating these four clusters into three would make S3 fall in the category of S2 or murmurs. In order to deal with such a situation, a murmur threshold was used as a fourth membership curve in all the inputs except in amplitude of envelopes input (since murmur can have any intensity level).

This fourth murmur membership function is modeled as polynomial based Z curve and is set to extreme left. Its duration, overlapping and intersecting point with its adjacent curve is determined by a murmur threshold level. Murmur threshold is individual for all three inputs but a constant value. This threshold is set by analyzing more than forty PCGs in such a way that most murmurs lie below this threshold value. To counter for abnormal cases, a provision is given in the extent of overlapping of this murmur curve with its adjacent curve. Most of the murmurs are identified in this way and are differentiated from S3. For duration of envelopes, murmur threshold is set as 300 samples with an overlap region of 300 to 600 samples at a sampling

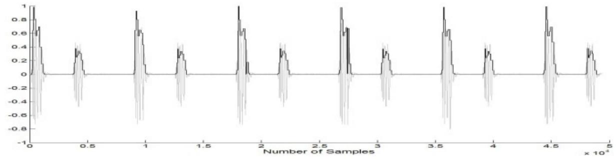


Figure 3(a) PCG of a normal subject with its envelogram

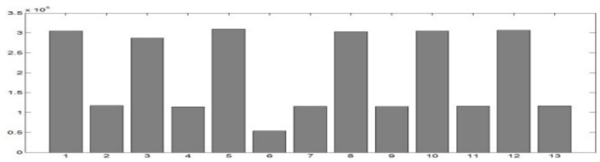


Figure 3(b) Bar Chart showing sequence of maximum amplitudes of the envelopes

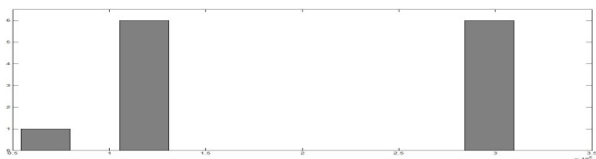


Figure 3(c) Histogram of the amplitude of lobes

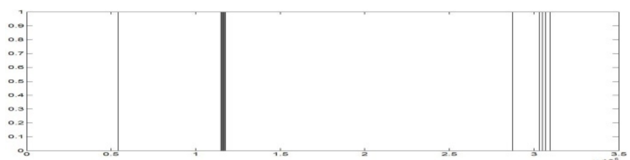
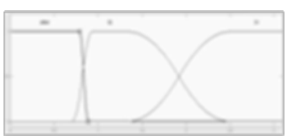
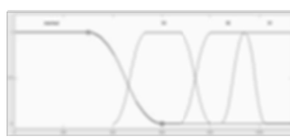


Figure 3(d) Clustering of amplitude levels of envelopes

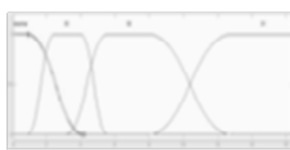


(i) Amplitude of envelopes



(ii) Duration of envelopes

(iii) Energy of envelopes



(iv) energy/duration of envelopes

Figure 3(e) Input membership functions

frequency of 11025 Hz as shown in figure 3e (ii). For energy of envelopes and ratio of energy of envelopes to the duration of envelopes, murmur thresholds are set as 0.25 (with an overlap region of 0.25—0.30) and 0.1 (with an overlapping region of 0.1—0.15) respectively, on a scale of 0—1, with original PCG and its features normalized to their absolute maximum. These threshold values can further be optimized by processing other PCG databases or a knowledge based optimization of thresholds may be performed so that every time a new PCG is processed, murmur thresholds are updated.

An important thing to realize at this stage is that since heart sound signals are highly nonstationary, if at times any sound is wrongly identified by a single input, rest of the three inputs would counter its effect, if they classify it correctly. This often happens in the analysis but the effect of four inputs helps the fuzzy inference system to classify according to the dominating characteristic of the signal. This is where fuzzy classifier reveals its potential to deal with uncertain cases very simply and effectively.

4.3 Rules

If-then rule statements are used to formulate the conditional statements that comprise fuzzy logic. These rules are straightforward obvious statements used in order to direct the fuzzy system. For example, one such rule for the classification of S1 is:

IF amplitude of the envelope is maximum,
AND duration of envelope is maximum,
AND energy of envelope is maximum,
AND the ratio, (energy/duration of envelope) is maximum
THEN envelope is “S1”.

Similarly, other rules depending upon the relationship of membership functions of the inputs to the outputs are formulated.

4.4 Ouput

Crisp values returned from the fuzzy system indicate degrees of association of an envelope with different heart sounds. At this stage, output would either be S1, S2, S3 or murmur. Output membership functions are Gaussian and overlap with each other. If an output lies in the overlapping region, it implies that envelope under inspection has characteristics of the both outputs and it may be further analyzed for accurate classification. Final classification of the output sequence is however made by comparing the output sequence with systole and diastole periods of the envelogram, which are usual markers for S1s and S2s. Systole, diastole identification itself is made by another fuzzy system which takes duration of zero segments of the envelogram as an input. Forward and backward chaining is utilized in order to classify S1s and S2s. Initial output is hence refined and more accuracy in results is achieved.

