Detection of S1 and S2 Heart Sounds by High Frequency Signatures

D. Kumar, P. Carvalho, M. Antunes[†], J. Henriques, L. Eugénio[†], R. Schmidt[‡], J. Habetha[‡]

Centre for Informatics and Systems, University of Coimbra, Portugal

{dinesh,carvalho,jh}@dei.uc.pt

[†] Cardiothoracic Surgery Centre, University Hospital of Coimbra, Portugal

antunes.cct.huc@sapo.pt

[‡] Philips Research Laboratories, Aachen, Germany

{ralf.schmidt, joerg.habetha}@philips.com

Abstract

A new unsupervised and low complexity method for detection of S1 and S2 components of heart sound without the ECG reference is described. The most reliable and invariant feature applied in current state-of-the-art of unsupervised heart sound segmentation algorithms is implicitly or explicitly the S1-S2 interval regularity. However, this criterion is inherently prone to noise influence and does not appropriately tackle the heart sound segmentation of arrhythmic cases. A solution based upon a high frequency marker, which is extracted from heart sound using the fast wavelet decomposition, is proposed in order to estimate instantaneous heart rate. This marker is physiologically motivated by the accentuated pressure differences found across heart valves, both in native and prosthetic valves, which leads to distinct high frequency signatures of the valve closing sounds. The algorithm has been validated with heart sound samples collected from patients with mechanical and bioprosthetic heart valve implants in different locations, as well as with patients with native valves. This approach exhibits high sensitivity and specificity without being dependent on the valve type nor their implant position. Furthermore, it exhibits invariance with respect to normal sinus rhythm (NSR) arrhythmias and sound recording location.

1. INTRODUCTION

Many heart disorders can be effectively diagnosed using auscultation techniques. In potentially deadly heart diseases, such as natural and prosthetic heart valve dysfunction or even in heart failure, heart sound auscultation is one of the most reliable, cheap and successful tools for early diagnosis. Auscultation is the preferred method for the detection of prosthetic valve dysfunction; it exhibits 92% sensitivity over echophonocardiography and cinefluroscopy [1]. To develop automatic heart disorder diagnosis tools based on phonocardiogram, it is important to first segment the heart sound into clinically meaningful segments or lobes, such as the S1 and the S2 sound components associated with closing valves during systole and diastole. Once these are detected, diagnostic features may be subsequently extracted for each type of sound. However, S1 and S2 sound detection is one of the major and most difficult problems in heart sound analysis.

Heart sound segmentation algorithms found in literature may be broadly classified into two main approaches: those require an ECG reference to synchronize the segmentation and those that do not. The latter may be further classified into supervised and unsupervised methods. In ECG reference based approach, first QRS complexes and T-waves are detected in order to locate the S1 and S2 segments, respectively [2]. In low quality ECG signals, T-waves are not always clearly visible. In such cases, S2 sounds may be classified by an unsupervised classifier [3]. To avoid extra hardware requirements and clumsy wiring arrangement for data acquisition, many researchers tried to identify S1 and S2 sounds by several means of signal processing and statistics without using ECG as a reference. In this context several supervised techniques have been suggested, such as artificial neural network [5] and decision trees [6]. Another class of approaches involves unsupervised techniques such as envelogram [7], spectrogram quantization method [8], and self organizing map using Mel frequency cepstrum coefficients [9]. In practice, it is observed that these methods do not perform well for all type of heart sounds (e.g. arrhythmic cases). Regarding the segmentation of heart sounds produced by prosthetic valves, it is well known that these sounds are dependent on several factors such as surgical techniques, location of implantation and type of prosthetic valves. In practice, the aforementioned methodologies do not provide the necessary invariance in order to be applicable for all kinds of heart valve implant patients.

The most reliable and invariant feature applied in current state-of-the-art heart sound segmentation algorithms is implicitly or explicitly the S1-S2 interval regularity. However, this criterion is inherently prone to noise influence. In order to avoid interference of spurious noisy sound segments using the S1-S2 interval, normally researchers assume an average heart rate [4][9]. Unfortunately this does not allow tackling appropriately heart sound segmentation of arrhythmic heart sounds.

