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A proposed algorithm for analysing heart sounds and calculating their time intervals

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Abstract:
Heart sounds play a crucial role in the clinical assessment of patients. Stethoscopes are used for detecting heart sounds and diagnosing potential abnormal conditions. However, several parameters of the cardiac sounds cannot be extracted by traditional stethoscopes. This paper presents a proposed algorithm based on peaks detection. Besides its ability of filtering the heart sounds signals, the time intervals of these sounds in addition to the heart rate were calculated by the proposed algorithm in an efficient way. Signals of the heart sounds from two sources were used to evaluate the efficiency of the algorithm. The first source was the data recorded from 14 participants, whereas the second source was the free data set sponsored by PASCAL. The algorithm showed different performance accuracy for detecting the main heart sounds based on the source of the data used in the study. The accuracy was 93.6% when using the data recorded from the first source, whereas it was 76.194% for the data of the second source.

Keywords: auscultation, heartbeats, heart sounds time intervals, lubb dubb, phonocardiogram (PCG), stethoscope

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Introduction

Cardiac performance can be assessed by several diagnostic methods. Auscultation is one of these methods, which is based on listening to the heart sounds. Auscultation is one of the most reliable, effective, simple, and cheap tools for diagnostic purposes [1], [2], [3].

The main heart sounds are categorized into four sounds: S1 (lubb), S2 (dubb), S3, and S4. Each sound is related to a specific event within the heart. S1 is resulted from the atrioventricular valves' closure, which indicates the commence of ventricular contraction (systole), whereas S2 is resulted from the closure of the semilunar valves at the beginning of ventricles' diastole [1], [4], [5]. S3 and S4 are faint and are hardly audible in normal cases. S3 is related to the blood flowing to the ventricles, whereas S4 is resulted from atrial contraction. The heart valves may not work efficiently in some abnormal cases, such as misshapen of valves cusps, dysfunction of chordae tendineae and papillary muscles. In these cases, a specific sound called murmur can be audible [1]. Figure 1 shows the heart sounds with respect to their specific events within the heart during the cardiac cycle.

Analyzing heart sounds or what is known as phonocardiogram (PCG) can play a crucial role in the diagnostic process of cardiac diseases [6]. Heart arrhythmia is one of the heart disorders that can be detected by the analysis of S1 and S2 and their intervals. Tachycardia, bradycardia, and eucardia are all rhythmic cases and relate to the heart rate. These cases can be detected through analyzing the PCG and its time intervals [7]. Bundle branch block and complete heart block are also examples of the heart disorders that affect the heartbeats' rhythm and their time intervals [8], [9].

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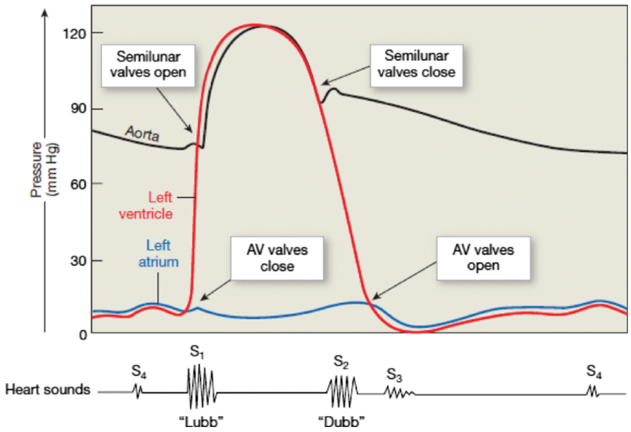

Figure 1: Heart sounds that reflect specific events within the heart.
Source: [1].

The heart sounds (PCG) captured by the stethoscope are subtle and are subjected to many limitations, such as noise, artifacts, and site variability. Consequently, PCG without processing and filtering cannot be used to diagnose the cardiac status [6].

This fact has pushed researchers to develop techniques and algorithms to extract the required information from the PCG. Several researchers in this field have used the ECG as reference to extract the required features in the PCG [6], [10], [11]. In 2005, Segiar and his colleagues used an electronic stethoscope to capture the PCG. They developed a digital algorithm based on short-time Fourier transform to filter the PCG and detect the first and second heart sounds (S1 and S2). They used the ECG as reference to detect S1 and S2 sounds. The detection rates of S1 and S2 were 100% and 97%, respectively [6]. Likewise, using the ECG as reference, Giordano and Knaflitz have proposed an algorithm based on envelope segmentation. Their proposed algorithm managed to reach 99.2% success rate for classifying and detecting heart sounds [10]. Bonnet macaques have also been included in the heart sounds researches. Kamran et al. in 2011 conducted a study on bonnet macaques to calculate the cardiac time intervals of the PCG with the ECG as reference. Cardiac time intervals were calculated with high accuracy [11].

However, many researchers have developed algorithms for extracting heart sounds without the need of using the ECG as reference [12], [13], [14]. Wavelet decomposition technique was used by Kumar and his colleagues in 2006 to extract heart sounds using a high-frequency marker. The mean sensitivity of S1 and S2 detection was 97.95% [12]. The beat finding segmentation technique was another method used by Dao in 2015 to detect heart sounds S1 and S2 with 92 ± 3% as success rate [13]. Autocorrelation for heart sounds detection was used by Stainton et al. in 2016. Their results have shown only 58% successful detection of the first and second heart sounds [14].

