AN ADAPTIVE APPROACH TO ABNORMAL HEART SOUND SEGMENTATION

D. Kumar, P. Carvalho, M. Antunes†, R. P. Paiva, J. Henriques

Centre for Informatics and Systems, University of Coimbra, Coimbra, Portugal
†Centre of Cardio-thoracic Surgery of the University Hospital of Coimbra, Coimbra, Portugal
E-mail: {dinesh, carvalho, ruipedro, jh }@dei.uc.pt, antunes.cct.huc@sapo.pt

ABSTRACT

Heart sound is one of the significant bio-signals to diagnose certain cardiac anomalies. Aiming to provide an automatic heart sounds analysis to medical professional, we present a method of heart sound segmentation based on simplicity and strength. The method has two phases: first phase identifies the timings of S1 and S2 sounds' start and end using simplicity and strength in wavelet domain, and the second phase determines the S1 and S2 using high frequency information. The method incorporates an adaptive approach for thresholding simplicity and strength profile in timings of the sound components detection, as well as main heart sounds components S1 and S2 in presence of abnormal sound, so called murmur. A comparable result to the state-of-the-art methods has been yielded.

Index Terms— heart sound, wavelet decomposition, simplicity, strength, Shannon energy.

1. INTRODUCTION

Auscultation has been a classical method to know mechanical condition of heart and also diagnostic/prognostic values for certain cardiac disorder, such as valve disorder or heart failure [1]. Therefore, a computer based interactive framework of heart sound analysis for the medical experts will assist in diagnosing heart related pathologies. One of main tasks in heart sound analysis segments its main components and recognize. The segmentation part of heart sound analysis constitutes with identifying starting and ending times of the main heart sound components, and recognizing the S1 and S2 sounds. In presence of abnormal sound, so called murmur, segmentation of S1 and S2 becomes more challenging which requires advanced and extensive processing.

The problem of segmentation for heart sound, namely in presence of murmur, has been attempted to tackle in recent past few years. Spectral power of wavelet decomposed heart sounds based approach was proposed in [2], a homomorphic filter was introduced in [3], and decision tree based segmentation was developed in [4]. Some researchers have also utilized ECG as a reference signal to find the locations of S1 and S2 that corresponds to QRS and T waves. The most recent contribution was found in [5][6]. It is preferable not to use ECG an auxiliary signal because of its requirement of clumsy wiring system and sticky electrodes. Furthermore, robust and versatile method is aimed to develop using an adaptive approach of certain parameters in order to keep it person specific independent.

In this paper, we present simplicity and strength in wavelet domain based method of heart sound segmentation. This method is the extension, supposedly an improvement, of our previous method of wavelet-simplicity filter [7]. Simplicity it the measure which was first used on heart sound by Nigam and Priemer [8] in order to extract complexities of S1, S2 sounds and murmur. The method is composed with two phases: in the first phase, audible sounds in the heart sounds are gated with the information of starting times and ending times. In the second phase, S1 and S2 sounds are recognized by utilizing the higher frequency information in S2 sounds compared to S1. Shannon energy is used to emphasize high frequencies in S2 while diminishing in S1.

The paper is organized in three main sections: first section has details of computation techniques of simplicity and strength measures, proposed segmentation algorithm followed by stating high techniques to determine S1 and S2 sounds. Second section contains data collection and results part while third section outlines major points as conclusions.

2. METHOD

The proposed method of segmentation includes three main tasks: (1) preparation of heart sound by normalization and filtering for the segmentation, 2) finding the starting time and ending time of the main components, namely S1 and S2 sounds, and 3) recognizing the S1 and S2 based on the knowledge of heart function domain. In this section, the techniques are briefly explained which are used in the segmentation algorithm. In subsequent subsections, segmentation and S1/S2 detection algorithm will also be described.

2.1. Heart sound preparation

In our work of data acquisition using a stethoscope developed by Welch Allyn Corporation, heart sounds are collected with the sampling frequency of 44.1 kHz. It is assumed that most high frequencies related to heart sound production can be captured. In order to overcome the gain, heart sounds are normalized between -1 and 1 sample values. Since in the heart sounds produced by the native valves contain frequency ranges of 25 Hz to 600 Hz. Hence, heart sounds are downsampled to 2205 Hz, and subsequently filtered with the 6^{th} order butterworth high pass filter of cut-off frequency of 25 Hz.

