Non Invasive Detection of Coronary Artery Disease Using PCG and PPG

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Abstract. Coronary Artery Disease (CAD) kills more than a million of people every year. However, there is no significant marker for identifying CAD patients unobtrusively. In this paper, we propose a methodology for non invasive screening of CAD patients from heart sound analysis. Instead of segregating the diastolic heart sound as mentioned in prior arts, the proposed methodology extracts spectral features from the entire phonocardiogram (PCG) signal, broken into small overlapping windows. Support vector machine (SVM) is used for classification. Our methodology produces 80% classification accuracy on a dataset of 25 subjects, containing PCG data of both cardiac an non cardiac patients as well as healthy subjects. Results also reveal that a simple transfer function can be formed to identify the CAD patients if photoplethysmogram (PPG) signal is available simultaneously along with PCG.

Keywords: Coronary Artery Disease · Phonocardiogram · Classification · Photoplethysmogram · Transfer function

1 Introduction

Simple, low cost and non-invasive solutions for health monitoring are increasingly gaining attention in both developed and developing nations. Such solutions deploy a set of low cost sensors to extract meaningful information regarding physical condition of a person. Although the performance of those solutions is not comparable to the costly medical devices and investigations, they can be useful for day to day monitoring, preventive health care and alert generation. Off the shelf solutions to estimate physiological vitals like heart rate, blood pressure, ECG are already available in the market. Some of them use dedicated wearable sensors (Fitbit[1]), whereas some utilize the inbuilt sensors of smart phones along with some extra attachments (Alivecor[2]) to increase their affordability.

[1] https://www.fitbit.com/.
[2] http://www.alivecor.com/home.

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Coronary Artery Disease (CAD) is a leading cause of death, killing more than a million of people across the world every year [8]. The reason of CAD is building up of fatty deposits (plaque) on the walls of coronary arteries [8]. This makes the cavity inside arteries narrower, restricting the blood flow, causing heart attack and death. As the natural elasticity of arteries deteriorates with ageing, the elderly population is more prone to the disease. However, proliferation of sedentary life style and unhealthy diet are exposing the young generation also towards CAD.

The most common symptom to identify CAD is angina or chest pain [8]. However, there is no definite marker for CAD. Typically the doctors advise various investigations after considering self and family history and life style of the patients, complaining of angina. Which is followed by echo cardiogram, angiography or exercise stress test to diagnose early or sense CAD. However, these are all costly and invasive medical tests. Thus the importance of non-invasive CAD markers comes into the scenario.

A coarse detection of CAD is possible from different physiological signals. The most commonly used non-invasive marker is the heart rate variability (HRV) [3,6,9]. Gold standard for HRV is to measure the R-R interval distance from the ECG waveform. Research shows that CAD patients typically have a reduced HRV, compared to a normal person [6]. However, this requires the analysis of ECG signal for a prolonged time interval. The other popular marker is to analyse the heart sound [12,13]. The heart sound signal, also known as phonocardiogram (PCG), is generally recorded using a digital stethoscope. The sounds generated from a healthy heart during opening and closing of heart valves is different than that of an abnormal heart. The power spectrum of the diastolic part of PCG signal was analysed in [4] and found that the spectral energy is more at a frequency region higher than 130 Hz for the CAD patients. However PCG is extremely vulnerable to ambient noise and thus a clear segregation of diastolic heart sound is a tricky task. Moreover patients having cardiac murmur, generally have a noisy heart sound, making the segregation task further difficult. Certain prior arts [2] claimed to identify heart disease from photoplethysmogram (PPG) signal. However the dataset used by [2] is too small to take any conclusive decision. PPG is a simple non-invasive technique that measures the volumetric blood flow in capillaries [1]. PPG signal is periodic in nature whose fundamental frequency indicates the heart rate.