Many researchers in different fields are using the MATLAB software to develop algorithms for processing and extracting specific features [15], [16]. Roy et al. in 2018 used an electronic stethoscope to record heart sounds. They used Kalman filter designed by MATLAB Simulink to extract the heart sounds. However, they did not mention any specific results that reflect the accuracy of their algorithm [16]. The empirical mode decomposition technique was used by Bajelani et al., in 2013 to detect the main heart sounds (S1 and S2). Their algorithm showed that the detection sensitivity of S1 and S2 was 83.3% [17].

Deperliğlu in 2018 segmented the PCG using the resampled energy segmentation method. The heart sounds were classified after that by an artificial neural network (ANN). The classification accuracy of the algorithm was 88.6% [18]. Deep learning based method was developed by Tsao et al. in 2019 using spectral resolution algorithm followed by multi-style training. The average accuracy of the algorithm was 87.8% [19].

Although the aforementioned techniques have the ability to analyze the cardiac sounds, these techniques still have their own limitations. These methods either need to use the ECG as reference for extracting heart sounds or are expensive and have problems with respect to the detection and classification accuracy.

This paper describes a simple algorithm based on peaks finding to analyze the cardiac sounds and to calculate their time intervals without the need of any reference. Besides its simplicity, the proposed algorithm has the ability to share all the data online through a simple Internet browser. The rest of the sections in this paper are organized as follows: the next section explains the materials and methods, followed by the results and the discussion sections. Finally, the last section presents the conclusions.

Materials and methods

Several systems and algorithms have been developed to record and process the heart sounds as mentioned in the previous section. In this paper a simple and cheap recording gadget was used. A small wired microphone (from Dongguan Xiangming Electronics Company in Guangdong, China) was inserted inside the tube of a stethoscope (from Yiwu Medco Health Care Company in Zhejiang, China) to record the heart sounds captured by the diaphragm of the stethoscope. The microphone was connected to the computer through its jack. Figure 2 shows the recording gadget (the stethoscope and the microphone). The specifications of the used microphone are summarized as follows:

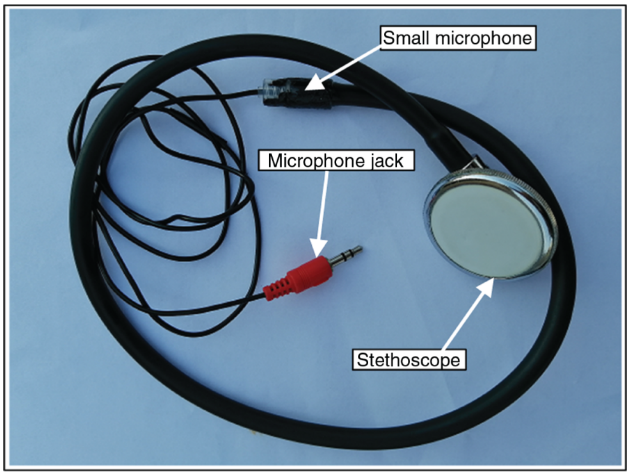

Figure 2: The stethoscope and the small microphone that were used to capture the heart sounds.

Sensitivity: −42 dB
Size: 6 × 2 mm
Operating Voltage: 1.0–10 V
Output Impedance: 2.2 kΩ
Communication: Wired
S/N Ratio: 58 dB
Current Consumption: 500 μA

The PCG data used in this study were gathered from two sources. The first source was the data recorded from 14 participants, 19–35 years old, under normal conditions, considering the noise in the surrounding environment. The recording time was set as a 10 s for each participant. The second source of data was the free data set sponsored by PASCAL, which was recorded by a digital stethoscope from a clinic trial in a hospital [20]. The lengths of the audio signals were between 4 and 30 s. We used only 15 heart sounds signals from PASCAL source that were categorized into three subgroups as follows: (1) five normal heart sounds signals; (2) five heart sounds signals with murmur; and (3) five extra systolic heart sounds signals. The total number of the heart sounds signals used in this study from the two sources was 29.

The algorithm

The proposed algorithm of this paper consists of three main stages. Figure 3 shows the flow chart of these three stages.

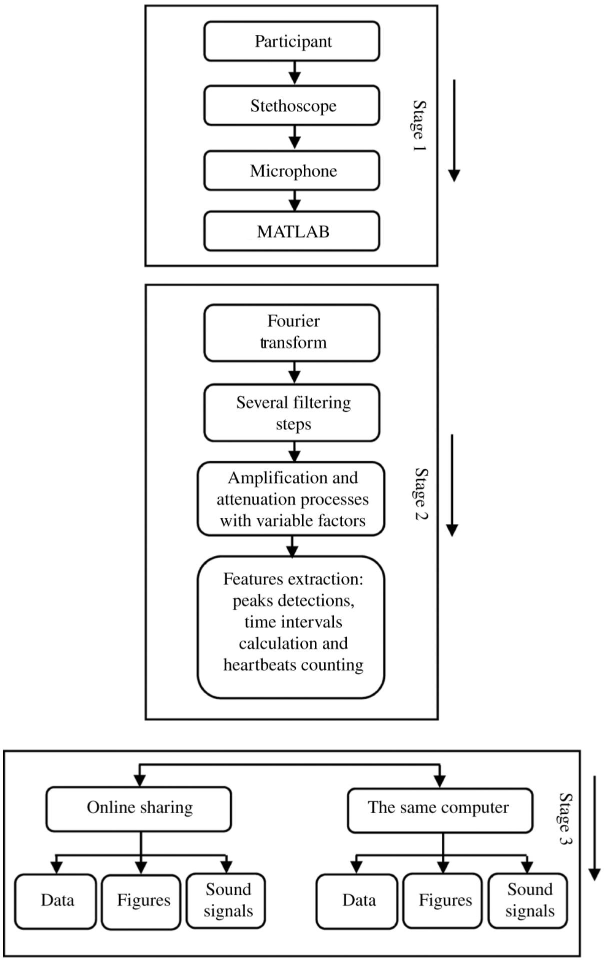

Figure 3: The flow chart of the hardware side and the proposed algorithm.