Before to start measuring simplicity and strength of the heart sounds component in the undercrossing heart sound signal, let say $x(t)$, it is decomposed in successive frequency bands. Fast wavelet transform (FWT) method of wavelet decomposition is adopted to decompose $x(t)$ in decreasing frequency bands. This method aids to multiresolution analysis of a signal in different frequency bands with respect to temporal change. Hence, transient changes in frequency or time domain can be observed. Daubechies wavelet basis, db6, is chosen as the mother wavelet because of its morphological similarities to heart sound components.

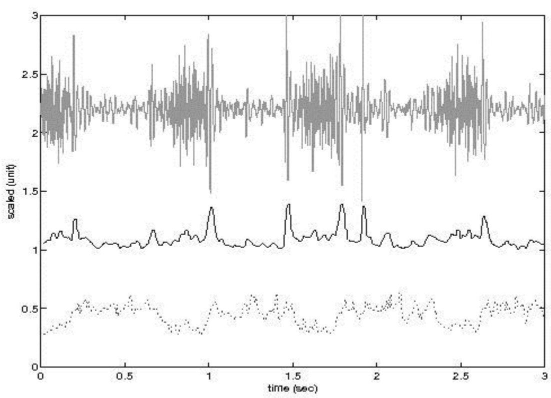

Figure 1: (top) heart sound; mitral regurgitation, (middle) strength, (bottom) simplicity.

2.2 Simplicity and Strength Computation

The S1 and S2 components of a heart sound exhibit high strength and simplicity, hence clear peaks can be seen in these curves, as depict in figure 1. In severe heart murmurs, murmurs overlap S1 or S2 sounds. Other unknown sounds may occur due to physiological events that exhibit similar characteristics of S1 and S2 components. Usually, S1 and S2 sounds exhibit relatively high simplicity as well as strength, whereas other artifacts exhibit high simplicity but on the contrary low strength. Hence, these two measures are utilized to perform segmentation. In this subsection, computation method of simplicity and strength is explained.

Suppose the heart is considered as a nonlinear dynamical system which state space is given as in (1),

$$\mathbf{X} = [\mathbf{X_1}, \mathbf{X_2}, \mathbf{X_3} \dots\dots\dots\dots\dots, \mathbf{X_P}]^{\mathbf{T}} \qquad (1)$$

where $\mathbf{X}_i$ is the state of the system at discrete time i, that generates the N-point heart sound time series $[x_1, x_2, x_3, \dots\dots.. x_N]$. A method of delay is applied to construct the embedding matrix in embedding space P, i.e.

$$[x_i, x_{i-\tau}, x_{i-2\tau}, \dots\dots.. x_{i+(m-1)\tau}\ ] \qquad (2)$$

where i = 1,2,3...P and $\mathbf{X}i$ are row vectors of the embedding matrix $\mathbf{X}$ of size $P \times m$. Application of an (m,τ) window to a time series of N data points results in a sequence of $P=N-(m-1)$ vectors. In the phase space reconstruction, it is important that the two integer parameters (m,τ) are suitably estimated. The τ parameter is estimated as the time lag where the first minimum occurs in the mutual information between data vector $[x_1, x_2, x_3, \dots\dots.. x_N]$ and time lagged data vector $\mathbf{X_i}$. Using the estimated τ, the embedded matrix dimension m is estimated by utilizing Cao's method [9]. Therefore, average value of m and τ of 81 heart sounds of 1 sec length are estimated 4 and delay 19 (τ= 19/samples period).

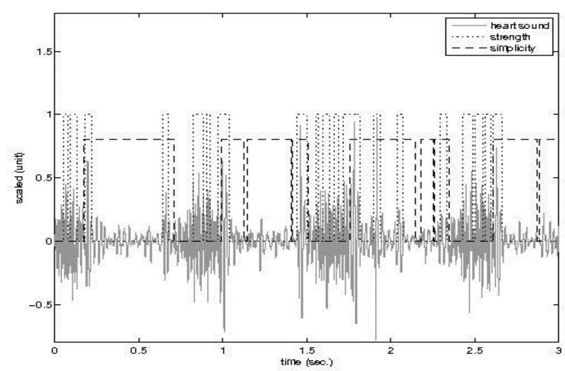

Figure 2: Gating by strength and simplicity.

