# Real Time Acquisition and Analysis of PCG and PPG Signals

Akash Kumar Bhoi, Karma Sonam Sherpa, Jitendra Singh Tamang, Devakishore Phurailatpam, Akhilesh Kumar Gupta

***Abstract*- Photoplethysmography (PPG) and Phonocardiography (PCG) are two important non-invasive techniques for monitoring physiological parameters of cardiovascular diagnostics. The PCG signal discloses information about cardiac function through vibrations caused by the working heart. PPG measures relative blood volume changes in the blood vessels close to the skin. This paper emphasizes on simultaneous acquisition of PCG and PPG signals from the same subject with the aid of NIELVIS II+ DAQ and the signals are imported to MATLAB for further processing. Heart rate is extracted from both the signals which are found to be distinctive. This analytical approach of processing these signals can abet for analysis of Heart rate variability (HRV) which is widely used for quantifying neural cardiac control and low variability is particularly predictive of death in patients after myocardial infarction.**

***Index Terms*- Phonocardiography, Photoplethysmography, Noise cancellation, Baseline drift Removal, Signal Analysis, Data acquisition, MATLAB**

## I. INTRODUCTION

Pulse wave analysis helps to study diabetes & arthritis & it is unique for each individual so it would also give unique identification as biometric identification [1].Heart sounds were identified as composite oscillations related to valve closure and heart murmurs seemed to derive from malfunctioning valves or from abnormal holes in the septal wall [2]. “Fig. 1” shows the relationship between ECG and PCG where, S1 occurs with low frequency vibrations approximately 0.05 second after the onset of QRS-complex of ECG signal. S2 starts approximately 0.03-0.05 second after the end on T wave of the ECG. S3 starts at 0.12-0.18 second after the onset of second heart sound and the fourth heart sound (S4) starts approximately 0.12-0.18 second after the onset of P wave of ECG signal.

Akash Kumar Bhoi is with the Applied Electronics & Instrumentation Engineering Department, Sikkim Manipal Institute of Technology (SMIT), India (email: akash730@gmail.com).

Karma Sonam Sherpa is with the Electrical & Electronics Engineering Department, Sikkim Manipal Institute of Technology (SMIT), India (email: karmasherpa23@gmail.com).

Jitendra Singh Tamang is with Electronics & Communication Department, SMIT, India (email: js.tamang@gmail.com) .

Devakishore Phurailatpam is with the Electrical & Electronics Engineering Department, National Institute of Technology, Manipur, India (email: bungcha@gmail.com).

Akhilesh Kumar Gupta is with the Applied Electronics & Instrumentation Engineering Department, SMIT, India (email: akhileshgupta94@gmail.com).

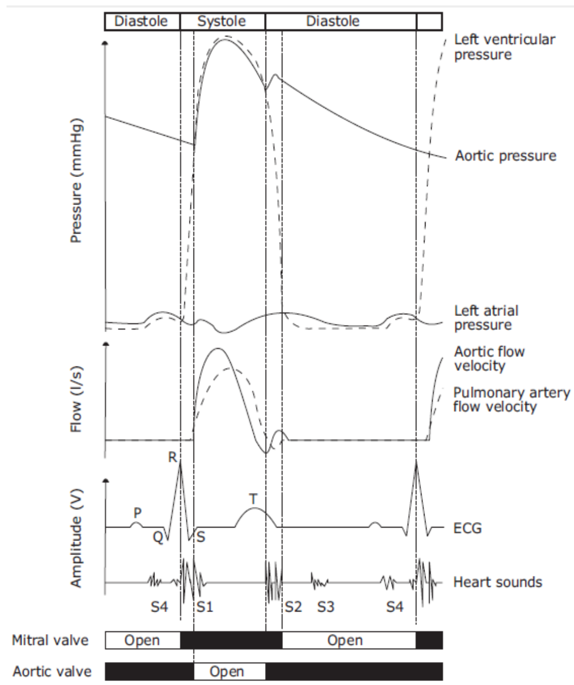


Fig.1. Wiggers diagram, showing pressures and flows in the left side of the heart over one heart cycle and how they relate to electrical (ECG) and mechanical (PCG) activity.