In this paper, a novel method aimed at the detection of S1 and S2 heart sounds is proposed which does not rely on ECG reference or any other prior information about patients. In the proposed algorithm, instantaneous heart rate (which implies instantaneous heart cycle duration) is estimated based upon a high frequency marker that is extracted from each heart sound cycle using the fast wavelet decomposition. This frequency marker was motivated by the accentuated pressure difference which is found across heart valves, both in native and prosthetic valves, which leads to distinct high frequency signatures of the valve closing sounds. First, all available heart sounds are segmented into sound lobes using the Shannon energy of the approximation coefficients of the wavelet decomposed heart sound, then using the frequency marker heart cycles are identified. Finally, S1 and S2 heart sounds are classified in each heart cycle by inspecting the nearest interval between two sound segments to the estimated systolic interval (duration of S1-S2).

The paper is structured as follows: in section 2 the proposed method for S1 and S2 heart sound detection is introduced. In section 3 some results are discussed, and finally in section 4 some main conclusions are pointed out.

2. METHOD

The proposed method has three main stages (see in figure 1). In the first stage, heart sounds are segmented into sound lobes by finding the exact boundary samples of each and every type of sound using the Shannon energy of the approximation coefficients of wavelet decomposed heart sound. Furthermore, the identified sound lobes are physiologically validated since many artifacts and ambient noise may be captured during data acquisition. In the second stage, heart cycles are detected by high frequency information using the Shannon energy of the detail coefficients. In the final stage, S1 and S2 heart sounds are identified based on the estimated systolic interval and the instantaneous heart rate. These steps are thoroughly explained in this section.

2.1. Segmentation of clinically meaningful sounds

2.1.1. Sound segmentation into lobes. The goal of this stage is to clearly identify the boundaries of all sound lobes

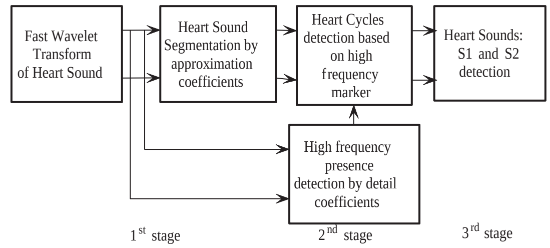


Figure 1. Block diagram for steps involved in S1, S2 detection.

presented in heart sound. This is achieved by first filtering the signal followed by the computation of its envelope. Boundary allocation of the sound lobes is carried out by analyzing zerocrossing of the normalized envelope. In order to avoid empirical tuning of a filter bank, the fast wavelet transform (FWT) is applied to remove high frequency components, namely due to the presence of respiratory lung sounds, from the heart sound samples. Here the db6 (Daubechies wavelet family) is selected because of its ideal shape for capturing the transient nature of the sounds. The FWT is performed until the 6 level (decomposition depth was experimentally tuned). However, approximation coefficients of the 5th level are considered for further processing. These coefficients represent the transient part of the low frequency heart sound obtained using this procedure. To extract the signal envelope from the approximation coefficients the following Shannon energy operator is applied :

$$E(x[n]) = -\frac{1}{N}\sum_{n=1}^{N}(x[n])^2 log(x[n])^2, \qquad (1)$$

where $x \in \{a1, d1, a2, d2, ...a6, d6\}$ and aj, dj are jth level approximation and detail coefficients of the wavelet transformed heart sound signal, respectively, and N is the number of samples in the selected window. This technique emphasizes the medium intensity signal and attenuates the effect of low intensity signals [7]. Shannon energy is computed using a sliding and centered window of 20 ms with 10 ms segment overlapped. Using the signal envelopes provided by the Shannon energy, sound lobe boundaries are identified from zerocrossing of the normalized Shannon energy,

$$E_n(a5) = E(a5) - < E(a5) >, \qquad (2)$$

where '<>' represents the average operator and $E_n()$ is the normalized Shannon energy operator. The segmentation results can be seen in figures (2 and 3). It should be noted that, since the Shannon energy operator comprises the square term of signal, which is important to emphasize the boundaries of S1 and S2 sounds, the heart sound energy is depicted rather than heart sound signal in all the figures shown in this paper.