Stage 1 deals with the heart sounds recording. The process starts through putting the stethoscope on the chest below the left nipple of each participant. The small microphone inside the tube of the stethoscope will convert the captured sounds signals into electrical signals. MATLAB 2018a (from MathWorks company, CA, USA) was used to record the sounds obtained from the small microphone within the stethoscope tube. The recording duration was set to 10 s. In the case where the free data set of PASCAL was used, the MATLAB reads the audio files from the computer hard disk. Figure 4 shows an example of 5 s of a heart sounds signal recorded from one of the participants.

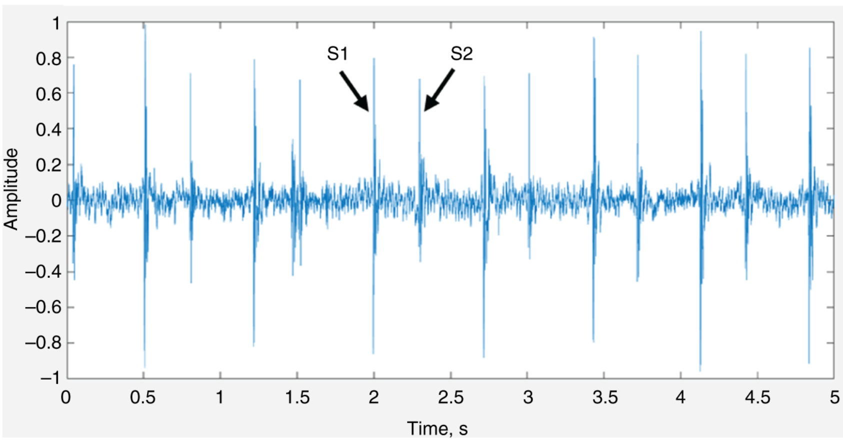

Figure 4: Five seconds of a heart sounds signal without any filtering.

Stage 2 deals with audio signal processing. Before filtering the heart sounds signals, it is important to plot their power spectral density over their frequencies in order to design efficient filtering processes. The filtering steps start with a band pass filter to remove the noise related to higher and lower frequencies. At this point the audio signals are still noisy, and the main sounds S1 and S2 are faint. Amplifying the whole signals at this point is not functional because the process will amplify the required features in addition to the accompanied noise. The algorithm sets two symmetrical thresholds (below and above the zero level of the signals). These thresholds work as reference points. The algorithm amplifies each value that passes the thresholds in the signals, whereas values below them are treated as noise and are attenuated by a specific factor. Figure 5 shows the filtered form of the heart sounds signal that is already clarified in Figure 4.

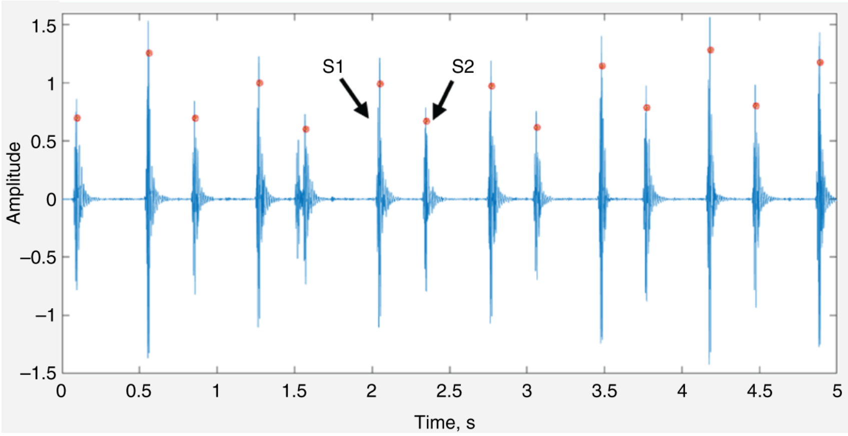

Figure 5: Five seconds of processed heart sounds signal at the end of stage 2

In order to calculate the time intervals of the heart sounds, the algorithm must find the specific positions of S1 and S2 for each cardiac cycle. Multi-smoothing steps were applied on the signals to obtain envelopes of the main sounds S1 and S2. As the negative and positive sides of the signals are symmetric, the negative side of each signal was neglected. The peak of each envelope and its position were determined by the algorithm. Black stars within circles were used by the algorithm to specify the peaks of the envelopes that represent the main sounds S1 and S2. The time intervals and heart rate were calculated from these peaks and their positions. Figure 6 shows one of the heart sounds signals passing through the main filtering steps.