Fast Fourier transform (FFT) analysis of pulse Oximeter signals have been shown to reduce the negative impact of motion artifact, alternate hemoglobin states, and low blood volume. However, FFT analysis has shown to perform poorly for quasi-periodic data sets . Different features of PCG signals like intensity, frequency content, split information, time relations etc. are helpful in detecting heart valve diseases, if any and the state of the heart function [3]. *Ian Cather* have presented artificial neural network (ANN) as a discriminative model for classification of five different heart sounds taken from 48 recordings of nine different subjects using wavelet based feature extraction technique [4]. *Ölmez et al.* have given a classification technique that utilizes Daubechies-2 wavelet detail coefficients at the second decomposition level for classification of seven different heart sounds collected from 28 subjects using ANN [5]. *Reed et al.* have described a computer-aided diagnosis mechanism for five different pathological cases using seven level wavelet decomposition, based on a Coifman fourth order wavelet kernel [6] and *Ari et al.* in a work, a binary decision on heart

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sound whether pathological or not in a Digital Signal Processor based system was proposed [7]. *Choi* proposed a technique for detection of valvular heart sounds as normal or pathological using wavelet packet decomposition and support vector machine with fifth order polynomial kernel function [8-10]. Practical applications of PPG can also be found in signal processing of accelerations for gait analysis [9], in digital communications and many others. *Chrysa D. Papadaniil et al.* have presented an efficient heart sound segmentation (HSS) method that automatically detects the location of first (S1) and second (S2) heart sound and extracts them from heart auscultatory raw data. The heart phonocardiogram is analyzed by employing ensemble empirical mode decomposition (EEMD) combined with kurtosis features to locate the presence of S1, S2, and extract them from the recorded data, forming the proposed HSS scheme, namely HSS-EEMD/K [11]. *Ana Gavrovska et al.* represented a step towards automatic detection of one of the most common pathological syndromes, so called mitral valve prolapse (MVP), using phonocardiogram and multi-fractal analysis [12]. *Mohamed Elgendi* discusses different types of artifact added to PPG signal, characteristic features of PPG waveform, and existing indexes to evaluate for diagnoses [13]. The ability to identify premature arterial stiffening is of considerable value in the prevention of cardiovascular diseases. The "ageing index" (AGI), which is calculated from the second derivative photoplethysmographic (SDPPG) waveform, has been used as one method for arterial stiffness estimation and the evaluation of cardiovascular ageing [14-18].

It is often followed by echocardiography when the auscultatory findings are abnormal. However, the lack of reliability of ordinary auscultation and the expense and awkwardness of echocardiography make it desirable to develop a more practical, inexpensive, reliable, non-invasive approach to auscultation, one that could also be adapted for continuous monitoring [19-23]. This paper introduces an approach for concurrent acquisition and processing of PCG and PPG signals for determination of heart rate which will certainly aid an alternate method (other than ECG) for monitoring heart rate.

## II. METHODOLOGY

The signal acquisition and analysis requires the use of several data sensing and processing equipments. This work performed in *biomedical instrumentation lab of SMIT* using Phonocardiograph (ST-2356) and Photoplethysmograph (ST-2357) for generation of PCG "fig.6 "and PPG "fig.5" signals respectively. NI ELVIS-II+ used as DAQ for bridging these devices with PC to acquired these signals and the signals are exported to MATLAB workspace for further processing.

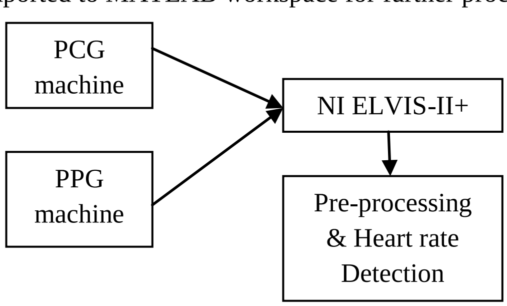


Fig.2. Block diagram of proposed methodology

"Fig. 2" depicts the block diagram of the proposed methodology. NI ELVIS-II+ DAQ make possible concurrent acquisition of these signals which is further analyzed. The several analytical approaches are now used to make diagnostic suggestions on the health of the patient. The advantage of this approach is to evaluate the basic cardio change *i.e.* heart rate from secondary signals such as PPG and PCG.

### *A. Baseline Drift Removal by Moving Average Filter*

It can be used as a low-pass filter to attenuate the noise inherent in many types of waveforms, or as a high-pass filter to eliminate a drifting baseline from a higher frequency signal. The procedure used by the algorithm to determine the amount of filtering involves the use of a smoothing factor. This smoothing factor, controlled by you through the software, can be increased or decreased to specify the number of actual waveform data points or samples that the moving average will span. Any periodic waveform can be thought of as a long string or collection of data points. The algorithm accomplishes a moving average by taking two or more of these data points from the acquired waveform, adding them, dividing their sum by the total number of data points added, replacing the first data point of the waveform with the average just computed, and repeating the steps with the second, third, and so on data points until the end of the data is reached. The result is a second or generated waveform consisting of the averaged data and having the same number of points as the original waveform [16]. The moving average (1) of a waveform can be calculated by:

$$a(n) = 1/s \sum_{n}^{s+(s-1)} \mathrm{y(n)} \qquad (1)$$

Where: a = averaged value n = data point position s = smoothing factor y = actual data point value.