In this paper, we propose a methodology to identify CAD patients from spectral features of PCG signal. Instead of segregating the diastolic heart sounds, the proposed methodology splits the entire signal into small overlapping windows, each having at least one complete heart cycle. We used our in-house low cost digital stethoscope [14] to collect the PCG data in order to cut down the overall cost of the system. Also we explore the feasibility of classifying CAD patients by forming a transfer function from simultaneously recorded PPG and PCG signals. It is important to mention that, our objective is not to replace the established clinical techniques for identifying CAD, but to propose a screening system, to

be used by the physicians before subjecting a patient for an invasive medical diagnosis.

The rest of the paper is organized as follows. The transfer function based approach is explained in Sect. 2. Our proposed PCG based methodology is detailed in Sect. 3. Experimental dataset is explained in Sect. 4. Followed by results and conclusion in Sects. 5 and 6 respectively.

2 Transfer Function from Simultaneously Recorded PCG and PPG Signals

Human cardiovascular system can be considered as a closed loop system, where the heart acts as a source to pump blood to the end capillaries. In this approach, we consider PCG as the input to the cardiovascular system, representing the function of opening and closing of heart valves (source) and PPG as the output signal, representing the blood flow at end capillaries (sink). Thus a simple transfer function of the system can be formed from them. As both PCG and PPG signals of a CAD patient is different from a non CAD person, the same is expected to reflect in the transfer function. In this paper we use an adaptive filter to get the same.

An adaptive filter is a kind of digital filter, whose transfer function is adjusted over time to adapt the properties of the output signal. Adaptive filters are commonly used for noise cancellation, identification of response of an unknown system, inverse system identification etc. The block diagram of an adaptive filter is shown in Fig. 1. Here u denotes the filter input, which is the PCG signal in our case. The desired signal d is the PPG signal. Our job is to adjust the tap weights of the adaptive filter in such a way, that the filter output y matches the desired signal d, minimizing the error e, where $e = d - y$. Normalized Least Mean Square (NLMS) algorithm [5] is popularly used for calculating the filter coefficients of an adaptive filter. In this iterative process, the output (y) of the FIR filter is calculated by convolving the input signal (u) and filter taps $(\hat{w})$. The overall error, estimated from the difference between the filter output (y) and the desired output (d) is used to adjust the tap weights based on the principle of steepest descent. NLMS guarantees the stability of LMS algorithm by normalizing the learning rate with respect to the input signal.

Simultaneously recorded PPG and PCG signals are required for the validation of the above-mentioned approach. We used a freely available dataset [11], that contains both the signals sampled at 1000 Hz. The dataset contains, 2 normal adult subjects and 2 CAD patients. The CAD patients include an 11 year old female subject having cardiac murmur with aortic stenosis and a 14 months old female subject having pulmonary stenosis, ventricular septal defect and pulmonary hypertension. Tap size of the filter is chosen as 1024. Frequency response of the transfer function for all 4 subjects present in the dataset is shown in Fig. 2(a). It can be visualized that, the overall spectrum is much noisier for the CAD patients due to the presence of high frequency components in their PCG signals due to cardiac murmur. For a detailed inspection, we divide the entire

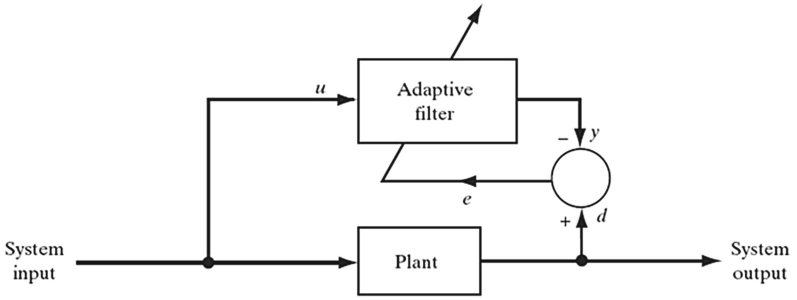


Fig. 1. Block diagram of adaptive filter

spectrum shown in Fig. 2(a) into 16 bins and the variance of spectral amplitude at each bin is shown in the bar chart of Fig. 2(b) for all the subjects. This clearly shows that above bin 5, the amplitude variance of the CAD patients is significantly higher compared to the normal subjects.

