Continuous Wavelet Transform based Phonocardiogram Delineation Method

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Research Article

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Abstract:

Time frequency-based methods have been employed for event detection in audio signals. The spectrogram can be used to extract loudness and energy functions by taking the row sum. The loudness function has been differentiated to obtain the on-set events of the audio. The same could be replicated in case of bio-signals such as phonocardiograms to extract on-set and off-set boundaries. Continuous Wavelet Transform based Time-Frequency algorithm for on-set and off-set Event-detection has been developed for Phonocardiograms and the same has been tested on the PCG dataset hosted in Physionet repository. To validate the simulation, real implementation has also been carried out with real heart sound recordings obtained from Bluetooth based stethoscope called the stemoscope. The simulation carried out using PCG sounds from the Physionet database gave an F1-score of 99.11%. Similar results were found using the real heart sound recordings from stemoscope with an F1- score of 99.30%. Experimental evaluation and Simulations both indicate that Continuous Wavelet Transform based time frequency algorithm can be used to derive on-set and off-set events of the sounds in the PCG signal.

Keywords: Stemoscope, Physionet, Phonocardiogram Wavelets, Event detection

I. Introduction:

Continuous Wavelet transform (CWT) is a time frequency transform that is used to convert the time series into time-frequency signal [1][27]. Time frequency methods like the short time Fourier transform (STFT), continuous wavelet transform (CWT), Stockwell Transform (ST) etc. are popular, but CWT enjoys numerous advantages over its counterparts. CWT uses a variable sized window for obtaining precise low frequency information with larger duration windows and for obtaining high frequency information with smaller duration windows. The same is not possible with STFT which uses a fixed sized window for all frequencies. Fixed duration larger sized windows for low frequency signal leads to loss in time resolution while fixed duration smaller sized windows for high frequency signal leads to loss in frequency resolution. ST is a good time frequency transform like CWT but suffers from cross-terms. Audio Segmentation for onset event detection of audio signals has been implemented in MIT USA using the spectrogram obtained from STFT [1][2][3][27]. It has been reported that loudness/ Energy function can be extracted and differentiated to obtain the on-set events of the audio signal with good accuracy. In this paper we show that just like any spectrogram STFT; CWT can also be used to segment the bio-signal such as PCG signal using onset and offset detection. PCG signal normally has two sounds, the First Heart sound (S1) and the Second Heart sound (S2) which alternate each other in the cardiac cycle. The CWT based PCG

delineation method is discussed in section 2. Results obtained and further discussions are described in section 3. The conclusion part is mentioned in section 4 of this paper.

II. Results and Discussion

In this section we analyze the performance of the proposed algorithm in terms of performance metrics. The state-of-the-art algorithms used in previous works have been discussed here. The section is divided into two subsections. The performance metrics used for PCG evaluation is discussed in Section A, PCG analysis using metrics is discussed in Section B, while the discussion section C follows the section B.

A. Performance metrics

Performance metrics namely Sensitivity (Se), Positive Predictive Value (P+), Accuracy (Ac) and F1 score were used to evaluate the CWT segmentation algorithm. 'Se' refers to the correct detection of an S1/S2 normal heart sound when noise components are present. A high value of 'Se' indicates that there is high chance of correct Segmentation of PCG in the presence of small residual noise even after preprocessing. 'P+' signifies the number of heart sounds detected when some of them are missed. A high 'P+' indicates that the rate of PCG segmentation is very high at the cost of very low number of missed sounds. 'Ac' refers to the overall rate of correct segmentation of normal PCG in the presence of noise and missed heart sound components. An accurate Segmentation algorithm shows a high degree of accuracy. F1 measure indicates the degree of accurate segmentation in the presence of murmurs and noises. F1 measure is closely related to 'Ac'. A high value of F1 measure is desirable.

B. PCG Analysis using Metrics

The PCG signals present in the Physionet dataset was adequately preprocessed using a two-stage filtering procedure. As a first step 180 Hz low pass Butterworth filter was used to remove 80% noise. As a second step EMD-Wavelet denoising procedure was applied to the sounds. This removed the left-over noise. The Signal to Noise Ratio parameter was used as a metrics to evaluate the denoising procedure. All sounds that showed good improvement in the sound quality of over 75% (SNR), were retained and a few other sounds which showed little/ no improvement were discarded. A total of 3239 sounds both normal and abnormal sounds were considered for evaluation. PCG delineation was performed using the CWT method as described in section 3.

Results obtained for both normal and abnormal PCG sounds using CWT delineation have been tabulated in the form of tables 1-2. Application of CWT delineation for normal sounds showed that four different events sound S1 (Red), Systole (Green), sound S2 (yellow) and diastole (light blue) were identified. The actual plot Fig 6 and the zoomed plot Fig 7 are shown. For abnormal sounds similar results were obtained even in the presence of extra sounds like murmurs. Corresponding actual plot Fig 8 and the zoomed plot Fig 9 are shown. A total of 2574 normal sounds were used for testing the algorithm. By applying CWT algorithm, we obtained an accuracy of 98.02% and F1-score of 99.00%. A total of 665 abnormal sounds were also tested. The CWT algorithm showed 99.98% accuracy and 99.49% F1 score. A total of

3239 sounds were used for the purpose of simulation after discarding a few sounds with improper recording and very high noise levels. An overall 98.23% accuracy and 99.11% F1-score was obtained from the sounds in the dataset.