- The span must be odd.
- The data point to be smoothed must be at the center of the span.
- The span is adjusted for data points that cannot accommodate the specified number of neighbors on either side.
- The end points are not smoothed because a span cannot be defined. [15]

In this case "smooth" function is applied to perform the smoothing operation for removal of baseline drift from the PPG and PCG signals "fig.7-10".

### *B. Noise Cancellation by Discrete wavelet transform*

The discrete wavelet transform (DWT) uses filter banks for the construction of the multi-resolution time-frequency plane.

*Filter banks*

A filter bank consists of filters which separate a signal into frequency bands [17]. An example of a two channel filter bank is shown in Fig.3. A discrete time signal x[n] enters the analysis bank and is filtered by the filters $H_1(z)$ and $H_0(z)$ which separate the frequency content of the input signal in frequency bands of equal width. The filters $H_1(z)$ and $H_0(z)$ are therefore respectively a low-pass and a high-pass filter. The output of the filters each contains half the frequency content, but an equal amount of samples as the input signal. The two outputs together contain the same frequency content as the input signal; however the amount of data is doubled. Therefore down sampling by a factor two, denoted by ↓ 2, is applied to the outputs of the filters in the analysis bank.

Reconstruction of the original signal is possible using the synthesis filter bank [17, 18]. In the synthesis bank the signals are up sampled (↑2) and passed through the filters $G_0(z)$ and $G_1(z)$. The filters in the synthesis bank are based on the filters in the analysis bank. The outputs of the filters in the synthesis bank are summed, leading to the reconstructed signal y [n]. The different output signals of the analysis filter bank are called sub bands, the filter-bank technique is also called sub band coding [18].

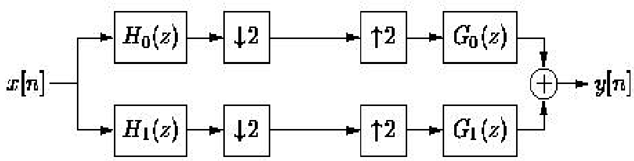

Fig.3. Two channel filter bank

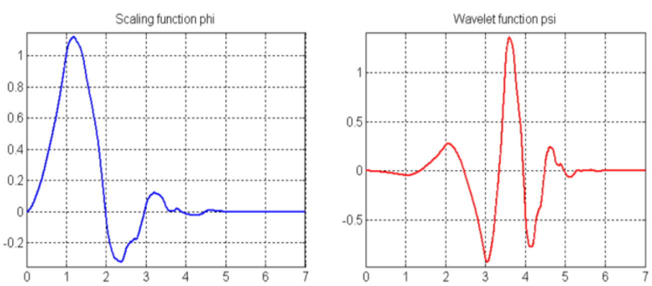

Fig.4. 'db4' wavelet

The different output signals of the analysis filter bank are called sub bands, the filter-bank technique is also called sub band coding [18]. The soft & hard thresholding by performed by implementing "ddencmp" & "wdencmp" function for 1D PPG and PCG using 'db4' wavelet. The performance is evaluated in the following section (*i.e.* result analysis) and "fig. 8-10" shows the filtering performances of PPG and PCG signals.

## III. RESULT ANALYSIS

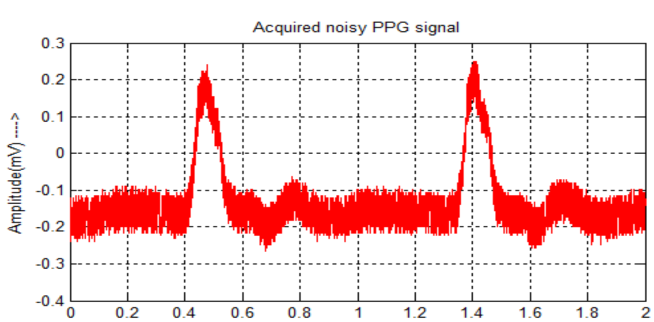

Fig.5. Acquired Noisy PPG signal of 2 sec time duration.

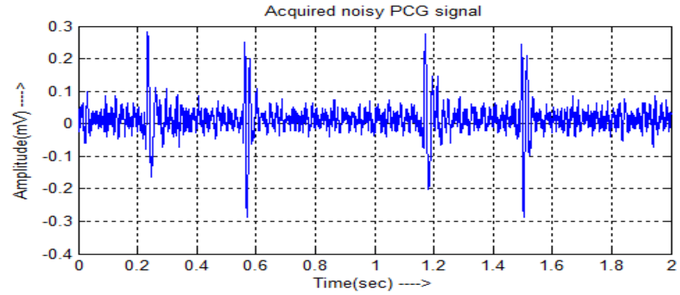

Fig.6. Acquired Noisy PCG signal of 2 sec time duration.