3 Proposed Methodology

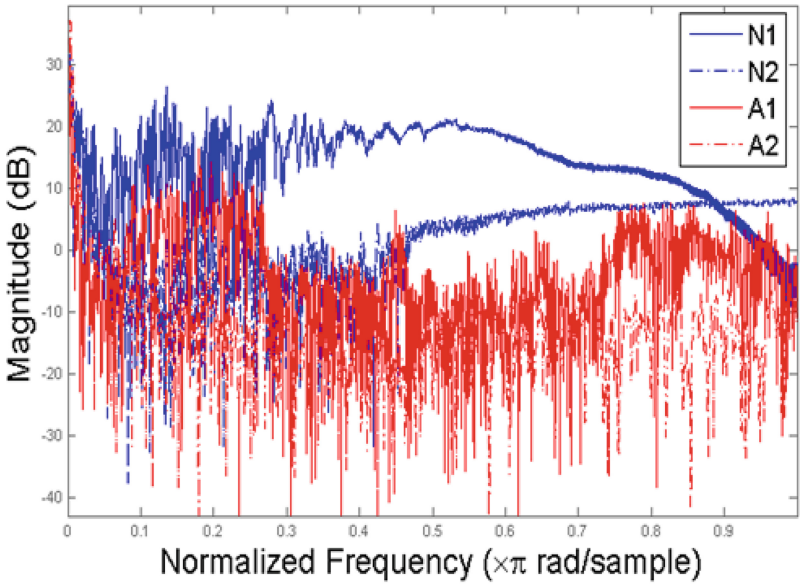
In spite of its simplicity and robustness, The method discussed in Sect. 2 has the following limitations,

- PPG and PCG signals, need to be completely synchronized
- Both signals should have equal sampling rate

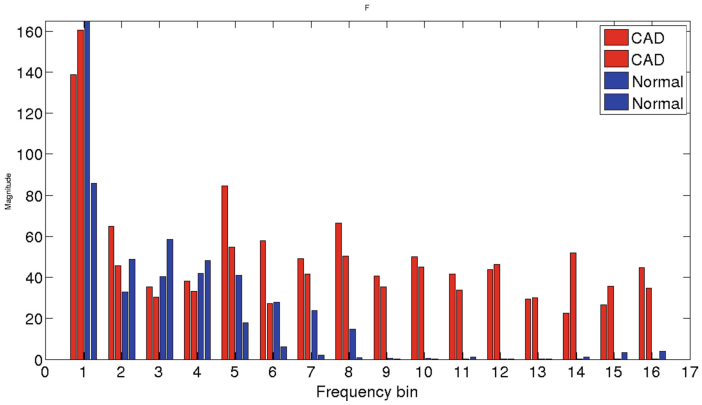
However, in practical scenario, the task of synchronizing multiple biomedical signals recorded at different sampling rates has severe deployment issues. Sampling rate of a commercial pulse oximeter, that captures PPG signal is around 100 Hz. On the other hand, raw audio signals are sampled at several KHz of sampling rate in a digital stethoscope. Up-sampling of PPG signal and/or downscaling of PCG signal introduce noise in both the signals, making the transfer function unreliable. Thus we propose an alternative approach, to identify CAD patients using PCG as the only source of input. Block digram of the proposed methodology is shown in Fig. 3. Different components are further illustrated in the following subsections.

3.1 Preprocessing

Being a wide band signal, PCG is highly susceptible to noise. Ambient signals present in the audible range is the major source of such noise. Noise, generated due to friction at the contact region of the diaphragm of stethoscope and the subject body also heavily corrupts the signal. Important information regarding heart sound is typically confined within 150 Hz. Thus, we remove all frequency components above 500 Hz using a low pass filter. Subsequently the signal is down sampled at 1000 Hz before further processing.