Analysis of the sounds acquired by real recording using stemoscope stethoscope was also analyzed using Matlab. A total of 100 normal sound recordings shown in tables 3-4 gave an accuracy of 98.96% and a F1-score of 99%. Similar analysis with 100 abnormal sounds gave an accuracy of 99.17% and a F1-score of 99.6%. The experimental results confirm the validation of CWT based PCG delineation algorithm implemented on the sounds taken from Physionet dataset.

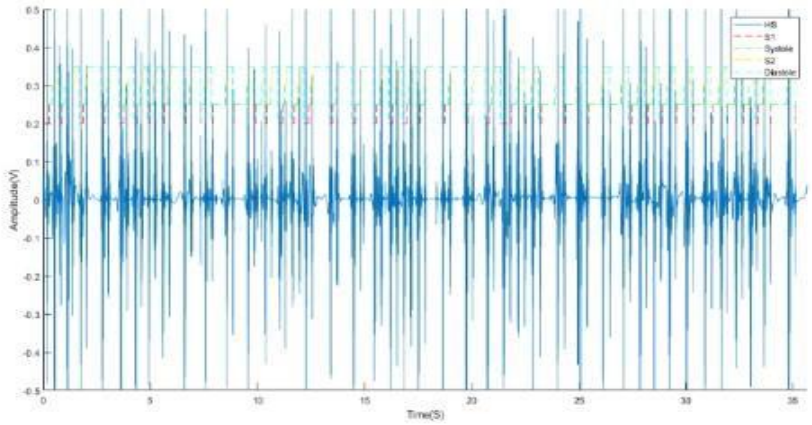

Fig 6 Normal PCG signal (blue), S1 (Red), Systole (Green), S2 (Yellow), Diastole (Light Blue)

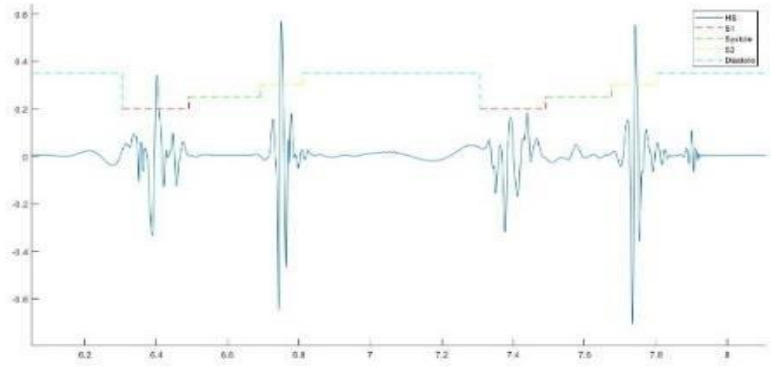

Fig 7 Normal PCG (Single Cycle) (blue), S1 (Red), Systole (Green), S2 (Yellow), Diastole (Light Blue)

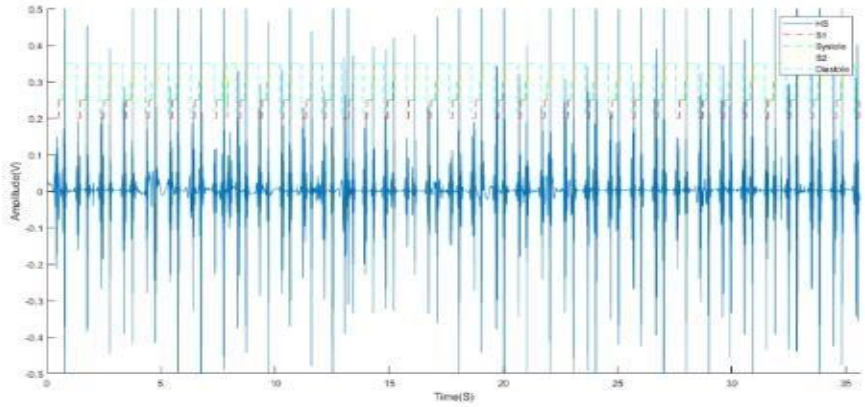

Fig 8 Abnormal PCG signal (blue), S1 (Red), Systole (Green), S2 (Yellow), Diastole (Light Blue)

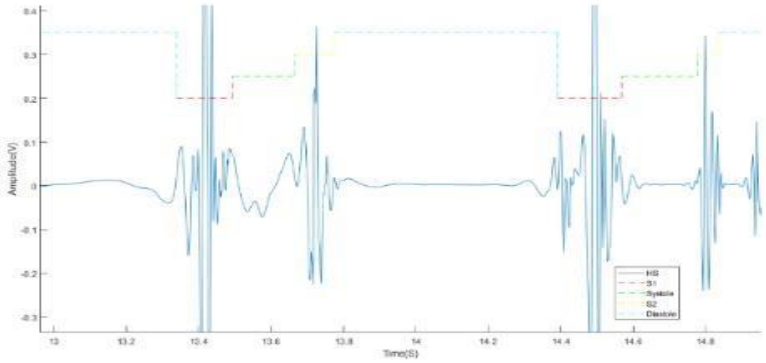

Fig 9 Normal PCG (Single Cycle) (blue), S1 (Red), Systole (Green), S2 (Yellow), Diastole (Light Blue)

Sounds	TP	FP	FN
Normal (2574)	133265	2693	0
Abnormal (665)	37065	383	0
Total (3239)	170330	3076	0

Table 1 True Positive, False Positive and False Negative of the various PCG sounds (dataset)