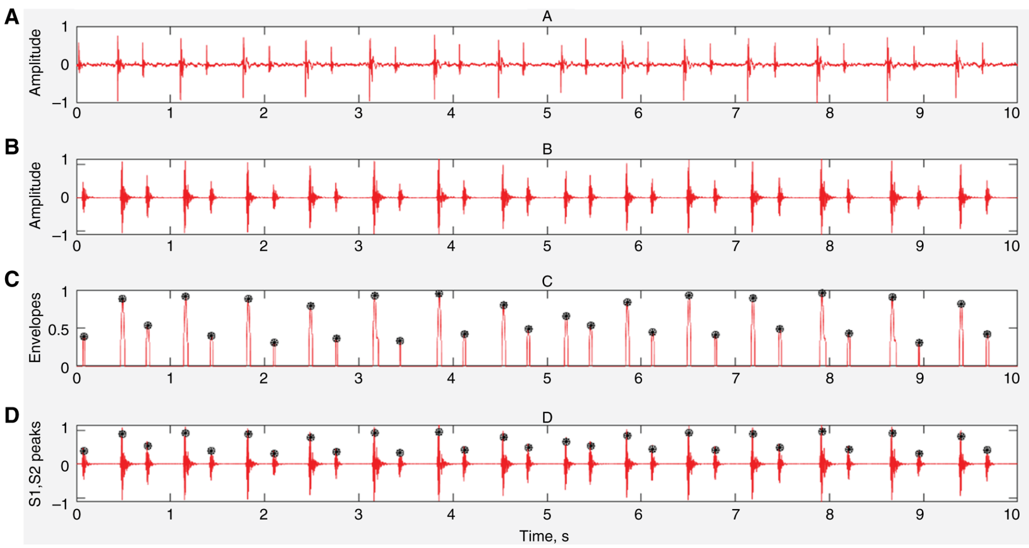

Figure 6: A heart sounds signal during the main filtering steps.
(A) A non-filtered heart sounds signal. (B) The filtered heart sound signal. (C) Envelopes of the of the main heart sounds (S1 and S2) with black stars within circles on their peaks. (D) Black stars within circles were added by the algorithm to the filtered signal to specify the required features of the heart sounds.

Stage 3 includes the output representation of the used algorithm. Two ways for presenting the outputs of the algorithms were used: (A) the graphical user interface (GUI) of MATLAB and (B) the MATLAB Web App Server for online data sharing. The GUI was designed to work as the control panel of the algorithm. Figure 7 shows the designed GUI of the used algorithm. The algorithm at this stage presents the data in one of the following three forms: first, original signals of heart sounds for hearing purposes with their graphs; second, the filtered heart sounds for hearing purposes with their graphs in addition to the graphs of their time intervals; and third, some of the numerical data such as heart rate, the time intervals between the main sounds S1 and S2, etc.

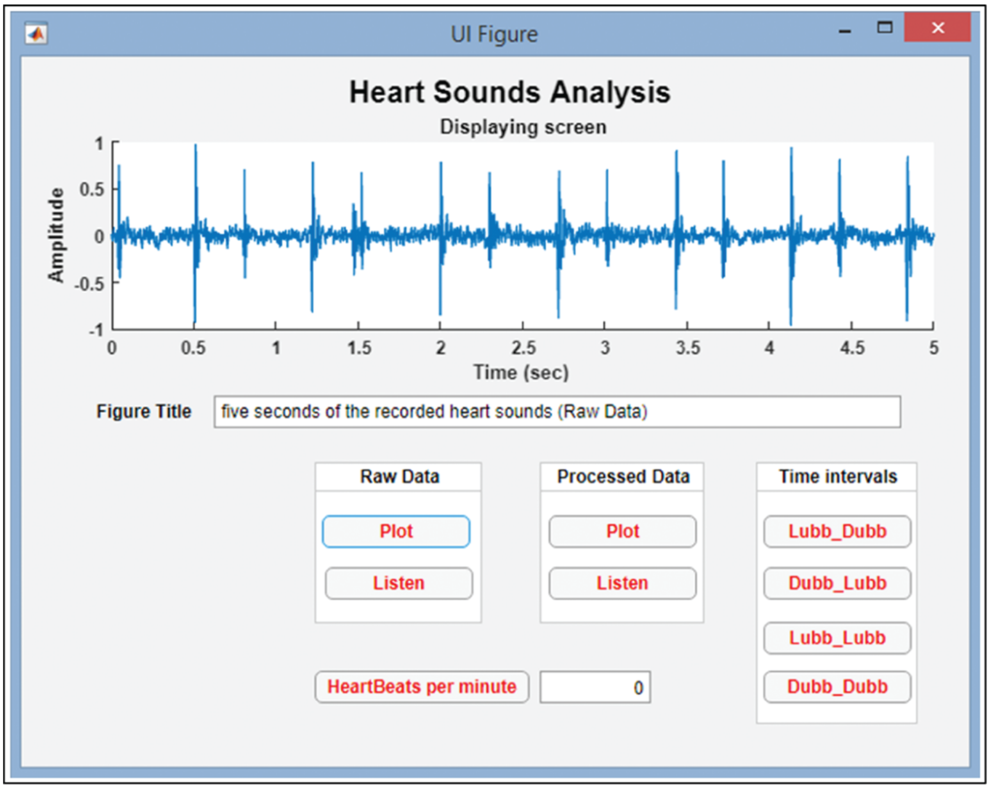

Figure 7: The designed GUI that has been used as control panel in this study.

The GUI's buttons were categorized into three groups as follows:

A. Raw data

1. Plot: This button is displaying the graph of the original heart sounds signals before filtering them.
2. Listen: This button is used to play the original heart sounds signals before filtering them.