2.1.2. Heart sound lobe validation. It is observed that some irrelevant sound lobes are identified with the described procedure. For instance, very long duration or noisy segments may not be conveniently filtered out using the FWT and the Shannon energy approach. These type of irrelevant sound segments are removed at this stage using four criteria based on physiologically inspired characteristics. In order to validate the sound lobes, there are three basic features of heart sound that are taken into consideration: the sound lobe duration (dt_i), interval between two consecutive sound lobes (T_i^{int}) and their loudness (root mean square(RMS_i). Let n_i^{start} be the start sample index and n_i^{stop} the stop sample index of the i^{th} segment, then they are computed according to,

$$dt_i = T_s(n_i^{stop} - n_i^{start}), \tag{3}$$

$$T_i^{int} = T_s(n_{i+1}^{start} - n_i^{stop}), \tag{4}$$

$$RMS_i = \sqrt{\frac{\sum_{j=n_i^{start}}^{n_i^{stop}} S(j)^2}{n_i^{stop} - n_i^{start}}}, \quad i = 1,2.....segments, \tag{5}$$

where T_s is the sampling period and S is the heart sound signal. For each sound lobe the following validation steps are considered:

(i) The duration of S1 and S2 sounds is not more than 250 ms and not less than 30 ms (this corresponds to the frequency of heart beats per minute) in normal population or even in cardiac patients. Hence, segments which exhibit duration outside this interval may be considered as noisy sound segments are discarded for further processing.

(ii) Interval T_i^{int} between two consecutive segments is considered to identify splitting in diastoles, i.e. splitting of the sound induced by the closing of the aortic and the pulmonary valves. It is seen that two sound segments which are separated by an interval less than 50 ms may belong to the same second heart sound. From the viewpoint of prosthetic valve dysfunction analysis, the aortic sound is more important than the pulmonary sound. Furthermore, the later has always lower loudness than the former. This criterion is considered in order to discard pulmonary sound lobes.

(iii) Sometimes it is observed that splitting in the second heart sound may not be clearly captured by the Shannon energy due to low loudness of low frequency sounds. However, in this circumstances pronounced local minima in the positive Shannon energy are clearly found. If this local minima is less than 25% of the maximum value of the Shannon energy of the sound segment under analysis, then splitting in the second heart sound is considered to occur at that position. In these conditions, only the subsegment that shows the highest loudness is kept for further processing.

(iv) During heart sound acquisition, high frequency long duration sounds may be mixed with heart sounds. In order to identify these noisy sounds, the periodic disturbances induced by high frequency noise are computed by jitter approach. Jitter represents the perturbation in stochastic and temporarily long sustained sounds (e.g. swallowing and speech) when valves do not close normally or when there are external disturbances. Let $T_p(m)$, $m = 1,2,....N_T$, where N_T is the total number of peaks in autocorrelation function, be the time separation between the m^{th} and the $(m+2)^{th}$ local maxima of the autocorrelation of the heart sound signal. Then jitter in heart sound segments is computed according to,

$$Jitter = \frac{\sum_{m=2}^{N_T-1} 2T_p(m) - T_p(m-1) - T_p(m+1)}{\sum_{m=2}^{N_T-1} T_p(m)}, \tag{6}$$

Autocorrelation is computed with a 50 ms sliding and centered window, which is sufficient to identify consecutive peaks in noisy segments. If for a given window jitter is detected, the lobe is marked as noisy and discarded for further processing.

2.2. Heart cycles detection using high frequency marker

The major part of S1 and S2 heart sounds is the consequence of vibration of the mitral and aortic valve leaflets, respectively. The frequency of valve vibration depends on the pressure difference across the valves. The relationship between pressure difference is given by $f = K.P^{1/3}$, where f is the frequency of the valve vibration, P is the pressure and K is a constant [10]. From the knowledge of cardiac functionality and genesis of S1 and S2 sounds it is known that aortic valves close with relatively large pressure difference across the valve; this high pressure difference justifies the high frequency mingling in S2 sounds. Thus, usually S2 sounds contain higher frequency with respect to S1 sound (excluding some rare exceptions). Nevertheless, this characteristic may be used as a marker, likewise QRS-complex in ECG, to identify heart cycle. Some rare exceptions may occur for some models of prosthetic valves, namely single tilted disk valves. In case of mitral implant position, these valves induce higher frequency prevalence in S1 sounds (see in figure 2(b)). From the figures (2 and 3), it is clearly noted that the difference of high frequency energies between two S1 and S2 sounds in all categories of