Sounds	Accuracy (Ac)	Positive Predictive Value (P_+)	Sensitivity (Se)	F1 measure
Normal (2574)	98.02%	98.02%	100%	99.00%
Abnormal (665)	98.98%	98.98%	100%	99.49%
Total (3239)	98.23%	98.23%	100%	99.11%

Table 2 PCG signal (dataset) Metrics (Accuracy, Positive Predictive Value, Sensitivity and F1 Measure)

Sounds	TP	FP	FN
Normal (100)	2400	25	0
Abnormal (100)	2400	20	0
Total (200)	4800	45	0

Table 3 True Positive, False Positive and False Negative of the various PCG sounds (Stemoscope)

Sounds	Accuracy (Ac)	Positive Predictive Value (P_+)	Sensitivity (Se)	F1 measure
Normal (100)	98.96%	98.96%	100%	99%
Abnormal (100)	99.17%	99.17%	100%	99.6%
Total (100)	99.07%	99.07%	100%	99.3%

Table 4 PCG signal (Stemoscope) Metrics (Accuracy, Positive Predictive Value, Sensitivity and F1 Measure)

C. Discussion

PCG delineation is used to identify the location and occurrence of variety of sounds present in the PCG signal. Several methods have been proposed by different authors which can be categorized as unsupervised [4]-[14] and supervised [15]-[27] in nature. The methods have been tested on a variety of datasets. Most of the experiments were carried out on small set of PCG signals due to the lack of available open-source dataset. Some of the experiments have been tested on a few types of pathological sounds. The results are far below optimum and they have not been validated using any particular system. This fails to certify that the system will work on real environments involving a standard tool such as a stethoscope. Another drawback of the segmentation algorithms listed in the below table 5 is that the methods involve a reference signal such as a carotid pulse or an ECG for beat identification. Incorporating an ECG instrument into the stethoscope makes the system complex. Apart from that simultaneous very accurate acquisition of two bio-signals and their storage/ transmission for analysis makes it difficult for doctors, since a small misalignment may lead to erroneous segmentation of the PCG signal [23][24]. So non-ECG based methods have gained popularity. Over the period of time artificial intelligence has gained good prominence and neural networks have been used a number of times to identify cardiac beats with good accuracy [25][26]. Neural networks are trained networks, their performance varies with dataset. Real time implementation requires a fast and high-end processor to identify the beats with maximum accuracy. The proposed CWT spectrogram-based method involves less complexity and a small processor. The PCG sounds were transmitted wirelessly, recorded and segmented with few computations. The method was simulated on a very large dataset (Physionet repository) and verified experimentally using a standard Bluetooth stethoscope system with good accuracy. With all methods mentioned below our proposed method gives the highest accuracy of 99.11%.

Authors and dataset used by them	**Reported metrics**	**Notes**
[4] 37 recordings (515 cycles) from children with murmurs (14 being pathological)	93.0% Ac	Unsupervised, optimised on entire dataset
[5] 77 (1165 cycles) recordings from children with both pathological and physiological murmurs	94.6% Ac	Unsupervised, optimised on entire dataset
[6] 55 recordings (7530 cycles), 51 with valve replacements	97.95% Se, 98.2% Sp	Unsupervised, optimised on entire dataset

[7] 71 recordings (357 cycles), nine different pathologies	97.47% Ac	No splits between train and test
[8] 166 clean heart cycles from normal and pathological patients	84.0% Ac	Unsupervised, no stated segmentation tolerance
[9] 41 recordings (340 cycles). Mix of normal (32%), systolic (36%) and diastolic murmurs (32%)	90.29% Ac	Unsupervised
[10] 27 recordings of 30 s (997 cycles) from healthy subjects	92.1% Se, 88.4% P+	Unsupervised
[11] 30 clean recordings (20 s) from healthy subjects	96.2% Ac	No split between train test set
[12] 120 recordings from children, 80 with congenital heart disease (totaling 1200 s, 823 cycles in test set)	93.6% Ac on test set	50% test train set
[13] Nine recordings (less than 5 s).	55% pathological 99.0% Ac on whole cycle detection	No split between train test set
[14] 9426.8 s of recordings, normal (22.2%) and various pathologies (ASD, PDA, VSD, and RHD)	S1 : 98.53% Ac, S2 : 98.31% Ac, Cycles: 97.37% Ac	Unsupervised, no stated segmentation tolerance
[15] 80 recordings from an unknown number of patients of 6–12 s (40 healthy, 40 pathological recordings)	96% and 97% Se, 95% and 95% P+ (healthy and pathological)	No split between train test set, no stated segmentation tolerance
[16] 26 clean recordings (565 cycles), 3 healthy subjects, and 23 with various pathologies	94.9% and 95.9% Ac (S1 and S2)	No split between train test set and no stated segmentation tolerance
[17] 50 2-min healthy and pathological recordings	99.0% Se and 98.6% P+	No split between train test set and segmentation reported on 20% dataset
[18] 64 teaching quality recordings of less than 10 s (701 cycles). Various pathologies	93.06% Ac, 99.43% Se. 93.56% P+	No split between train test set and segmentation reported on partial dataset, no stated segmentation tolerance