B. Processed Data

1. Plot: This button is displaying the graph of the heart sounds signals after filtering them.
2. Listen: This button is used to play the heart sounds signals after filtering them.

C. Time intervals

1. Lubb_Dubb: This button is displaying a bar graph of the time intervals (in second) between S1 (Lubb) and S2 (Dubb) of each cardiac cycle.
2. Dubb_Lubb: This button is displaying a bar graph of the time intervals (in second) between S2 (Dubb) and S1 (Lubb) of the next cycle.
3. Lubb_Lubb: This button is displaying a bar graph of the time intervals (in second) between S1 (Lubb) and S1 (Lubb) of the next cardiac cycle.
4. Dubb_Dubb: This button is displaying a bar graph of the time intervals (in second) between the S2 (Dubb) and S2 (Dubb) of the next cardiac cycle.

The final button is the "HeartBeat per minute." This button calculates and displays the heart rate in the editing box beside it.

The MATLAB Web App Server provides an online sharable URL link of the GUI contents. This method facilitated the monitoring process of any case from any place without the need to install the MATLAB on the receiving computer. Figure 8 shows the MATLAB Web Apps Server in the browser of the receiving computer.

Figure 8: The MATLAB Web Apps Server in the browser of the receiver computer.

Results

The proposed algorithm showed clear improvements with respect to the filtering processes of the heart sounds signals. The filtering processes of the algorithm managed to get rid of most of noise accompanying the signals and enhanced the quality of the targeted features in the signals (i.e. S1 and S2). The signal to noise ratio (SNR) of the signals before and after the filtering processes was estimated. In order to calculate the SNR of any signal, the noise of that signal should be known. The noise of the heart sounds signals (before and after filtering) in their current forms is unknown. However, returning to the recorded heart sounds, most of the noise are accumulated between each two cardiac cycles (i.e. S2 to S1). Figure 9 shows a schematic diagram to describe the structure of a heart sounds signal. Audacity software was used to estimate the noise of each heart sound signal through taking a short section located between two adjacent cardiac cycles (S2 to S1) and repeating that section many times to get a noise signal with the same length for each signal. The SNR was calculated for each signal with its estimated noise by the MATLAB. Figure 10 shows a heart sounds signal before and after filtering with the noise of both cases.

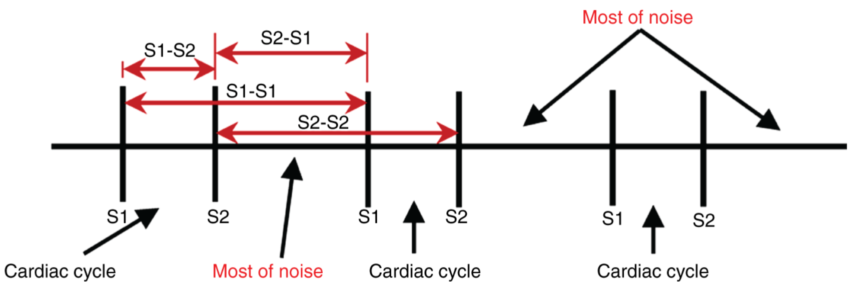

Figure 9: Simple schematic diagram of cardiac cycles.