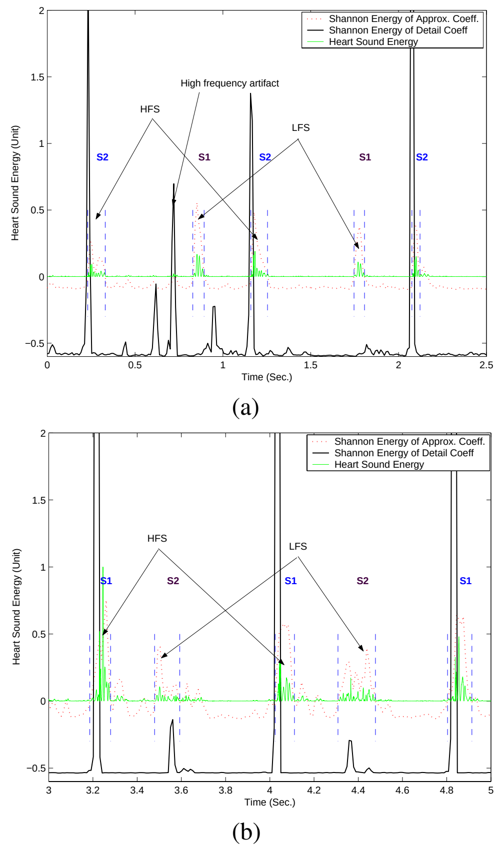


Figure 2. Shannon energy of high frequency components of heart sounds above the defined threshold. Mechanical valve (single tilted disc) implant in (a) aortic position and (b) Mitral position.

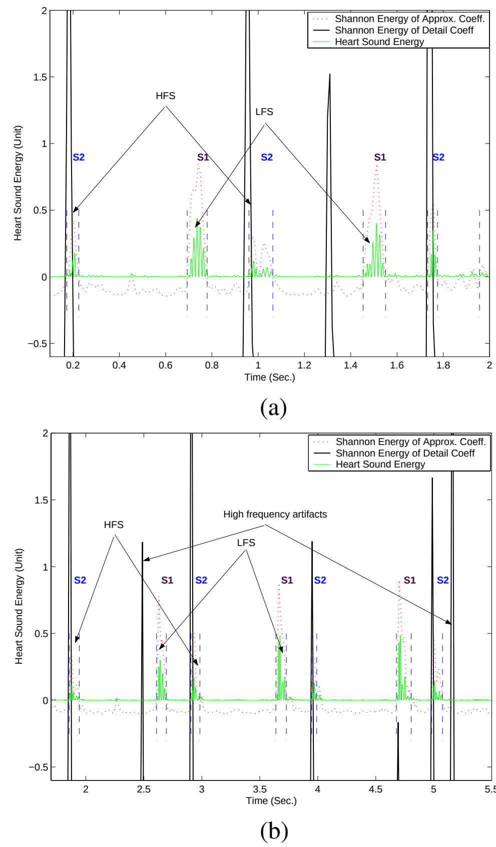


Figure 3. Shannon energy of high frequency components of heart sounds above the defined threshold: (a) Bioprosthetic valve. (b) Native valve.

heart sound is significant, which assist in discrimination of these two sounds using an adaptive threshold.

2.2.1. Heart cycle detection. In order to find the presence of high frequency information in at least one type of heart sound, detail coefficients of the FWT are considered. To extract the high frequency envelopes in sound segments, the Shannon energy operator is applied to the detail coefficients. In order to detect the heart cycles, an adaptive threshold is defined for this Shannon energy envelope. This threshold is given by,

$$th = E(d6) - \lambda < E(d6) >, \tag{7}$$

where λ is a constant which is initially fixed to 3.0 and later adapted in certain situations.