[19] 52 recordings (14 controls, 38 with murmurs), 43 in test set (2602 cycles)	83.05±15.14% Ac 94.56±6.58 G −measure	Ac denoted for correctly segmented cycles. G −measure is geometric mean of Se and P
[20] 80 patients, 8 pathological. Recordings of 20 s from four auscultation sites (10045 S1, 9818 S2 sounds	S1: 94.6% Se and 97.7%P+ S2: 95.2% Se and 96.1%P+	No split between train test set
[21] 46 clean recordings from eight patients (2286 s). No pathologies mentioned	97.6% Ac	Ac computed from average of eightfold cross validation
[22] 17 patients, 44 recordings (30–60 s). No pathologies mentioned	S1: 98.6% Se and 96.9% P+ S2: 98.3% Se and 96.5% P+	Result computed from average four - fold cross validation
[23] 113 recordings of 8 s, 8% with coronary artery disease	98.8% Se, 98.6% P+ on test set	73 tests, 40 training recordings
[24] 10 172 s of PCG recorded from 112 patients	F1 score of 95.63±0.85%	Large dataset, Uses ECG reference
[25] 10 172 s of PCG recorded from 112 patients	F1 score of 96.17±0.7%	Large dataset, No advance learning of states
[26] 10 172 s of PCG recorded from 112 patients	F1 score of 96.5±0.17%	Large dataset, Automated segmentation using LSTM
(Proposed) 10 172 s of PCG recorded from 112 patients	**F1 score of 99.11%**	**Large dataset, No ECG and no noise threshold**

Table 5 Latest Segmentation algorithms proposed by the authors

III. Conclusion

Of late many researchers have developed many PCG delineation algorithms for cardiac beat to beat identification. This has aided doctors in analyzing the timing and occurrence of the presence of various sounds in the PCG leading to abnormality in the heart. Several methods tested on a variety of datasets have shown promising results. But real time implementation in clinical environment of such methods remains a question. In our work we have explained with neatness the simulation of the proposed CWT based PCG delineation and in-hospital implementation of the algorithm using a Bluetooth based stethoscope system. A very high accuracy of 99.11% and the ability of the CWT algorithm to identify cardiac sounds in real hospital environment explains the feasibility of implementation of the PCG delineation system.

IV. Materials and Methods:

1. Dataset

The PCG signals used in this work were taken from the ensemble of sounds that were made publicly available for the PhysioNet/CinC challenge 2016 [2]. The database includes 3239 PCG sounds recorded from 130 patients in different clinical and non-clinical environments. From those, 665 sounds were collected from patients with pathological heart lesions (most commonly mitral valve prolapse), as assessed by echocardiography. The remaining 2574 sounds were collected from healthy patients. Sound recordings in this database have variable durations in the range from 5:12 to 35:5 seconds and were sampled at 1 kHz. They were collected from several spots over the chest and they were possibly corrupted by different sources and noise levels [2].

2. Pre-processing

The PCG signals present in the Physionet database [2] have been found to be noisy and appropriate pre-processing method has been used to reduce the noise levels. At first a Chebyshev low pass filter with cut-off frequency of 180 Hz has used to remove up to 80% of the noise and all of the murmurs (abnormal sounds only) in the PCG [28]. Then the pre-processing method involving the Empirical Mode Decomposition (EMD) has been used to decompose the noisy PCG into intrinsic mode functions (IMFs) [27]. The first IMF consisting of high frequency noise has been discarded. The last IMF consisting of power line disturbance due to noise from instrument has also been discarded. The remaining less noisy IMFs have been denoised using Wavelet de-noising techniques developed by Donoho et al [28]. 'db8' wavelet has been used for this purpose, due to morphological similarity of the wavelet with PCG and its high noise removal ability [27][28]. The denoised IMFs have been reconstructed to obtain the denoised PCG. Two datasets have been created, one consisting of denoised normal PCG and the other consisting of denoised abnormal PCG. The denoised datasets have been then subjected to segmentation algorithm using CWT and ACF. Pictorial representation of Preprocessed Normal and Abnormal PCG sounds have been shown in Fig 1.

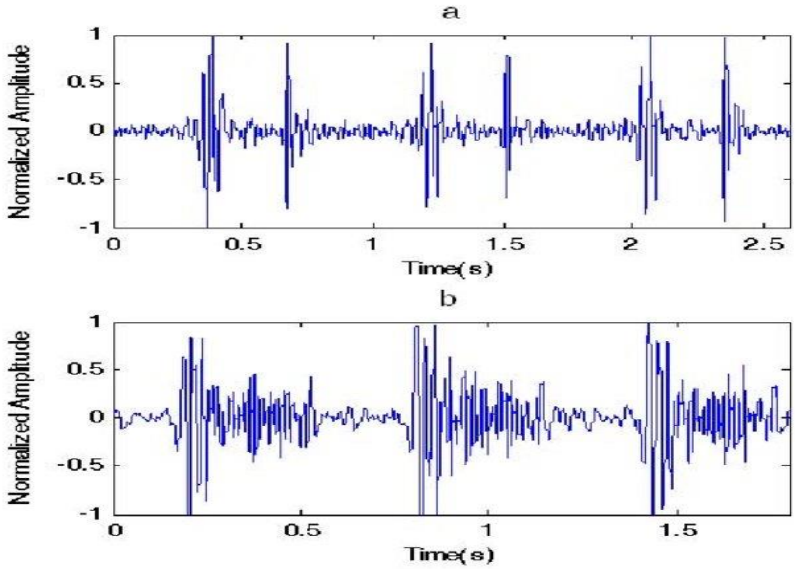

Fig 1 Zoomed Plot of Normal PCG signal (a) Abnormal PCG signal (b) after Preprocessing