In order to compute simplicity from the embedding matrix $\mathbf{X}$, correlation matrix is formed from it as in (3).

$$\boldsymbol{C} = \mathbf{X}^T\mathbf{X} \qquad (3)$$

where T denotes the transpose of the $\mathbf{X}$. Further, the eigen values, which are positive quantities, of $\boldsymbol{C}$ are computed. Let $\lambda_1, \lambda_2, \lambda_3, \dots.. \lambda_m$ be the eigen values of the matrix $\boldsymbol{C}$, and the normalized values are $\hat{\lambda}_1, \hat{\lambda}_2, \dots\dots \hat{\lambda}_m$, then normalized eigen values are computed according to (4).

$$\hat{\lambda}_i = \frac{\lambda_i}{\sum_{k=1}^{m} \lambda_k} \qquad (4)$$

Now, entropy, denoted as H, is computed using the normalized eigen values as in (5).

$$H = -\sum_{i=1}^{m} \lambda_i \log_2 \lambda_i \qquad (5)$$

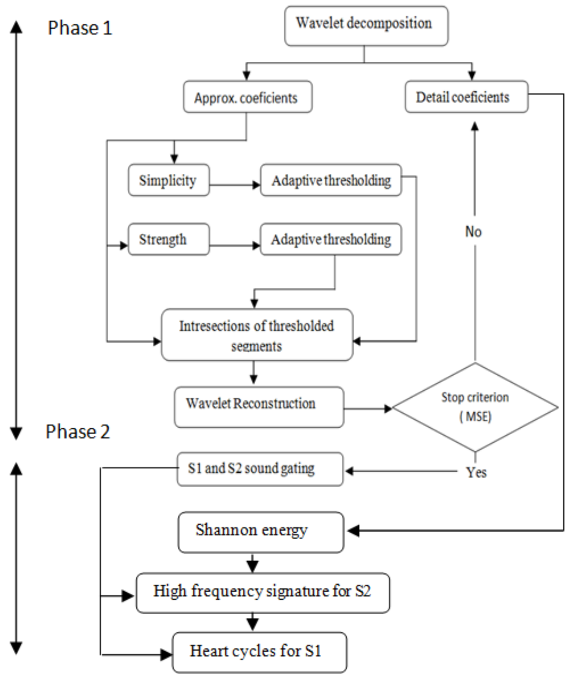

Figure 3: Segmentation (boundaries of relevant sound components, S1 and S2 recognition).

Using the above values of entropy simplicity is computed as in (6).

$$Simplicity\ (S) = \frac{1}{2^H} \tag{6}$$

Another feature, named as strength, is computed that measures the loudness of the signals in selected analysis window. Strength of the signal is computed using the embedded matrix **X** according to (7).

$$Strength\ (Sg) = \frac{1}{P}\sqrt{\frac{\|\mathbf{X}\|}{mP}} \tag{7}$$

Where m and P are the number of column and rows of the embedded matrix **X** respectively.

3.1 Steps of segmentation algorithm: Phase I

Regarding the wavelet-simplicity filter algorithm, it follows the same steps of the algorithm we developed using the Wavelet-Simplicity transform Therefore, only fundamental changes in the steps of the basic algorithm are described herein. Murmurs occur between S1 and S2 or S2 and S1 sounds. Therefore, the first task consists of the identification of the boundaries of the S1 and S2 sounds. The main steps for achieving S1, S2 and murmur separation using the strength and simplicity features are (see fig.2):

Step 1: The approximation coefficients of wavelet decomposed heart sound signal are used in further processing.

Step 2: Simplicity (S) and strength (Sg) are computed.

Step 3: S and Sg curves, separately, are thresholded using iterative approach based peak peeling algorithm (PPA) [10]. Initial values of the parameters in PPA are set based on the timing of S1/S2 and systolic/diastolic. Subsequently, start and end times of S1 and S2 sounds are achieved and can be gated. The segmented time gates using both feature curves are shown in figure 2.

Step 4: It is observed from figure 2 that correct start and top times of S1 and S2 sounds can be achieved by common segmented time gates in both thresholded feature curves; see in Figure 4 (top).

Step 6: The suitable decomposition depth is found by applying the mean square error criterion on gated decomposed heart sound signal [10].

In figure 3, the phase I part that includes segmentation part can be seen. Furthermore, result of first phase of segmentation, wavelet decomposition depth level 3rd, can be seen in figure 4 (top).

2.3 S1 and S2 detection: Phase II

In this phase, S1 and S2 are identified from the information collected from phase I. The gated segments are assumed to have S1 and S2 sounds. From the knowledge of heart physiology S2 sounds are believed to contain higher frequencies that S1 sound. High frequency signatures are viewed in the Shannon energy of details coefficients of the heart sound at the depth segmentation was performed.