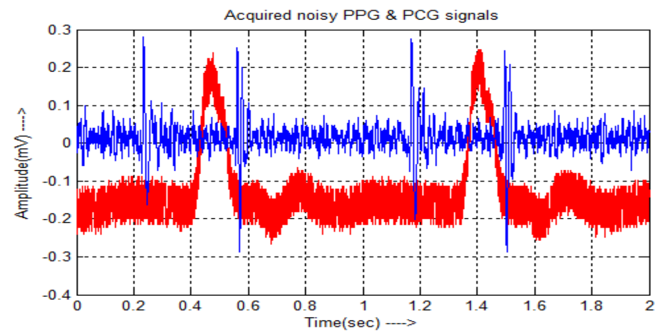

Fig.7. Concurrent plotting of acquired Noisy PPG and PCG signals.

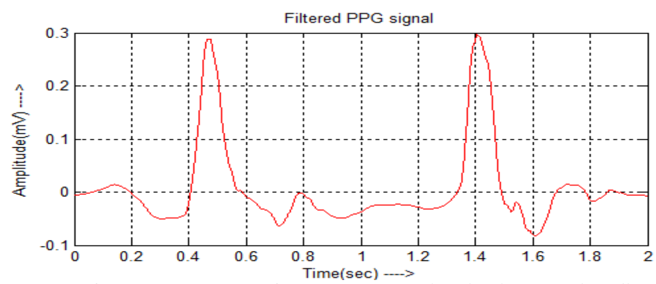

Fig.8. Noise free and baseline drift removed PPG signal using wavelet 'db4' & MAF

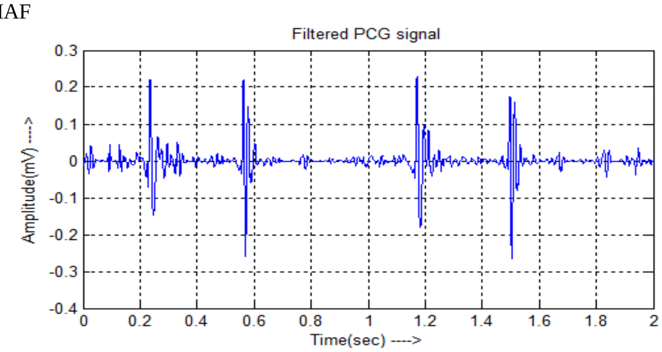

Fig.9. Noise free and baseline drift removed PCG signal using wavelet 'db4' & MAF

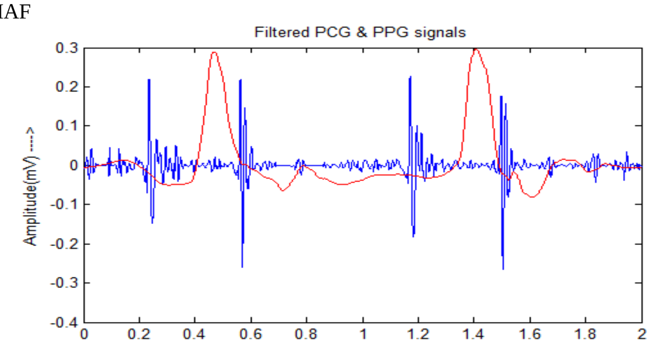

Fig.10. Concurrent plotting of noise free and baseline drift removed PPG & PCG signals using wavelet 'db4' & MAF

*Heart Rate Detection*

The filtered signals are applied through threshold technique and which identifies and counts the maximum number of samples in the signal having amplitude greater than the threshold value. This peak detection is necessary for calculation of heart beat.

- The heart beat count is calculated (2) using following equation :-

$$\frac{\text{No. of peaks}}{\{(N/fs)/60\}} \qquad (2)$$

where, N = Total length of the signal *i.e.* total number of samples & Fs = Sampling frequency.

For the subjected signals (*i.e.* PPG and PCG) the heart rate is found to be 90 bpm.

## IV. CONCLUSION

This analysis will help in correlating different features of PCG and PPG signal simultaneously. Moreover the occurrences of these signals are due to heart functioning and the basic changes such as time intervals can also be identified when concurrent analysis is done. Here we have acquired signals from healthy subject of young age whose heart rate is found to be similar *i.e.* 90 bpm. The pre-processing work *i.e.* baseline drift removal and noise cancellation is significantly performed by MAF and DWT. The further research involves in features extractions of these signals and correlative analysis in relation to different cardiovascular problems.

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