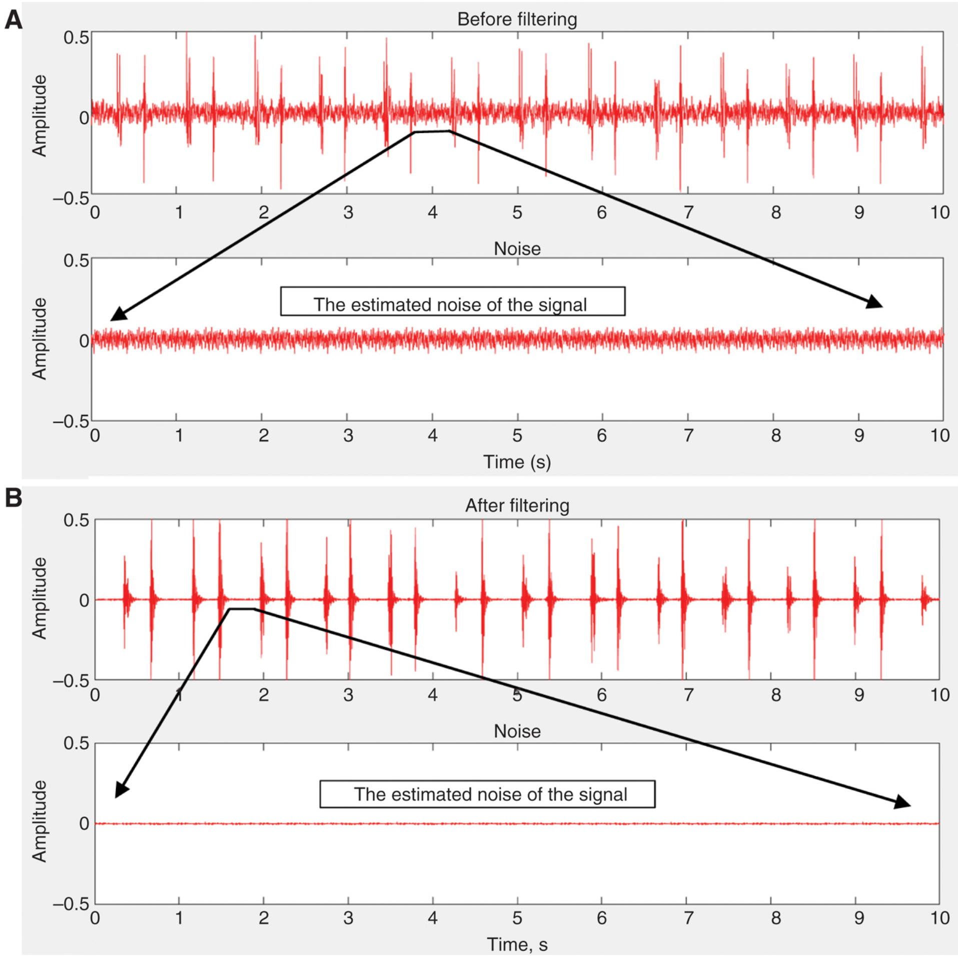

Figure 10: A heart sounds signal with its estimated noise.
(A) A signal of heart sounds before filtering with its noise. (B) The same heart sounds signal in (A) after filtering with its noise.

The SNR in dB was calculated for the signals from the participants and signals from the free data set of PASCAL as shown in Table 1 and Table 2.

Table 1: The signal to noise ratio (SNR) in dB of the heart sounds signals before and after the filtering processes from the 14 participants.

Subjects	SNR in dB before filtering	SNR in dB after filtering
1	12.2188	33.1086
2	15.0715	33.8929
3	13.5747	34.4515
4	10.1078	34.0987
5	12.3870	32.5226
6	11.9457	35.5693
7	11.5052	32.2200
8	12.5872	33.1963
9	11.7023	34.4233
10	4.6806	32.1996
11	10.0735	31.6349
12	11.0668	31.8316
13	6.7027	28.9121
14	8.0611	29.4679
Mean, dB	10.835	32.681

Table 2: The signal to noise ratio (SNR) in dB of the heart sounds signals before and after the filtering processes from the free data set sponsored by PASCAL.

Subjects	SNR in dB before filtering	SNR in dB after filtering
Normal heart sounds		
1	12.5996	23.6599
2	11.8109	27.8126
3	13.7919	31.9248
4	16.8419	30.8605
5	18.1279	34.4952
Heart sounds with murmurs		
6	12.0394	27.4597
7	11.0022	32.5274
8	12.8269	29.9733
9	9.7777	24.4410
10	10.6257	25.8771
Extra systole heart sounds		
11	15.5594	27.1776
12	8.1998	26.0170
13	12.8570	26.0952
14	10.4241	24.0210
15	19.7810	33.9226
Mean, dB	13.084	28.418

In order to present the time intervals of the heart sounds in a simple and clear way, bar graphs were used to do the task. The height of the bars (in seconds) represents the time intervals between two specific heart sounds while the number of the bars represents the number of the recorded cardiac cycles. Figure 11 shows a heart sounds signal from one of the participants before and after filtering, and Figure 12 shows the time intervals (in bar graphs) of the same heart sounds signal of Figure 11.

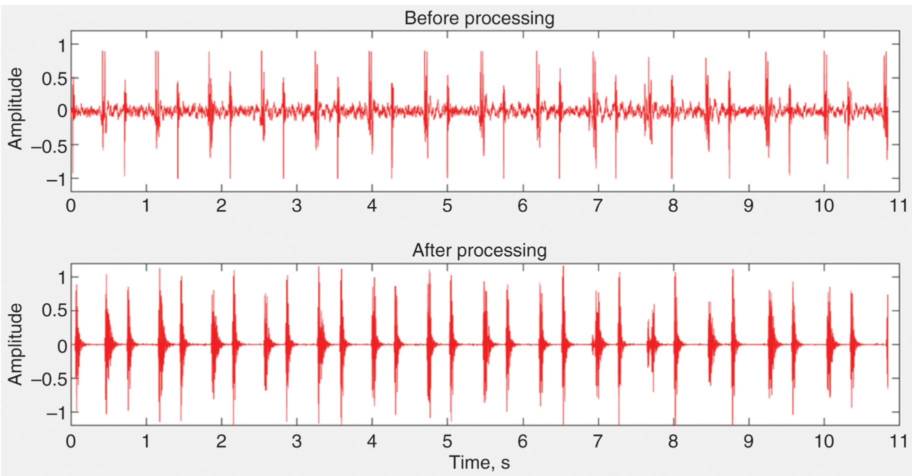

Figure 11: Heart sounds signal from one participant before and after filtering processes.