(a) Frequency Response of Transfer Function N1, N2:Normal, A1, A2: CAD



(b) Variation of Spectral Amplitude at Different Frequency Bins

Fig. 2. Results of transfer function based approach on dataset [11]

3.2 Windowing

A PCG signal is non-stationary in nature due to heart rate variability. Thus the raw signal is broken into rectangular windows with 50% overlapping to restore the temporal information. Selecting of the optimum window length is a tricky task. A prolonged window size may end up in mixing up multiple cardiac cycles in a single window. Thus the window size should be short enough to preserve the temporal information corresponding to individual cycle. We can safely assume

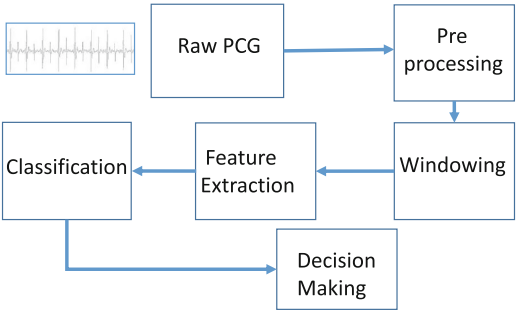


Fig. 3. Block diagram of proposed methodology

that heart rate of a cardiac patient also can not go below 30 bpm. Thus, the window size is chosen as 2 s in our application to ensure the presence of at least one complete cardiac cycle in each window.

3.3 Feature Extraction

Feature extraction is the most important task in any classification problem. Several time and frequency domain PCG features are explored in this paper and the relevant feature set is chosen based on their Maximal Information Coefficient (MIC) [10] scored. MIC measures the statistical relationship existing between a pair of dataset by constructing grids with various sizes to find the largest mutual information between the data pair. MIC gives a score between 0 and 1 to indicate that relationship strength.

Most of the available literatures [4,13] segregate S_1 and S_2 heart sounds from PCG signal for feature extraction. However, segregation of heart sounds is not always very trivial. The second heart sound (S_2) is often suppressed due to ambient noise. Moreover, PCG signal of a cardiac patient having murmur may contain extra heart sounds (S_3, S_4) corrupting S_1 and S_2. Figures 5 and 6 show the detection of S_1 and S_2 from PCG signal of a normal healthy subject and a subject having cardiac murmur using the state of the art approach presented in [7]. Results show that detection of S_2 is often missed especially in case of cardiac murmur. Thus instead of segregating the S_1 and S_2 regions, we attempt to process the entire signal, by splitting into small overlapping windows.

For extracting frequency domain features, we compute short-time Fourier transform (STFT) of every window to get the spectrum. For k^{th} time window $W_k(t)$, if $S_k(\omega)$ be the corresponding amplitude of spectral power in frequency domain and N be the length of the window, then the optimum feature set based on top 5 MIC scores includes

(1) Ratio of spectral power between 0–100 Hz and 100–150 Hz
(2) spectral centroid ($cen = \sum_{\omega=1}^{N} \omega * S_k(\omega) / \sum_{\omega=1}^{N} \omega$)
(3) spectral roll-off ($SR = 0.85 * \sum_{\omega=1}^{N} S_k(\omega)$)