After applying a threshold to the Shannon energy of the detail coefficients, two kinds of sound segments can be seen in the segmented heart sounds: (i) segments which have high frequency (HFS - high frequency segments), (ii) segments which have not high frequency (LFS - low frequency segments). These segments are found in all heart sound samples (see figures (2 and 3)). According to the previous explanation, in most of the cases (excluding the exception of single tilted disk mechanical valves), heart sound segments which exhibit high frequency (HFS) are S2 heart sounds and segments which have low frequencies (LFS) are S1 sounds. It is known that heart cycles are defined with the duration of S1 (or S2) to the next S1 (or S2) sound. All detected HFS exhibit one class of sound (S1 or S2). In general, heart cycles are constructed by pair of lobes of the same class of sounds (S1 or S2) and at least one sound of another class present between them. For instance, if there is only one S1 sound between two S2 sounds or only one S2 sound between two S1 sounds then, these sequences form a heart cycle. Usually, as it is clear from figures (2 and 3) heart cycles have at least one LFS between each two contiguous HFS and HFS-LHS-HFS sequences construct complete heart cycle. Hence, all heart cycles are detected by identifying these sequences. Furthermore, the duration of each HFS-HFS pair which also represents the instantaneous heart rate is computed by,

$$T^k_{cycle} = \frac{dt_k}{2} + T_s(n^{stop}_{k+1} - n^{start}_k) + \frac{dt_{k+1}}{2}, \qquad (8)$$

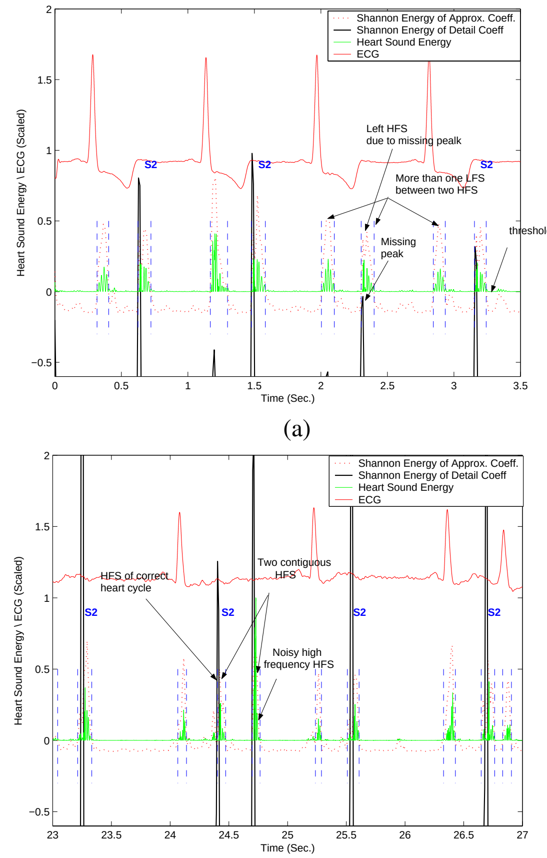
where T^k_{cycle} is the duration between k^{th} and $(k+1)^{th}$ HFS, and dt_k is the duration of HFS. In some situations HFS-HFS pairs may occur without LFS between them or with very high duration (almost twice of the heart cycle duration). These situations lead to incorrect heart cycle identification which may be corrected using the following analysis:

Case 1: This situation occurs when high frequency marker goes below the defined threshold (see figure 4(a)) and two or more LFS are found between two contiguous HFS. In this situation, the duration of the corresponding heart cycle is greater than the average of the three recent previous cycles, i.e. $T^k_{cycle} > \frac{1.6}{3}\sum_{i=1}^{3} T^{k-i}_{cycle}$. This provides the information of missing cycles. The above mentioned criterion of average duration of three most recent cycles is sufficient to find missing cycles even in arrhythmic heart sounds [11]. In this situation, λ, in equation (7) is increased ($\lambda \leftarrow \lambda + \delta\lambda$, where $\delta\lambda$ is 0.1) until missing HFS is detected.

Case 2: This situation is met when noisy small duration segments occur (see figure 4(b)). In this situation, the correct HFS are found by adjacent cycle prior to the cycle under analysis. As it can be seen from figure 4(b), in such situations the first HFS will be the relevant sound, because of its presence in the previous heart cycle.