3. CWT based Delineation Method:

3.1 PCG signal cardiac cycle extraction

From the denoised PCG we have extracted a single cardiac cycle by using the Auto-correlation Function (ACF). If $x(t)$ is the denoised PCG signal then its ACF, $Rxx(t)$ is given by

$$\boldsymbol{R_{xx}(\tau) = \int_{-\infty}^{\infty} x(t)x(t+\tau)dt} \quad (1).$$

ACF is obtained by convolving PCG signal with its time shifted version to obtain a signal with a constantly decreasing amplitude of the successive peaks. Hamming window of length 200 has been used for following reasons. Hamming window is chosen due to its better smoothing effect. The average length of an S1 and S2 sound in a cardiac cycle is 50ms [3]. With sampling frequency of 2000 Hz, there will be 200 samples of S1 and S2. The ACF describes the correlation between the various components of the PCG. Generally, in an ACF the maximum peak occurs at the start of the PCG (t = 0s). Following the maximum peak, successive peaks occur all of which decrease with amplitude. The largest peak has maximum correlation with itself the correlation decreases with other components of the PCG. To extract a single cardiac cycle, the second largest peak has been used as shown by solid triangle in Fig 1 (pane 2) and fig 2 (pane 2). The first two peaks correspond to first S1 and first S2. Fig 1 and Fig 2 explains the denoised PCG, ACF of denoised PCG and extraction of single cardiac cycle. Later, CWT segmentation has been applied to the extracted cardiac cycle for boundary detection of S1 and S2 sounds. After first cardiac cycle extraction, ACF has been applied for all remaining sounds in the dataset.

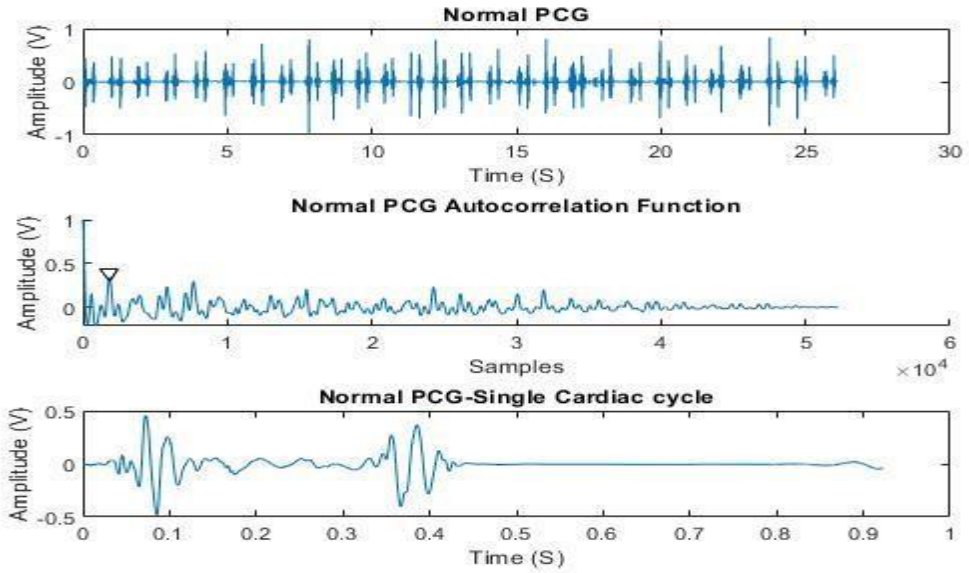

Fig 1 Normal PCG, ACF, One Cardiac cycle

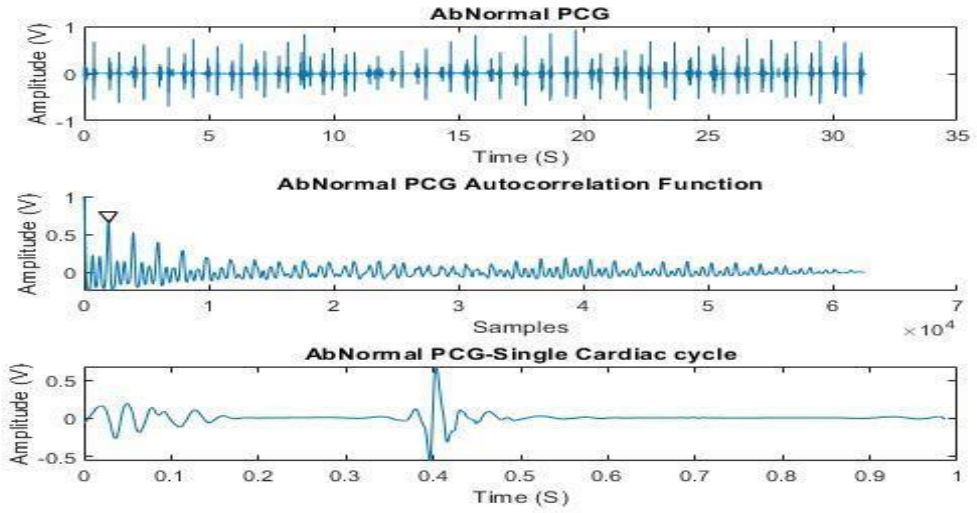

Fig 2 Abnormal PCG, ACF, One Cardiac cycle

3.2 CWT computation and Event Detection

For evaluating the CWT of the PCG signal, an appropriate mother wavelet was chosen. Various types of mother wavelets were analyzed like the Haar, Daubechies, Morlet, Hadamard. Based on the morphological similarity and the shape of the wavelet, Duabechies-10 wavelet was found to be more appropriate for our analysis. The CWT was estimated as

$$\boldsymbol{C_M(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a.b}(t).} \quad (2)$$