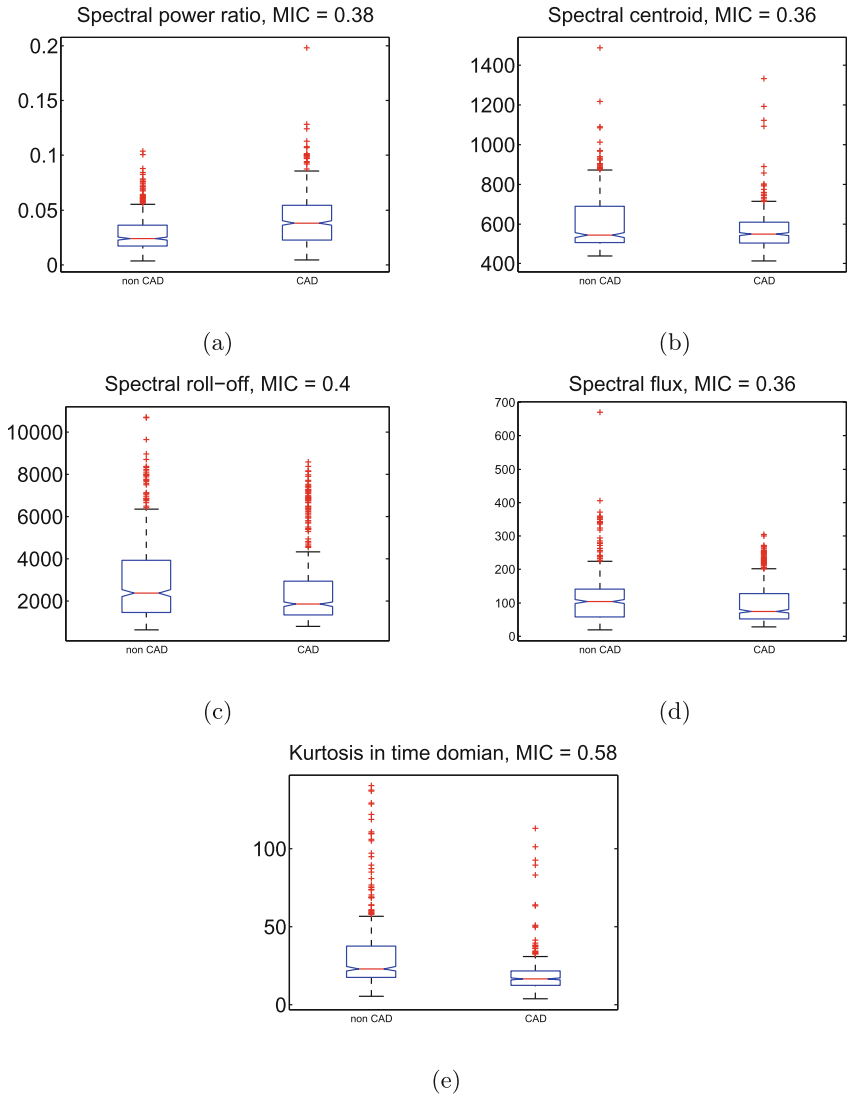
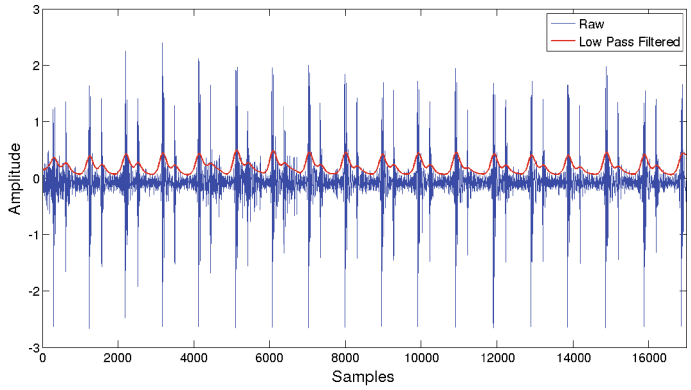


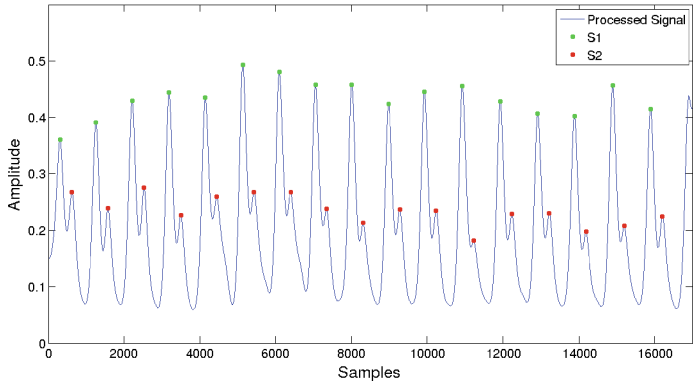
Fig. 4. Box plots of PCG features for CAD and non CAD subjects