As it can be seen in Figure 4(bottom), that energy measurement approach of Shannon energy is utilized to capture high frequency concentration in S2 sounds, it is given as in (8).

$$SE = -\sum x(t)^2 log_{10} x(t)^2 \tag{8}$$

Shannon energy (SE) is computed of detail coefficients. Based upon the Shannon energy, S1 and S2 detection is performed in following steps:

Step 1: SE is computed of detail coefficients of depth level achieved from the phase I.

Step 2: Since S2 is believed to show higher SE value than S1, hence, a threshold is set to distinguish high frequency contained segments (HFS) from low frequency contained segments (LFS) which is given as in (9).

$$Threshold\ = \frac{x^d(t) - \lambda\mu\left(x^d(t)\right)}{\sigma\left(x^d(t)\right)} \tag{9}$$

Where λ is a multiplier that varies from 1.0 to 10, μ is the mean, σ is the standard deviation, and $x^d(t)$ denotes the detail coefficients of the heart sound. HFS segments contain high frequency contents, as in the figure 4 shows availability of Shannon energy in HFS. All the HFS hold SE above the threshold while LFS below. The multiplier λ is varied in order to yield distinction between HFS and LFS. In one heart cycle there is one at least one LFS is prevalent between two HFS. Subsequently, HFS are regarded as S2 while LFS are believed to be S1 sounds.

Step 3: To validate LFS and HFS as S1 and S2 sounds, respectively, those segments which are instigated by internal body and environmental noise are pruned based on the fundamental physiological knowledge related to the heart sounds. For instance, one heart cycle contains two S1 and S2 sounds; duration of a heart cycle (in adults) is in the range of 400 ms to 1200 ms, durations of S1 and S2 sounds are in the range of 40 ms to 100 ms, etc.

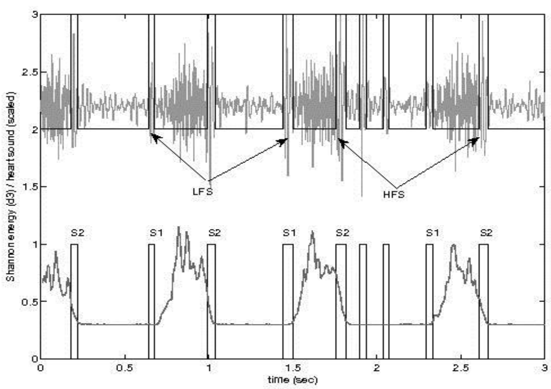

Figure 4: (top) Gated S1 (LFS) and S2 (HFS) sounds, (bottom) Shannon energy as high frequency signatures showing in S2 sounds.

4. RESULTS AND DISCUSSIONS

The heart sound with various grade murmurs were collected from the Cardiothoracic Surgery Center of the University Hospital of Coimbra. During acquisition, patients were asked to maintain silence and to make the least possible physical movements in order to maintain the integrity of heart sound samples. Recording was performed with an electronic stethoscope from Welch Allyn Corporation. The stethoscope has an excellent signal to noise ratio and extended frequency range (20 – 20,000 Hz). All heart sounds were digitized using a 16-bit ADC at 44.1 kHz sampling rate. Sound samples were recorded for the maximum duration of one minute. A total of 81heart sound clips with murmurs, corresponding to 2047 beats, were collected from 51 patients. The main biometric characteristics of the population were: BMI = 25.41±2.16; age = 64.65±8.64; number of males = 48; number of females = 3.

The algorithm was applied on 7 classes of abnormal heart sounds: 1) Aortic Regurgitation (AR), 2) Aortic Stenosis AS), 3) Mitral Regurgitation (MR), 4) Pulmonary Regurgitation (PR), 5) Pulmonary Stenosis (PS), 6) ubaortic Stenosis + Ventricular Septal Defect (SAS+VSD), 7) Systolic Ejection (SE). Results are presented in two tables: table I shows precision error in starting/ending times of the S1 and S2 sounds, while detection of S1 and S2 are measured in terms of sensitivity and specificity, that are shown in Table II.