CWT coefficients were evaluated by windowing of the PCG signal with the Mother wavelet. The normal and abnormal PCG scalograms for CWT implementation is shown in Fig 3 and Fig 4 respectively. The scalogram represents the time frequency plot of the CWT coefficients of the PCG signals. The Wavelet Energy Index Function $\boldsymbol{W_E(t)}$ was estimated from the CWT coefficients as the row sum of the CWT coefficient matrix. $\boldsymbol{W_E(t)}$ is a time series defined as

$$\boldsymbol{W_E(t) = \sum C_M(a,b).} \quad (3)$$

The Wavelet Energy Index Function $\boldsymbol{W_E(t)}$ includes all the frequencies of the PCG signal evenly distributed over the time series. The mean M of the time series was evaluated as the average of all points of $\boldsymbol{W_E(t)}$ given by

$$\boldsymbol{M = \frac{1}{N}\sum W_E(t).} \quad (4)$$

The mean M is subtracted from $\boldsymbol{W_E(t)}$ to obtain the PCG Wavelet Event Function given by

$$\boldsymbol{W_{EV}(t) = W_E(t) - M} \quad (5)$$

$\boldsymbol{W_{EV}(t)}$ is time-series of the Wavelet Energy which intersects with the reference axis (X-axis). The points of intersection correspond to the on-set and off-set of the Wavelet Energy and hence the boundaries of the PCG sounds S1 and S2. Generally, two onsets and two offsets were noted in a cardiac cycle which were alternating, the first offset follows the first onset and the second offset follows the second onset. Once the boundaries are identified the S1 and S2 was detected from the two types of PCG signals in the cardiac cycle by calculating the duty cycle of the cardiac cycle. The duty cycle $\boldsymbol{D}$ is mathematically represented by

$$\boldsymbol{D = \frac{Second\ onset - First\ onset}{length\ of\ the\ PCG} \times 100.} \quad (6)$$

Normal sounds have a large duty cycle due to a longer systole and a shorter diastole. However, the exact Duty cycle varies from person to person and also on the point of Auscultation on the

chest. Abnormal Sounds have a smaller duty cycle due to small first and second PCG sounds and a shorter systole and a comparative diastole.