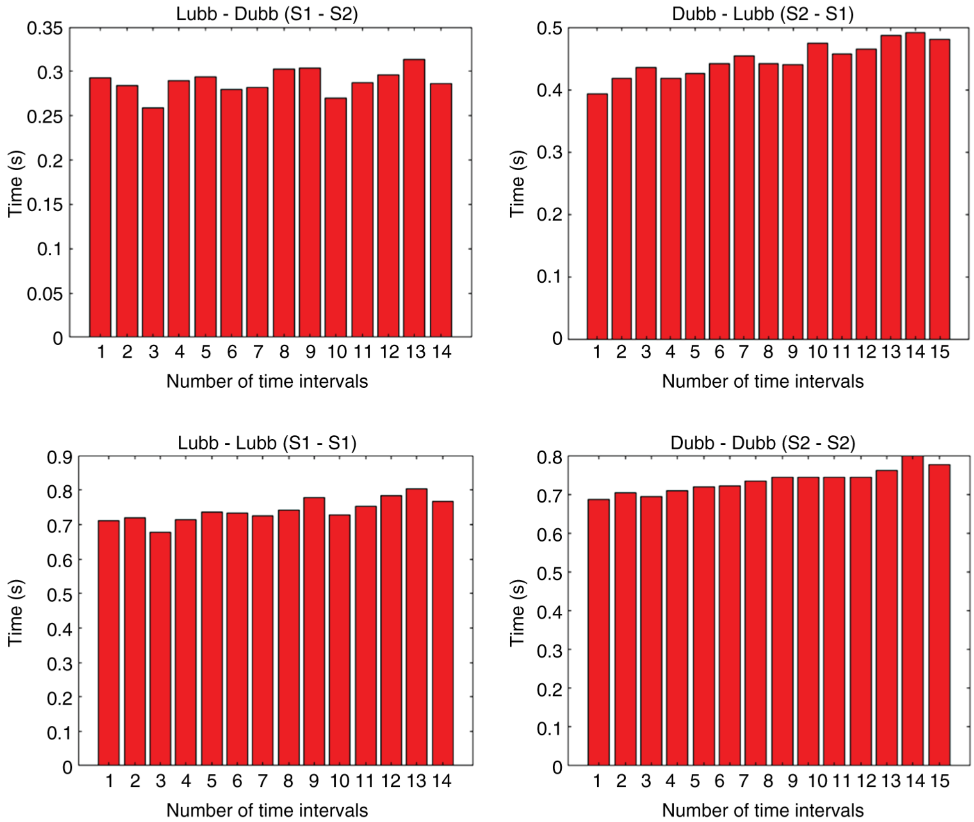

Figure 12: The time intervals of the main heart sounds S1 and S2 for the same participant in Figure 10, which are represented by bar graphs.

Discussion

Table 1 that summarizes the SNR data of the 14 participants showed an increase in the estimated SNRs of the filtered signals in comparison with the non-filtered signals. The averages of the SNRs after and before filtering were 32.681 and 10.835 dB, respectively. The increase in the SNRs reflects the algorithm ability of filtering the heart sounds signals. However, Table 2 that summarizes the data from PASCAL showed a lower increase in the SNRs in comparison with these in Table 1.

The proposed algorithm depended on peaks finding for detecting the main heart sounds (S1 and S2) and calculating their time intervals. Hence, the accuracy of the algorithm is reflected by its ability to detect the real peaks (S1 and S2) and calculating their time intervals. The accuracy of the algorithm was calculated through taking the percentage ratio of the true positive detection of peaks (S1 and S2) in a signal into both of the total real peaks (S1 and S2) and the unwanted peaks detection (peaks resulted from noise) in the same signal.

$$\text{Accuracy} = \frac{\text{True positive detection of } (S1, S2)}{\text{Total peaks } (S1, S2) + \text{unwanted peaks detection}} \times 100\% \tag{1}$$

The algorithm showed a variation in its performance based on the source of the data used in the study. By using the data recorded from the 14 participants, the algorithm showed a high performance accuracy with an average reaching to about 93.6%. However, this percentage dropped to about 76.194% when using the free data set of PASCAL. Table 3 shows the accuracy of the algorithm for each participant and their average, whereas Table 4 presents the algorithm accuracy of 15 subjects from the free data set of PASCAL.

Table 3: The accuracy of the algorithm expressed in percentages for each of the 14 participants.

Subjects	Accuracy of detecting S1 and S2, %
1	98.1
2	97
3	100

4	96.2
5	100
6	93.3
7	95.3
8	92.6
9	96.1
10	93.2
11	90.2
12	90.4
13	83.3
14	84.7
Average, %	93.6

Table 4: The accuracy of the algorithm expressed in percentages for the free data set of PASCAL.

Subjects	**Accuracy of detecting S1 and S2, %**
Normal heart sounds	
1	96.2
2	84.3
3	77
4	66.3
5	85.7
Heart sounds with murmurs	
6	83.1
7	70.3
8	79.8
9	51.6
10	62.4
Extra systole heart sounds	
11	81.8
12	84.1
13	79.4
14	62.3
15	78.6
Average, %	76.194

Many reasons stand behind the variation in the algorithm accuracy that is shown in Table 3 and Table 4. The high level of the noise in the PASCAL data set in comparison with the low noise level of the data recorded from the 14 participants was one of the reasons that stand behind the drop in the algorithm accuracy. Another reason was the low quality of the PASCAL data set that were recorded by an electronic stethoscope in comparison with the high quality of the heart sounds recorded by our recording system. All of these reasons increased the difficulty to differentiate the real peaks of the heart sounds (S1 and S2) from other noisy peaks in the signals.

The proposed algorithm also calculated the heart rate through counting the number of peaks (S1 and S2) for a specific recording time, and then the heart rate was estimated for 60 s. The following equation expresses the idea of calculating heart rate:

$$\text{Heart rate per minute (recording time is 10 s)} = \frac{\text{the detected peaks}(\text{S1, S2})}{2} \times 6 \quad (2)$$

Table 5 summarizes the heart rate of the data recorded from the 14 participants in this study.

Table 5: The heart rates of the 14 participants that were calculated by the algorithm.

