1. Abdulrahman W.H. AL-Askari [1]

Northern Technical University, Iraq

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Computer-aided auscultation system for cardiac monitoring

Abstract. The heart is a vital organ responsible for blood circulation throughout the body, delivering oxygen and nutrients to every living cell. Diagnosing and treating medical conditions is important to preserve human life accurately. To achieve this, an electronic stethoscope has been developed to record and analyse heart sounds. This study aims to computationally segment and identify cardiac signals using an envelope-based strategy with reference data, utilising the PASCAL Classifying Heart Sounds Challenge database. The findings indicate that the proposed method for detecting and partitioning the typical cardiac acoustic waveform exhibits a precision rate of 95.30% and an F1-score of 91.00%. The technique is well-suited for application to the two prominent peaks in heart sound signals, namely S1 and S2, which exhibit continuous variation across samples due to differences in auscultatory sites.

***Streszczenie.** Serce jest ważnym narządem odpowiedzialnym za krążenie krwi w całym ciele, dostarczając tlenu i składników odżywczych do każdej żywej komórki. Ważne jest, aby precyzyjnie zdiagnozować i leczyć warunki medyczne w celu zachowania życia ludzkiego. Aby to osiągnąć, opracowano elektroniczny stetoskop, który elektronicznie rejestruje i analizuje dźwięki serca. Celem tego badania jest segmentacja obliczeniowa i identyfikacja sygnałów sercowych przy użyciu strategii opartej na kopercie z danymi referencyjnymi, z wykorzystaniem bazy danych PASCAL Classifying Heart Sounds Challenge. Wyniki wskazują, że proponowana metoda wykrywania i podziału typowej formy fali akustycznej serca wykazuje dokładność 95,30% i wynik F1 91,00%. Technika jest dobrze przystosowana do stosowania do dwóch wybitnych szczytów sygnałów dźwiękowych serca, a mianowicie S1 i S2, które wykazują ciągłe zmiany w próbkach z powodu różnic w miejscach auskultacyjnych. (**Komputerowo wspomagany system osłuchiwania do monitorowania pracy serca**)*

Keywords: Heart sound segmentation and identification; auscultation; electronic stethoscope;.
Słowa kluczowe: Segmentacja i identyfikacja dźwięku serca; auskultacja; elektroniczny stetoskop;

Introduction

An innovative method for diagnosing cardiac disorders uses an electronic stethoscope and computer-aided auscultation to monitor heart sounds through the chest walls, recording and amplifying heart sound impulses [1]. Subsequently, the specimens can be observed and analysed within a computational framework utilising signal processing techniques and mathematical algorithms [2]. To eliminate the unnecessary load, it is necessary to separate multiple heart-beat waves from the recorded cardiac sound signal into a unique heart-beat pattern. The segmentation of the Heart sound is difficult due to the timing of the first and second sounds and the murmur, which can be affected by frequency content, intensity, auscultatory location, physiological changes, skin thickness, and blood velocity.

Many different techniques were depended in this kind of researches for heart sound segmentation [4,5], such as ECG based technique, [6,7] Probabilistic Model-based technique, [8] learning based technique, [9] Time-Frequency representation-based technique, [10] and Envelope based technique [12,13]. The last technique is the most used approach in the research because of the ability to preserve the signal's peak information in the time series and simplicity as well as it can be used for instantaneous phase [15], autocorrelation function [17], zero crossing points [16] and peak conditioning [18] Heart sound signal segmentation, the weighted average Shannon energy [14], Shannon probability [15], Hilbert transform [16], and heart sound trademark waveform [12] are a few of the most frequently employed methods for envelope extraction. Consequently, the primary objective of this study is to divide the recorded heart sound signal into discrete time segments and establish its parameters for analysis in a system for computer-assisted auscultation using the suggested methodology.