2.3. S1 and S2 sounds classification

Heart sounds S1 and S2 are detected in all correct heart cycles which have been identified with the procedure described in the previous subsection. Each heart cycle represents instantaneous heart rate. In order to perform correct detection of S1 and S2 sounds by the instantaneous heart rate, each heart cycle is picked and the corresponding systolic interval, i.e. duration of S1-S2 sounds, is estimated and compared with the duration of every segment pair HFS-LFS (or LFS-HFS). The smallest deviated pair of HFS-LFS (or LFS-HFS) from the estimated systolic interval of corresponding heart cycle are assessed as S1 and S2 sounds. The systolic interval is invariant in most of the heart sound, however, it changes in extreme arrhythmic cases which is taken care of in the proposed method. The heart sounds S1 and S2 are identified and classified through the following steps:



(a)

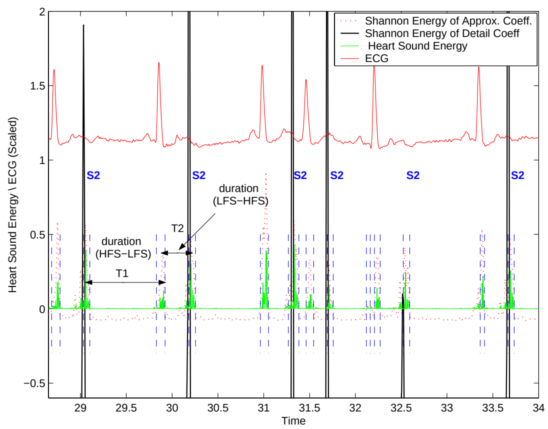
(b)

Figure 4. Cases of (a) missing HFS and (b) HFS-LFS. In the latter, correct HFS is detected using the previous cycle.

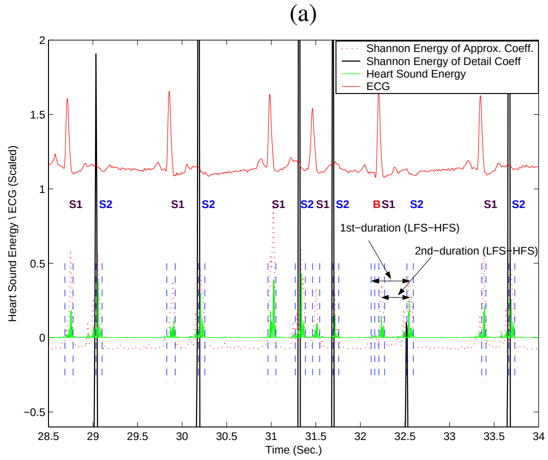
Step1: The first step is devoted to type of HFS identification. Since high frequency feature of S2 sounds is suffered with an aforementioned exception, hence, all high frequency mingled segment (HFS) can not be assessed as S2 sounds. To make the method automatic and free from prior knowledge, first, the type (S1 or S2) of HFS is identified. In this process, one heart cycle is chosen from the set of correctly detected heart cycles, which has 2 HFS and 1 LFS (see in figure 5(a)). The systolic interval for one heart cycle is estimated using an empirical relationship between the duration of heart cycle (T^k_{cycle}) and systolic interval. It is given by,

$$T^{est,\,k}_{sys} = 0.2T^k_{cycle} + 160(ms), \qquad (9)$$

where $T^{est,\,k}_{sys}$ is estimated systolic interval of k^{th} selected heart cycle. This relationship provides a very close estimation of the systolic interval [12]. Next, duration of HFS-LFS and HFS-LFS are computed, i.e. T1 and T2, as figure 5(a) depicts. Now, it is evident which one of these durations has smallest deviation with respect to $T_{sys}^{est,k}$ that one will be the systolic interval of the corresponding selected cycle. In the example provided in figure 5(a) T2 has the smallest deviation with respect to $T_{sys}^{est,k}$. Therefore, LFS-HFS is a systolic pair. Once the correct systolic pair is detected, the HFS in the pair LFS-HFS is identified as S2 for the selected cycle. Since all HFS belong to the same class of heart sound, therefore, the type (S1 or S2) of HFS can be detected, as it is in figure 5(a) that all the HFS are S2 sound. From heart sound obtained from single tilted disk in mitral position, HFS-LFS pair would be a systolic pair, consequently, all HFS would be S1 sounds.