Participants	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Heart rate	77	81	84	79	85	82	87	78	81	73	80	81	84	82

Conclusions

Despite the increase in the numbers of studies that deal with cardiac sounds analyses, the traditional method of heart diagnosing by stethoscopes is still dominant. Yet, stethoscopes have many restrictions with respect to the high level of noise and the difficulty of identifying the time intervals of cardiac sounds. This paper proposed an algorithm based on peaks detection for filtering and detecting the main heart sounds (S1 and S2) and calculating their time intervals. The proposed algorithm showed high-accuracy detection of S1 and S2 (about 93.6%) when using the data recorded by our system. However, its accuracy has fallen to 76.194% when using the free data set from PASCAL because of their lower recording quality. The algorithm also calculated both the heart rate and the time intervals of the S1 and S2 and represented these intervals by bar graphs.

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References

[1] Martini FH, Nath JL, Bartholomew EF. Fundamentals of anatomy and physiology, 9th ed. San Francisco: Pearson Education, 2012.
[2] Potes C, Parvaneh S, Rahman A, Conroy B. Ensemble of feature-based and deep learning-based classifiers for detection of abnormal heart sounds. 2016 Computing in Cardiology Conference (CinC). Vancouver, BC, Canada: IEEE, 2016:621-4. Available from: https://ieeexplore.ieee.org/abstract/document/7868819.
[3] Varghees VN, Ramachandran KI. A novel heart sound activity detection framework for automated heart sound analysis. Biomed Signal Process Control 2014;13:174–88.
[4] Gamero L, Watrous R. Detection of the first and second heart sound using probabilistic models. Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat No03CH37439). Cancun, Mexico: IEEE, 2003:2877-80. Available from: https://ieeexplore.ieee.org/abstract/document/1280519.
[5] Wang H, Chen J, Hu Y, Jiang Z, Samjin C. Heart sound measurement and analysis system with digital stethoscope. 2009 2nd International Conference on Biomedical Engineering and Informatics. Tianjin, China: IEEE, 2009:1-5. Available from: https://ieeexplore.ieee.org/abstract/document/5305287.
[6] El-Segaier M, Lilja O, Lukkarinen S, Sörnmo L, Sepponen R, Pesonen E. Computer-based detection and analysis of heart sound and murmur. Ann Biomed Eng 2005;33:937–42.
[7] Garcia TB, Garcia DJ. Arrhythmia recognition: the art of interpretation. Burlington, MA: Jones & Bartlett Publishers, 2019.
[8] Sillanmäki S, Lipponen JA, Tarvainen MP, Laitinen T, Hedman M, Hedman A, et al. Relationships between electrical and mechanical dyssynchrony in patients with left bundle branch block and healthy controls. J Nucl Cardiol 2019;26:1228–39.
[9] UCSFHealth.org. Complete Heart Block, University of California San Francisco. Available at: https://www.ucsfhealth.org/conditions/complete_heart_block/. Accessed: 7 Sep 2019.
[10] Giordano N, Knaflitz M. A novel method for measuring the timing of heart sound components through digital phonocardiography. Sensors 2019;19:1868.
[11] Kamran H, Salciccioli L, Pushilin S, Kumar P, Carter J, Kuo J, et al. Characterization of cardiac time intervals in healthy bonnet macaques (Macaca radiata) by using an electronic stethoscope. J Am Assoc Lab Anim Sci 2011;50:238–43.
[12] Kumar D, Carvalho P, Antunes M, Henriques J, Eugenio L, Schmidt R et al. Detection of S1 and S2 heart sounds by high frequency signatures. 2006 International Conference of the IEEE Engineering in Medicine and Biology Society [Internet]. New York, NY, USA: IEEE, 2006:1410-6. [cited 18 February 2020]. Available from: https://ieeexplore.ieee.org/abstract/document/4462026.

[13] Dao AT. Wireless laptop-based phonocardiograph and diagnosis. PeerJ 2015;3:e1178.
[14] Stainton S, Tsimenidis C, Murray A. Characteristics of phonocardiography waveforms that influence automatic feature recognition. 2016 Computing in Cardiology Conference (CinC). Vancouver, BC, Canada: IEEE, 2016:1173-6. Available from: https://ieeexplore.ieee.org/abstract/document/7868957.
[15] Qassim HM, Eesee AK, Osman OT, Jarjees MS. Controlling a motorized electric wheelchair based on face tilting. Bio-Algorithms Med-Systems 2019;15:1–7. DOI: 10.1515/bams-2019-0033.
[16] Roy J, Roy T, Mandal N, Postolache O. A Simple technique for heart sound detection and identification using kalman filter in real time analysis. 2018 International Symposium in Sensing and Instrumentation in IoT Era (ISSI). Shanghai, China: IEEE, 2018:1-8. Available from: https://ieeexplore.ieee.org/abstract/document/8538255.
[17] Bajelani K, Navidbakhsh M, Behnam H, Doyle JD, Hassani K. Detection and identification of first and second heart sounds using empirical mode decomposition. Proc Inst Mech Eng Pt H J Eng Med 2013;227:976–87.
[18] Deperliğlu Ö. Classification of segmented heart sounds with Artificial Neural Networks. Int J Appl Math Elec 2018;6:44–39
[19] Tsao Y, Lin TH, Chen F, Chang YF, Cheng CH, Tsai KH. Robust S1 and S2 heart sound recognition based on spectral restoration and multi-style training. Biomed Signal Process Control 2019;49:173–80.
[20] Gomes EF, Bentley PJ, Coimbra M, Pereira E, Deng Y. Classifying heart sounds: approaches and results for the PASCAL challenge. In: Proc. 6th International Conference on Health Informatics, HealthInf 2013, Barcelona, Spain, 2013.