Methodology & Approach:

The echo sounds can be recorded and saved electronically by adding a small integrated circuit with low power consumption compared to the ordinary stethoscope. The block layout for autonomous heart sound signal fragmentation and parameter identification is shown below Fig.(1). This system consists of three major phases:

The pre-processing stage detrended the signal to fit it at the zero line of the y-axis. A Butterworth band-pass filter with five orders and a cutoff frequency between 25 and 250 Hz was selected to normalize the data, as seen in Equation (1) below.

$$X_{\mathrm{norm}}(K) = \frac{X(K) - X\min(K)}{X\max(K) - X\min(k)} \quad (1)$$

Segmentation involves enveloping, smoothing, and zeroing processes to segment the normalized heart sound output. The Savitzky Golay filter is used to smooth objectives to minimize erroneous positives during abrupt change detection and peak preservation [22]. Equation (2) [21] is the abrupt changes detection algorithm that finds differences in the heart sound signal's RMS level.

$$J(K) = \sum_{r=0}^{K-1} (k_{r+1} - k_r + 1) \log\left(\frac{1}{k_{r+1} - k_r + 1} \sum_{r=k_{r+1}}^{k_r} x_r^2 \right) \quad (2)$$

where the 1st and last samples of the signal are k0 & kk, respectively. Observed that to lessen residual mistake, according to a normal distribution, the maximization of log likelihood was determined as follows:

$$Log\ likelihood = -\frac{N}{2}(\log 2\pi + \log\sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(x_i - \mu)^2 \quad (3)$$

where N is a random sample, is the mean, and 2 is the variance.

As shown in Fig. 2, this procedure is essential for determining the values of systole, diastole, S1, S2, and heart cycle durations for various segmented instances. The red cross and vertical blue line represent abrupt shifts in points, and the systole to diastole ratio was measured to distinguish between pathologic and normal cardiac sounds [22]. Body mass index (BMI) and heart rate affect how long the systole and diastole last [23].

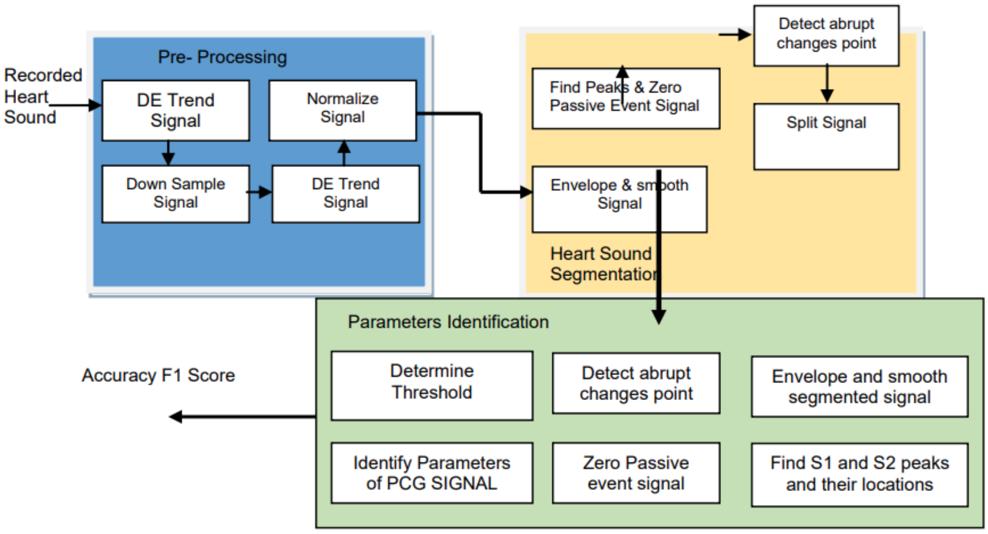

Fig. 1. The suggested automated framework for spotting heart sound signal parameters

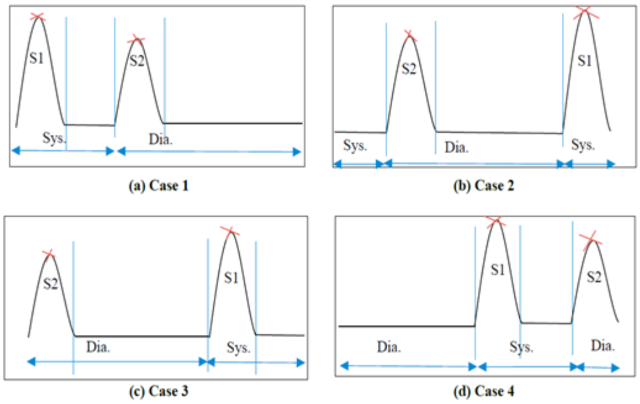

Fig 2. The suggested automated framework for spotting heart sound signal parameters

parameters identification stage: Two pairs of recorded heart sound signals were included in the PASCAL database19 used for this study's analysis. The segmentation and parameters identification process mainly used the sudden alternations algorithm and apex finding approach.