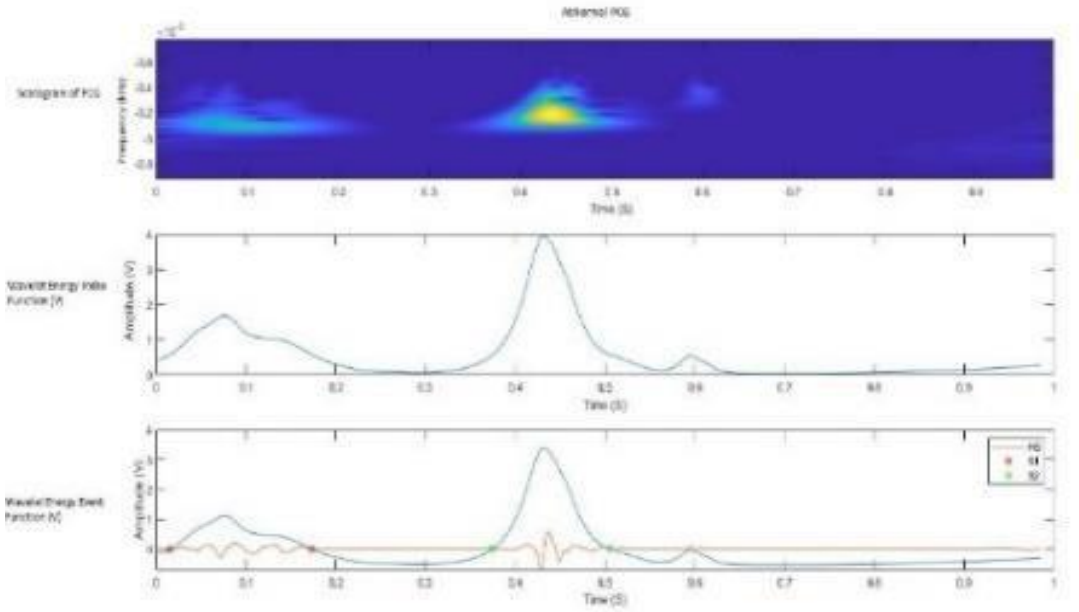

Fig 3 Normal PCG scalogram, Cardiac Events and PCG cycle

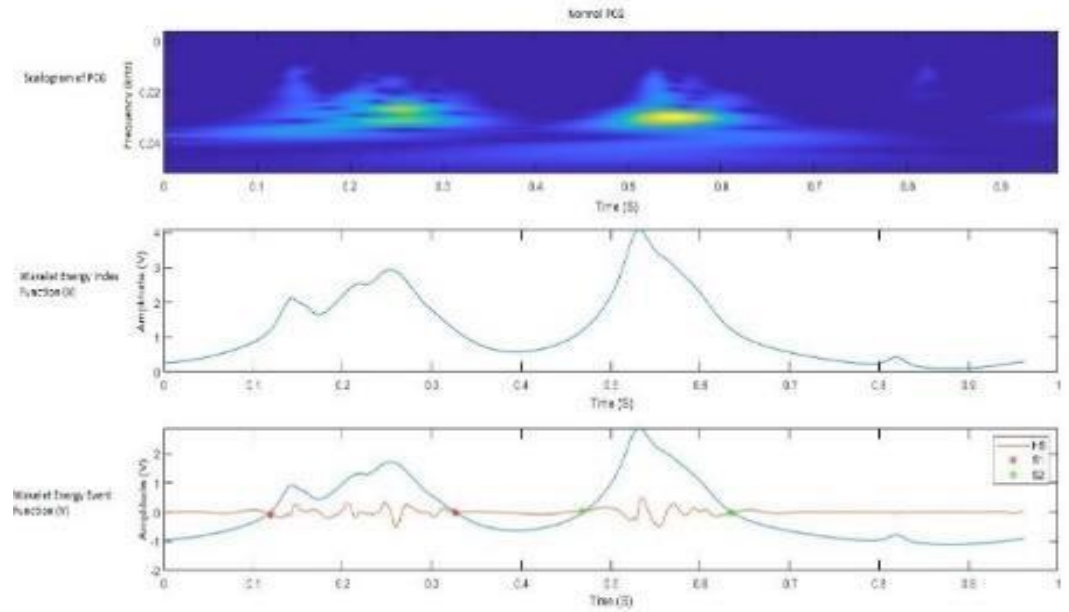

Fig 4 Abnormal PCG scalogram, Cardiac Events and PCG cycle

4. Real Implementation using Bluetooth Stethoscope

For acquiring real PCG sounds from the chest of the subject a Bluetooth stethoscope called stemoscope was used. Stemoscope is a low power Bluetooth based wireless stethoscope that connects to the smartphone via the stemoscope android app. The block diagram of the system

implementation is shown below in Fig 5. The wireless Bluetooth stethoscope was placed on the chest of the subject under study. The PCG sounds were streamed to the smartphone via Bluetooth. The Android stemoscope app enabled real reception of the acquired sound and subsequent real playback via the audio jack. The audio jack was connected to the PC via audio jack bridge and the sound was recorded in the PC using Matlab. The system was used to record 100 sounds from normal subjects and an equal number of sounds were recorded from subjects suffering from Cardio-Vascular diseases (CVDs) like Mitral stenosis, Mitral Regurgitation, Aortic Stenosis, Aortic Regurgitation etc. A dataset was created with these sounds for validating the simulations carried out with Physionet dataset.

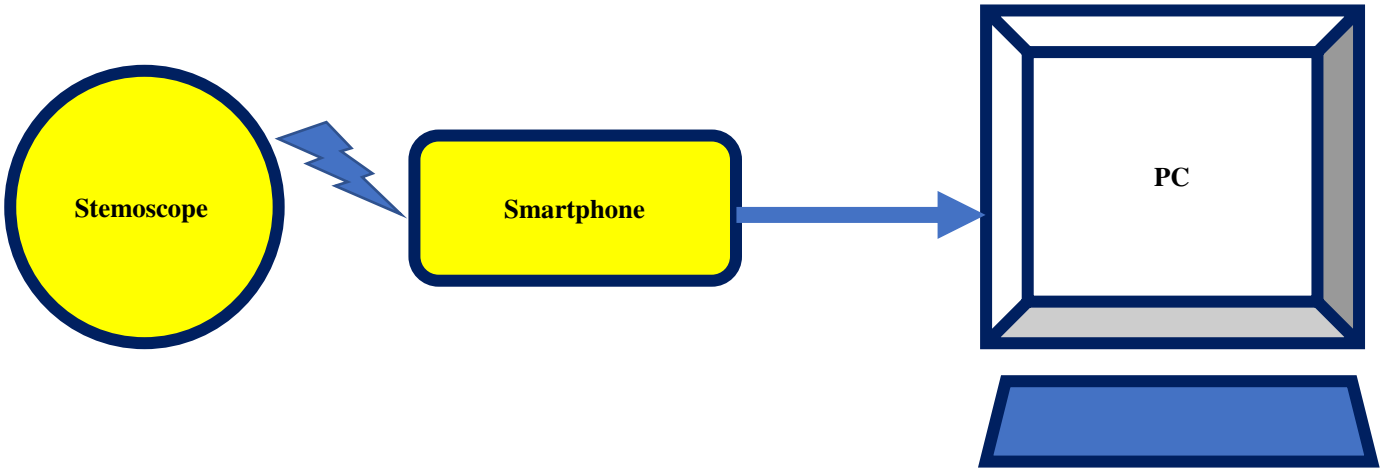

Fig 5 Block diagram of Real Implementation of PCG delineation using CWT algorithm and stemoscope stethoscope.

DECLARATION

1. **Ethical Approval and Consent to participate**

Authors provide ethical approval and consent to the publication of the manuscript in the Journal.

2. **Availability of data and materials**

Not Applicable

3. **Competing interests**

There is no competing interest in the publication of the manuscript in the Journal.

4. **Funding**
No funding was involved.

5. **Authors' contributions**

The author was involved in the research work and drafting of the paper.