4.5 Murmur Classification

If a murmur is identified from the output of the fuzzy system, PCG is further analyzed and passed through another fuzzy engine which categorizes murmurs according to their pathological nature. Figure 4 illustrates simplified architecture of the murmur classifier. There are three inputs to the classifier each based on performance parameters of the PCG as discussed below.

4.5.1 Relative Energy of murmurs

Ratio of the total energy of murmur classified envelopes to the total energy of S1s, S2s and S3s gives an

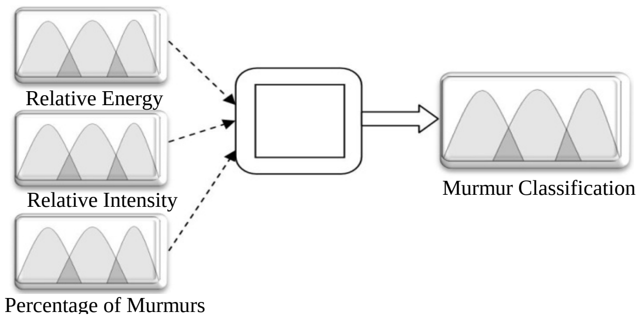


Figure 4 Fuzzy System for murmur classification.

idea of relative energy of the murmurs with reference to other major sounds.

$$\text{Relative Energy} = \frac{\text{Energy of murmurs}}{\text{Total Energy of S1s, S2s, S3s}}$$

Output would range from 0—1. Values closer to zero would imply low risk but values from 0.20 onwards may be pathological.

4.5.2 Relative Intensity of murmurs

Murmurs having high amplitudes usually indicate an alarming situation such as those in Systolic Aortic Stenosis, Mitral Prolapse and regurgitations. Ratio of mean murmur height to the mean of S1, S2 and S3's height characterizes relative intensities of murmurs by comparing the intensity levels of murmurs to the major heart sounds.

$$\text{Mean Relative Murmur Intensity} = \frac{\text{Mean amplitude of murmurs}}{\text{Mean amplitude of S1, S2 and S3}}$$

Values closer to 1 are critical than those closer to 0.

4.5.3 Percentage of murmurs

Ratio of total number of murmurs to the total number of major heart sounds detected by the classifier gives quantitative description of the kind of murmurs in the PCG.

$$\text{Percentage of murmurs} = \frac{\text{Total number of murmurs}}{\text{Total number of S1s,S2s,S3s and murmurs}} \text{ X } 100$$

This value indicates total number of murmurs per cardiac cycle and helps in identifying percentage of murmur clustering which is very useful for the classification of severe aortic stenosis and regurgitations.

5 Classifying Procedure

Figure 5 is a flowchart summarizing sequence of events undertaken in the classification of heart sounds.

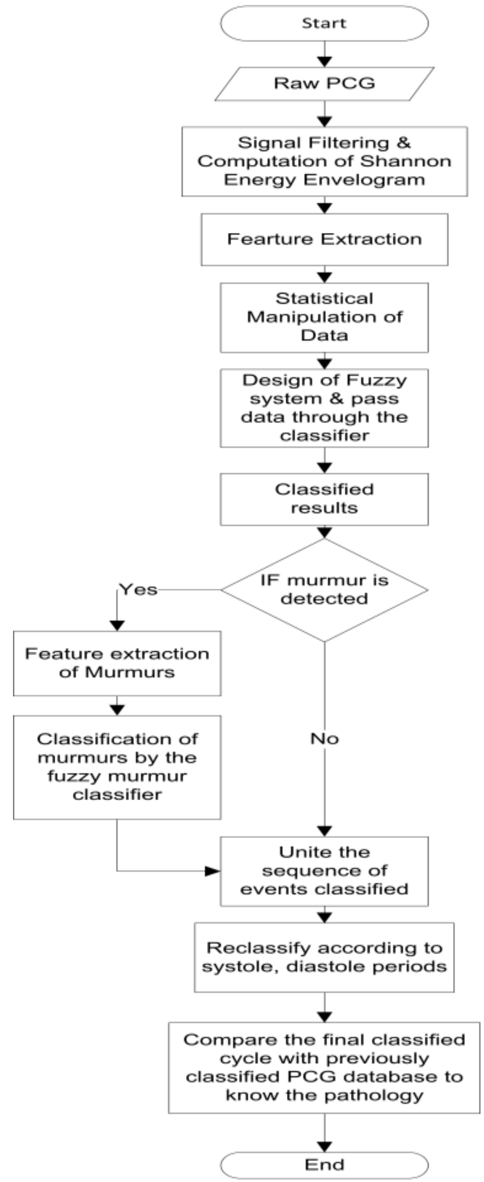


Figure 5. Classification of Heart Sounds

6 Conclusion

Fuzzy Classifier is an aboriginal approach for computerized identification of different heart sounds. The presented classifier design is simple and based on usual human interpretation of the signal but is intelligent enough to classify different heart sounds with good accuracy. Results for the normal and nearly normal cases are highly accurate up to 100 percent. The design can be further improved by adding other membership functions according to the characteristics of the phonocardiograms. Moreover optimizing murmur threshold levels would be a major leap forward to differentiate murmurs from similar sounds e.g. S4.