As shown in Equations from (4) to (11), the accuracy, precision, sensitivity, and F1-score are used to assess the efficacy of the automated heart sound system (7). These success metrics were calculated using three numerical variables, including FN and TP and FP.

$$Accuracy\ (Acc.) = \frac{TP}{TP + FP + FN} \times 100\% \quad (4)$$

$$Precision\ (Pre.) = \frac{TP}{TP + FP} \times 100\% \quad (5)$$

$$Sensitivity\ (Sen.) = \frac{TP}{TP + FN} \times 100\% \quad (6)$$

$$F1 - score = \frac{2 \times Pre. \times Sen.}{Pre. + Sen.} \times 100\% \quad (7)$$

When the subdivided cardiac sound signal's characteristics are correctly identified, TP is defined as a true positive.

FP, or false positive, which detected predictions for the parameters of the cardiac sound signal incorrectly. False negatives, or FNs, are characteristics of split heart sound signals that were incorrectly disregarded.

Results and Discussion

Using computer-aided auscultation systems to detect heart abnormalities via electronic stethoscopes has shown promising results in recent studies. These systems utilize machine learning algorithms to analyze heart sounds and identify abnormalities that may indicate an underlying cardiac condition. The accuracy of these systems is comparable to that of traditional diagnostic methods, such as echocardiography and electrocardiography. Furthermore, these systems have the potential to improve diagnostic efficiency and reduce the cost of healthcare by enabling remote monitoring and screening. However, further research is necessary to assess the effectiveness of these systems in real-world clinical settings and to evaluate their impact on patient outcomes.

The PASCAL database assessed the proposed address label technique with peak and catastrophic change point detection. The sets (A) & (B) make up this collection. Set (A) has 34 pathologic heart tones and 33 normal cardiac tones. Set(B) contains 166 pathological heart sounds and 193 normal heart sounds. Examples of the unfiltered pattern and encased pattern with sudden shifts recognition for healthy and pathological cardiac sound waves are shown in Figures 3(a) and 3(b), respectively.

Figures 3(i) and 3(ii) depict the original heart sound signal for two distinct instances. Figures 3(iii) and 3(iv) show just one cardiac cycle after being split into segments and saved for identifying healthy and unhealthy cardiac cycles, respectively.

Typically, during the real-time data acquisition process, two distinct peaks fluctuated constantly for the pathological and normal heart sound signals.

When the heart sound signal was recorded at the aortic auscultation location, the first sound may have had a lower-intensity peak signal than the second sound. The first cardiac sound's apex is louder than the second at the mitral auscultation location. The first cardiac sound is caused by the shutting of the tricuspid & mitral valves; the shutting of the aorta and pulmonary valves results in the second cardiac sound, on the other hand. Therefore, based solely on apex information or rapid time data, it is challenging to separate and identify the various components of the cardiac sound pattern. The chart contains data on the cardiac cycle, S1 time frame, S2 time frame, and the ratio of systole to diastole, in addition to identifying cardiac parameters.

Heart sound measures at their ideal value 22, and the mean and standard deviation (SD) were used to compute all the parameters. Otherwise, a visual examination of the tabular data of the extracted cardiac sound parameters has been done to assess the effectiveness of the division process. Calculations of the selectivity, clarity, and accurateness, Table (2) displays the suggested algorithms' F1-scores.