Heart sound	S1 (μ(error)± σ(error)) (ms)		S2 (μ(error)± σ(error)) (ms)	
	Starting time	Ending time	Starting time	Ending Time
AR	4.67 (0.84)	5.62(0.77)	4.92(0.962)	3.32 (0.44)
AS	3.96 (0.28)	6.03(0.63)	5.10(0.632)	4.08 (0.73)
MR	4.05 (0.51)	5.62(0.77)	4.92(0.962)	3.92 (0.84)
PR				
PS				
SAS+VSD				
SE				

Table 1: Error estimated for S1 and S2 sounds identified timings.

As it can be noticed in table I that mitral regurgitation exhibits lowest error compare to other heart sounds. Due to overlap of murmur to S1 and S2 sounds, simplicity and strength are not capable to demarcate precise times of starting and ending of sound components. Nevertheless, it has achieved reasonable precision.

Heart sound	Sensitivity (%)		Specificity (%)	
	S1	S2	S1	S2
AR	93.14	91.0	94.10	89.67
AS	96.15	95.41	87.00	92.89
MR	90.45	93.78	91.32	88.80
PR				
PS				
SAS+VSD				
SE				

Table 2: Recognition results of S1 and S2 separately.

The S1/S2 detection results are reported to be in terms of sensitivity and specificity. From the table II, it is observed that the class of aortic stenosis is showing best sensitivity and specificity, while worst showing performance is from class of aortic regurgitation. It is observed that high grade murmurs are suited best to algorithm for segmentation as well detection.

--More to be written when table is complete.

5. CONCLUSIONS

A two phase heart sound segmentation method has been proposed. First phase includes, starting and ending times of heart sound components using simplicity and strength measures in wavelet domain. These two measures have ability to extract S1 and S2 distinct characteristics to assist segmentation with more precision than many of the state-of-the-art methods. The presented algorithm is highly adaptive by allowing iterative selection of wavelet decomposed coefficients and thresholding in similarity and strength profiles. Second phase the method deals with detection of S1 and S2 sounds. High frequency signature, which was extracted by Shannon energy, based approach is utilized to identify S2; subsequently S1 is detected with the knowledge of heart in biomedical domain. This method yields substantial results and comparable to the state-of-the-art with the advantage of being highly adaptive and precision of S1/S2 timings.

11. REFERENCES

[1] G. Mintz, E. Carlson, and M. Kolter, "Comparison of noninvasive techniques in evalution of the nontissue cardiac valve Prosthesis", *Med Eng Technol*, 15(6), pp 222–231, 1991

[2] T. Olmez and Z. Dokur "Classification of heart sounds using an artificial neural network", *Pattern Recognition Letters,* 24, pp. 617-623, 2003.

[3] C. N. Gupta, R. Palaniappan, and S. Swaminathan, "Classification of Homomorphic Segmented Phonocardiogram Signals Using Grow and Learn Network", *In Proc. of IEEE Engineering in Medicine and Biology*, pp. 4251-4254.

[4] S. A. Pavlopoulos, A. C. Stasis, and E. N. Loukis, "A decision tree – based method for the differential diagnosis of Aortic Stenosis from Mitral Regurgitation using heart sounds", *In J. of BioMedical Engineering Online*, pp.1-15, 2004.

[5] P. Carvalho, P. G., J. Henriques, M. Antunes, and L. Eugénio, "Low complexity algorithm for heart sound segmentation using the variance fractal dimension", *in Proc of IEEE Int. Sym. on Intelligent Signal Processing (WISP'05)*, pp. 194-199, 2005.

[6] M. El-Segaier, O. Lilja, S. Lukkarinen, L. S¨ornmo, R. Sepponen, and E. Pesonen, "Computer-based detection and analysis of heart sound murmur", *Annals of Biomedical Engineering*, **33**(3), pp. 514-519, 2005.

[7] D. Kumar, P. Carvalho, M. Antunes, J. Henriques, L. Eugenio, R. Schmidt, and J. Habetha, "Wavlet Transform and Simiplicity based Heart Murmur Detection", *In Proc. Int. Conf. Computers in Cardiology*, pp. 173–176, 2006.

[8] V. Nigam and R. Priemer, "Accessing heart dynamics to estimate durations of heart sounds", *in J. of Physiological Measurements*, pp. 1005-1018, 2005.

[9] L. Cao, "Practical method for determining the minimum embedding dimension of a scalar time series", *In the J. Physica*, pp. 43–50, 1997.

[10] L.J. Hadjileontiadis and I.T Rekanos, "Detection of xplosive lung and bowel sounds by means of fractal dimension," *IEEE Signal Processing Letters*, vol. 10, no. 10, October 2003.