(a)



(b)

Figure 5. (a) Class of HFS detected by systolic interval of one cycle (b) S1 and S2 detection in arrhythmic heart sound. B stands for irrelevant heart sounds.

Step2: In this step, the all relevant second class of sound S1(or S2), i.e. LFS, are identified. Since the type of HFS is already identified from the previous step, hence, the type of LFS can be identified using each heart cycle (HFS-LFS-HFS). If there is only one LFS between two contiguous HFS, it obviously belongs to the other class of heart sound, i.e., S1 if HFS are S2, or S2 if HFS are S1, as figure 5(b) depicts .

Despite of the validation process all low frequency physiologically irrelevant segments may not be eliminated. In this situations, more than one LFS between two HFS are found, and the correct LFS is identified by the comparison between the LFS-HFS (or HFS-LFS) duration and the estimated systolic interval. In this process, first systolic interval of corresponding cycle is estimated. Next, all the LFS-HFS (or HFS-LFS) durations are computed. These durations are compared with the estimated systolic interval ($T_{sys}^{est,k}$). The LFS-HFS or HFS-LFS pair which exhibits the smallest deviation from $T_{sys}^{est,k}$, will be the systolic sound pair, i.e. S1-S2. In the presented example, since all the HFS are S2 sounds and LFS are suspected to be S1 sounds, therefore, durations of LFS-HFS are computed and compared with $T_{sys}^{est,k}$. The correct systolic pair LFS-HFS are found and the type of LFS is detected. It is shown in figure 5(b) that duration of 2^{nd} LFS-HFS pair comes closer to the estimated systolic interval, subsequently, LFS of corresponding LFS-HFS pair is identified as S1 sound. In exceptional cases when all HFS are S1 sounds, the durations of all the HFS-LFS are computed and compared with $T_{sys}^{est,k}$.

3. Results and Discussions

Heart sounds were recorded from 55 patients with different prosthetic valve implants in different positions; 42 patients had the medatronics single-leaflet mechanical valve implanted (2 patients were extremely arrhythmic), 9 patients had the Edward-Lifescience bio-prosthetic valve and 4 were healthy persons with native valve. Heart sound samples were collected in the Cardiothoracic Surgery Centre at the University Hospital of Coimbra from July 2005 to September 2005, approximately two weeks after valve implant surgery under the guidance and instructions of an experienced cardiologist. 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 Meditron. The stethoscope has an excellent signal to noise ratio and extended frequency range (20 - 20,000 Hz). Although ECG is not considered in the present work, it was also recorded simultaneously to assess the segmentation efficiency of the algorithm. All heart sounds were digitized using a 16-bit ADC at 44.1kHz sampling rate. Sound samples were recorded for the max-

Table 1. Result for the S1, S2 detection

Heart Sound (Prostheses)	S1-S2 (detected/ present)	False Negative	False Positive	Sensitivity (%)	Specificity (%)
Mechanical	5893/6097	122	108	97.80	98.20%
Bio-prosthetic	729/779	26	19	96.77	97.62%
Native	642/654	4	6	99.38	99.07%
Average Detection	7264/7530	152	133	97.95%	98.20%

imum duration of 2 minutes. All collected heart sounds were first preprocessed using a 4th order Butterworth high pass filter with cut-off frequency of 40Hz in order to eliminate low frequencies produced by muscle and stethoscope movements.

The proposed algorithm was tested for the collected heart sounds. The achieved results are summarized in table 1. In the worst case heart sound sample, 95.67% sensitivity and 96.12% specificity were obtained, while in best case 100% sensitivity and 100% specificity are found. It has been noticed that wrong detection are normally caused by noise removal; when noise such as speech, cough, sudden movements are removed adjacent relevant sound segments are also affected. The achieved sensitivity of noise detection by jitter approach is 92.20%. A total of 46 noisy segments out of 50 were detected in all tested sound samples. High frequency noisy segments which have duration less than 50 ms were not detected by the jitter approach. The achieved results were verified by manually inspecting QRS-complexes and T-waves of the corresponding ECG.