Table I. Results of phonocardiogram classification

PCG Samples	S1s	S2s	S3s	Murmurs	Correct Classification	Analysis
NORMAL	12/12	12/12	0/0	1/1	**100%**	1 innocent murmur
PCG with S3	6/6	7/7	6/6	0/0	**100%**	Sequence of S1s, S2s and S3s
Early systolic	7/7	6/6	0/0	36/36	**100%**	Highly pathological murmur(s)
Ejection Click	6/6	6/6	0/0	10/10	**100%**	Highly pathological murmur(s)
Normal Split	6/6	6/6	0/0	0/0	**100%**	Split not enhanced by envelogram
Diastolic Fixed S2 Split	12/12	12/12	0/0	0/0	**100%**	Split not enhanced by envelogram
Early Aortic Stenosis	6/6	6/6	0/0	34/34	**100%**	Highly pathological murmur(s)
Diastolic Atrial Gallop	6/6	6/6	0/0	9/9	**100%**	(Gallops identified as murmurs)
Opening snap	7/7	7+5/14	0/0	0/0	**82%**	2 OS. incorrectly identified as S3
Diastolic Phys. S2 Split	6/6	6+4/6+4	0/0	183/227	**86%**	4/4 Splits identified
Pan Systolic	7/7	7/7	0/0	83/83	**100%**	Highly pathological murmur(s)
TOTAL	85/85	86/88	6/6	356/400	**92.1%**	
Relative Percentage	**100%**	**98%**	**100%**	**89%**		

Advanced intelligent classifiers can be made by merging different domains of classifiers. For example a knowledge based Neuro-fuzzy classifier would unite characteristics of three classifiers and will certainly result in better output. Finally, it is proposed that final sequence of classifier results be compared to a larger duration database of heart sounds so that an added advantage of accurate diagnosis of any pathology, if present, is made.

7 References

[1] H. Liang, S. Lukkarinen, I. Hartimo, “Heart Sound Segmentation Algorithm Based on Heart Sound Envelolgram”, Computers in Cardiology, IEEE, Vol. 24, pp. 105—108, 1997.

[2] L. G. Gamero, R. Watrous, “Detection of the First and Second Heart Sound Using Probabilistic Models”, Proceedings of the 25' Annual International Conference of the IEEE EMBS, IEEE, Cancun, Mexico, pp. 2877-2880, September 17-21,2003.

[3] (2008, Oct.) eGeneral Medical. [Online]. http://www.egeneralmedical.com

[4] Mamdani, E.H. and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," International Journal of Man-Machine Studies, Vol. 7, No. 1, pp. 1-13, 1975

[5] Shaparas Daliman and Ahmad Zuri Sha'ameri, “Comparison of Time-Frequency Analysis Performance on Hearts and Murmurs”, Student Conference on Research and Development (SCOReD), Putraiaya, Malaysia, pp. 1-4, 2003.

[6] P. Carvalho, P. Gil, J. Henriques, L. Eugénio, M. Antunes, “Low Complexity Algorithm for Heart Sound Segmentation using the Variance Fractal Dimension”, IEEE, Faro, Portugal, pp. 194-199, 1-3 September, 2005.

[7] Cao Zehan, Zhou Shiyong, Fu Li, Pei Yuli, Xiao Shouzhong, “The Quantitative Analysis Approach for a Heart Sound Information System”, Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, Vol. 20, No 3, pp. 1620-1621, 1998.

[8] M. El-Hanjouri, W. Alkhaldi, N. Hamdy, O. Abdel Alim, “Heart Diseases Diagnosis Using HMM”, IEEE MELECON, IEEE, Cairo, Egypt, pp. 489-492, May 7-9, 2002.

[9] S Dalian, A Z Sha’ameri, “Time-Frequency Analysis of Heart Sounds and Murmurs”, ICICS-PCM , IEEE, Singapore, pp. 840-843, 15-18 December 2003.

[10] Jacques P. de Vos and Mike M. Blanckenberg, “Automated Pediatric Cardiac Auscultation”, IEEE Transactions on Biomedical Engineering, Vol. 54, No. 2, IEEE, pp. 244-252, February 2007.

[11] Zhao Zhidong, Zhao Zhijin, Chen Yuquan, “Time-Frequency Analysis of Heart Sound Based on HHT”, IEEE, pp. 926-929, 2005.

[12] Cota Navin Gupta, Ramaswamy Palaniappan, Sreeraman Rajan, Sundaram Swaminathan, S.M.Krishnan, “Segmentation and Classification of Heart Sounds”, CCECE/CCGEI, IEEE, Saskatoon, pp. 1674-1677, May 2005.

[13] P. Wang, Y. Kim, L. H. Ling and C. B. Soh, “FIRST Heart Sound Detection for Phonocardiogram Segmentation”, Proceedings of the 27th Annual Conference in Medicine and Biology, IEEE, Shanghai, China, pp. 5519-5520, September 1-4, 2005.