REFERENCES

[1] Snyder B, Music and Memory: An Introduction, MIT Press, Cambridge, MA, 2000.
[2] www.physionet.org/challenge/2016/:accessed date: November 11 2021.
[3]. Zwicker E and Fastl H, Psychoacoustics: Facts and Models, Springer Verlag, Berlin, 2nd edition, 1999.
[4] H.Liang etal.,"Heart sound segmentation algorithm based on heart sound envelogram," in Proc. Comput. Cardiol., Lund, Sweden, 1997, vol. 24, pp. 105–108.
[5] H. Liang et al., "A heart sound segmentation algorithm using wavelet decomposition and reconstruction," in Proc. 19th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Chicago, IL, USA, 1997, vol. 4, pp. 1630–1633.
[6] D. Kumar et al., "Detection of S1 and S2 heart sounds by high frequency signatures." in Proc. 28th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., New York, NY, USA, 2006, vol. 1, pp. 1410–1416.
[7] S.Ariet al.,"A robust heartsound segmentation algorithm for commonly occurring heart valve diseases." J. Med. Eng. Technol., vol. 32, no. 6, pp. 456–65, Jan. 2008.
[8] J. Vepa et al., "Segmentation of heart sounds using simplicity features and timing information," in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., Las Vegas, NV, USA, 2008, pp. 469–472.
[9] C.Gupta etal.,"Neural network classification of homomorphic segmented heart sounds," Appl. Soft Comput., vol. 7, no. 1, pp. 286–297, Jan. 2007.
[10] T. Chen et al., "Intelligent heart sound diagnostics on a cellphone using a hands-free kit," in Proc. AAAI Spring Symp. Artif. Intell. Dev., Stanford University, Stanford, CA, USA, 2010, pp. 26–31.
[11] T. Oskiper and R. Watrous, "Detection of the first heart sound using a time-delay neural network," in Proc. IEEE Comput. Cardiol., Memphis, TN, USA, 2002, pp. 537–540.
[12] A. A. Sepehri et al., "A novel method for pediatric heart sound segmentation without using the ECG," Comput. Methods Programs Biomed., vol. 99, no. 1, pp. 43–48, Jul. 2010.
[13] Z.Yan etal.,"The moment segmentation analysis of heart sound pattern," Comput. Methods Programs Biomed., vol. 98, no. 2, pp. 140–50, May 2010.
[14] S. Sun et al., "Automatic moment segmentation and peak detection analysis of heart sound pattern via short-time modified Hilbert transform," Comput. Methods Programs Biomed., vol. 114, no. 3, pp. 219–230, May 2014.
[15] A. Moukadem et al., "A robust heart sounds segmentation module based on S-transform," Biomed. Signal Process. Control, vol. 8, no. 3, pp. 273– 281, May 2013.
[16] H. Tang et al., "Segmentation of heart sounds based on dynamic clustering," Biomed. Signal Process. Control, vol. 7, no. 5, pp. 509–516, Sep. 2012.
[17] H. Naseri and M. R. Homaeinezhad, "Detection and boundary identification of phonocardiogram sounds using an expert frequency-energy based metric," Ann. Biomed. Eng., vol. 41, no. 2, pp. 279–292, Feb. 2013.
[18] V. N. Varghees and K. Ramachandran, "A novel heart sound activity detection framework for automated heart sound analysis," Biomed. Signal Process. Control, vol. 13, pp. 174–188, Sep. 2014.
[19] C.D.Papadaniil and L.J.Hadjileontiadis,"Efficient heart sound segmentation and extraction using ensemble empirical mode decomposition and kurtosis features," IEEE J. Biomed. Health Informat., vol. 18, no. 4, pp. 1138–1152, Jul. 2014.
[20] L.Gamero and R.Watrous,"Detection of the first and second heart sound using probabilistic models," in Proc. IEEE 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Cancun, Mexico, 2003, pp. 2877–2880.

[21] A. Ricke et al., “Automatic segmentation of heart sound signals using hidden Markov models,” in Proc. Comput. Cardiol., Lyon, France, 2005, pp. 953–956.
[22] D. Gill et al., “Detection and identification of heart sounds using homomorphic envelogram and self-organizing probabilistic model,” in Proc. Comput. Cardiol., Lyon, France, 2005, pp. 957–960.
[23] S. E. Schmidt et al., “Segmentation of heart sound recordings by a duration-dependent hidden Markov model,” Physiol. Meas., vol. 31, no. 4, pp. 513–529, Apr. 2010.
[24] Springer D B, Tarassenko L and Clifford G D, 2016, “Logistic regression-HSMM based heart sound segmentation”, IEEE Trans. Biomed. Eng., Vol. 63, pp. 822–32.
[25] Yao Chen, Yanan Sun, Jiancheng L, Bijue Jia and Xiaoming Huang, “End-to-end heart sound segmentation using deep convolutional recurrent network”, Complex & Intelligent Systems, 2021, vol.7, pp. 2103–2117.
[26] Tharindu Fernando, Sridha Sridharan, Houman Ghaemmaghami, Simon Denman, Nayyar Hussain, and Clinton Fookes, “Heart Sound Segmentation using Bidirectional LSTMs with Attention”, IEEE Journal of Biomedical and Health Informatics, Vol.24, No.6, 2020, pp. 1601-1609.
[27] C. Liu et al., “An open access database for the evaluation of heart sound algorithms,” Physiological Measurement, vol. 37, no. 12, pp. 2181–2213, 2016.
[28] Donoho, D. L. “De-noising by Soft-Thresholding.” IEEE Transactions on Information Theory, Vol. 42, Number 3, pp.613–627, 1995.
[29] Torrence, C., and Compo, G. P., A practical guide to wavelet analysis. Bull. Am. Meteorol. Soc. 79:61–78, 1998.