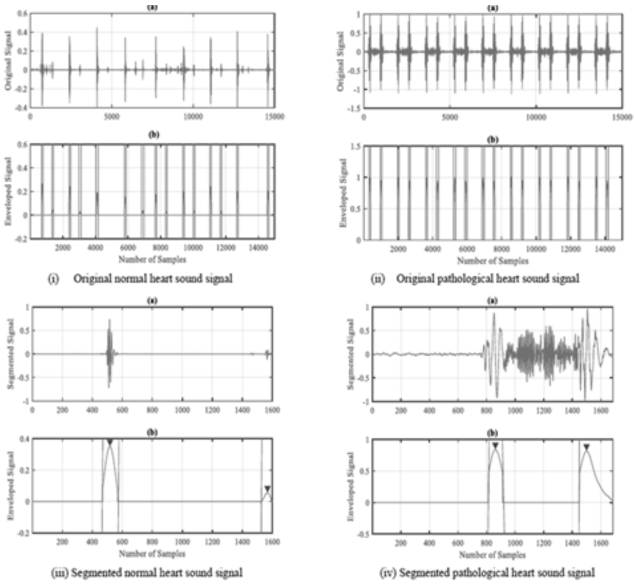

Fig 3. Heart sound output for both healthy and pathological cases, in raw and segmented form"

Table 1. Comparison of Parameters in Normal and Pathologic (Mean ± SD)

Dataset Heart Sound		Sys_dur (s)	Dia_dur (s)	Cdc_cyc (s)	S1_dur (s)	S2_dur (s)	S/D ratio
Set A	Normal	0.27 ± 0.07	0.41 ± 0.11	0.68 ± 0.15	0.02 ± 0.05	0.04 ± 0.07	0.68 ± 0.18
	Pathologic	0.34 ± 0.22	0.61 ± 0.15	0.97 ± 0.21	0.02 ± 0.01	0.08 ± 0.20	0.66 ± 0.53
Set B	Normal	0.28 ± 0.09	0.40 ± 0.14	0.68 ± 0.18	0.01 ± 0.03	0.02 ± 0.08	0.75 ± 0.21
	Pathologic	0.30 ± 0.13	0.45 ± 0.17	0.75 ± 0.23	0.03 ± 0.06	0.04 ± 0.10	0.83 ± 0.78

Table 2. Comparison of Parameters in Normal and Pathologic (Mean ± SD)

Dataset		Total	TP	FP	FN	Se. %	Pre. %	Acc. %	F1 %
Set A	Normal	31	22	1	8	73.33	95.65	70.97	83.01
	Pathologic	34	21	5	8	72.41	80.77	61.76	76.36
Set B	Normal	200	182	9	9	95.29	95.29	**91.00**	**95.29**
	Pathologic	66	56	8	2	96.55	87.50	84.85	91.80
[8]		-	-	-	-	95.34	95.92	92.52	95.63
[15]		-	-	-	-	99.43	93.56	-	96.41

During the segmentation and identification procedure, the suggested approach for the ordinary heart's sounds signal condition performs better than the pathological heart sounds signal condition.

This results from the murmur's location and shape varying the murmur's complex pattern of pathological heart sounds.

The accuracy of the suggested algorithm is 70.97% for the instance of an ordinary heart's sounds signal in information set (A), compared to 91% for information set (B). However, the outcomes for abnormal instances in the two databases are not very promising. In 83.01% & 95.29% of the cases, respectively, the proposed algorithm accurately predicts the division & reorganization of the signal for the typical cardiac sounds in Information sets (A) & (B).

Conclusion

An innovative approach to automated heart sound analysis using reference data for abrupt changes and peak location values has been proposed.

Additionally, because the pathological case's heart sound is lower than normal, segmentation and parameter recognition were more difficult for the pathological case than for the normal case. Because of the auscultatory location, the study's prominent peak could be applied to the segmentation of heart sound signals, which had a varying prominent peak.

In summary, a computer-aided auscultation system that utilizes an electronic stethoscope has the potential to revolutionize the detection of heart abnormalities. This system allows for more accurate and objective diagnoses of heart conditions, and it has the potential to reduce the reliance on subjective interpretations of heart sounds by human experts. The system additionally facilitates the remote monitoring of patients, a feature that proves particularly advantageous in scenarios where healthcare accessibility is restricted. Although additional research and development are necessary to enhance the precision and efficacy of this system, it is a technology that exhibits promise and has the capacity to significantly enhance the diagnosis and treatment of cardiac ailments, ultimately resulting in improved health outcomes for patients.

***Authors**:*
Abdulrahman W.H. AL-Askari (Assist. Lecturer), university presidency, Northern Technical University / Iraq. Email: abdulrahman21@ntu.edu.iq.

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