The entire algorithm was simulated in MATLAB using a pentium 4 (3GHz). It takes between 6 to 10 seconds for the complete segmentation of each 2 min heart sound sample.

4. Conclusions

This paper proposes an algorithm for S1 and S2 heart sound segmentation that does not rely on the ECG reference. The boundaries of the sounds were identified and sound lobes were validated using physiological based criteria. Next, heart sound (S1 and S2) were identified based on a high frequency marker, which is identifiable from accentuated pressure differences found across heart valves, both in native and prosthetic valves, that leads to distinct frequency signatures of the valve closing sounds. Unlike other methods of segmentation, the proposed algorithm exhibits excellent performance in case of SNR arrhythmic heart sounds. Besides this, it is completely automatic, therefore, is highly appropriate for eHealth.

Despite of the excellent performance for the correct detection of S1 and S2 sounds in phonocardiogram, this method still fails to segment heart murmurs which are the major signs of heart diseases and prosthetic valve dysfunction. Precise boundary detection of heart murmurs present between S1 and S2 or S2 and S1 is the future challenge in this course of research.

ACKNOWLEDGMENT

This work was performed under the IST FP6 project MyHeart (IST-2002-507816) supported by the European Union.

References

[1] G. Mintz, E. Carlson, M. Kolter, ”Comparison of noninvasive techniques in evalution of the nontissue cardiac valve prothesis”, *J. Med. Eng. Technol.*, 15(6), 1991, page. 222-231.

[2] M. El-Segaier, O. Lilja, S. Lukkarinen, L. Srnmo, R. Sepponen and E. Pesonen, ”Computer-Based Detection and Analysis of Heart Sound Murmur”, *Annals of Biomedical Engineering*, vol. 33, no. 7, 07-2005, pages. 937-942.

[3] P. Carvalho, P. Gil, J. Henriques, M. Antunes and L. Eugénio, ”Low Complexity Algorithm for Heart Sound Segmentation using the Variance Fractal Dimension”, *Proc. of the Int. Sym. on Intelligent Signal Processing*, 2005, page. 593-595.

[4] T. Olmez and Z. Dukar, ”Classification of heart sounds using an artificial neural network”,*Journal of Pattern Recognition Letters*, 08-2003, page. 617-629.

[5] J. E. Hebden and I. N. Torry, ”Neural Network and Conventional Classifiers to Distinguish between First and Second Heart Sound”, *in IEE Colloquium (Digest)*, 08-1996, page. 1-6.

[6] A. Ch. Stasis, E. N. Loukis, S. A. Pavlopoulos, D. Koutsouris, ”Using decision tree algorithm as a basis for a heart sound diagnosis desicion support system”, *in IEE Colloquium (Digest) of Artificial Intelligence Methods for Biomedical Data Processing*, 08-1996, page. 1-6.

[7] H. Liang, S. Lukkarinen and I. Hartimo, ”Heart Sound Segmentation Algorithm Based On Heart Sound Envelogram”, *Proc. of IEEE Computers in Cardiology*, 1997, page. 105-108.

[8] H. Liang, S. Lukkarinen and I. Hartimo, ”A boundary modification method for heart sound segmentation algorithm”, *in Proc. of IEEE Computers in Cardiology*, 1998, page. 593-595.

[9] D. Kumar, P. Carvalho, P. Gil, J. Henriques, M. Antunes and L. Eugénio, ”A new algorithm for detection of S1 and S2 heart sounds”, *in Int. Conf. of Acoustic and Speech Signal Processing (ICASSP), 2006, page. 1180-1183*.

[10] K. O. Lim, Y. C. Liew and C. H. Oh, ”Analysis of mitral and aortic valve vibrations and their role in the production of the first and second heart sounds”, *in Journal of Physics in Medicne and Biology*, 1980, page. 727-733.

[11] J. Pan, W. J. Tompkins, ”A real-time QRS Detection Algorithm”, *in IEEE Transaction on Biomedical Engineering, vol. BME-32, No. 3, March 1985, page. 230-236.*

[12] J. D. Bronzino, ”The Biomedical Engineering Handbook”, *CRC Press*, 1995, NewYork.