(4) spectral flux ($||S_k(\omega) - S_{k-1}(\omega)||$)
(5) kurtosis of the signal window in time domain

In descriptive statistics, box plot is a standardized graphical way of displaying the distribution of data, based on five metrics e.g. minimum, first quartile, median, third quartile, and maximum. Figure 4, shows the box plots as well as MIC scores of different PCG features applied on our dataset detailed in Sect. 4. It can be observed that CAD patients typically have a higher spectral power



(a) PCG Signal of a Normal Subject



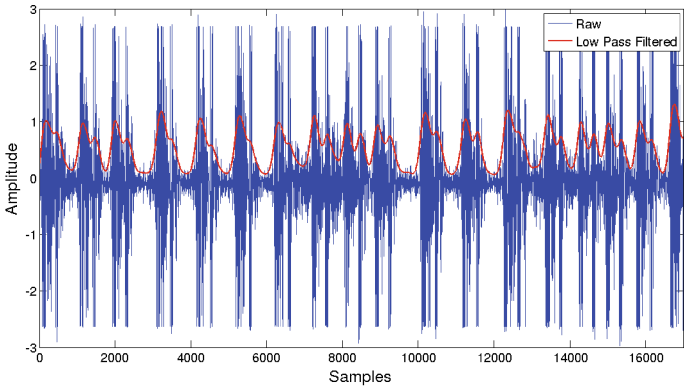
(b) Detection of S_1 and S_2

Fig. 5. Detection of S_1 and S_2 heart sounds on normal PCG signal

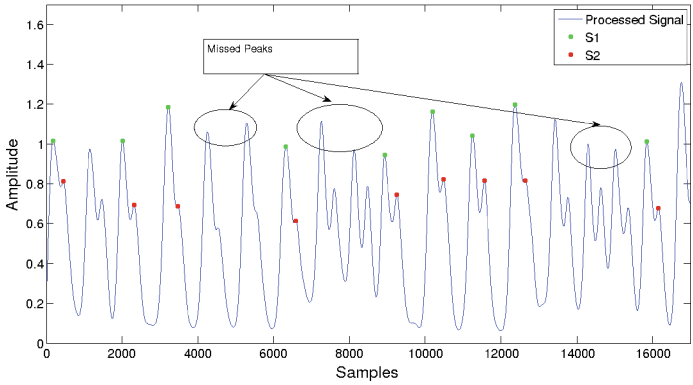
ratio but a lower spectral centroid, spectral roll off, spectral flux and kurtosis values compared to non CAD subjects.

3.4 Classification

Support Vector Machine (SVM) is used for classification. Both linear and non linear SVM were explored and it is found that non-linear SVM with Radial Basis Function (RBF) kernel produces the optimum classification performance. Like feature extraction, classification is also performed on individual window. The final decision making (CAD or non CAD) is done based on majority voting across all the windows present in a particular test signal.



(a) PCG Signal of a Subject having Cardiac Murmur



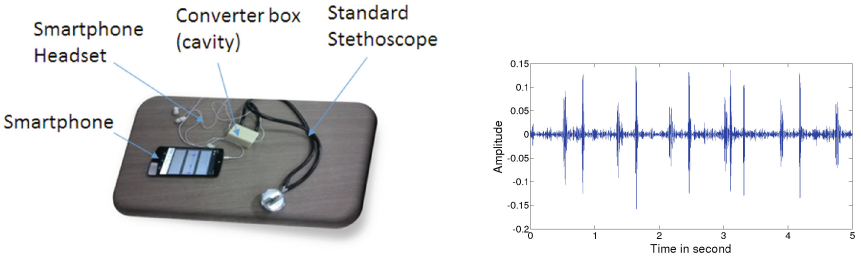
(b) Detection of S_1 and S_2

Fig. 6. Detection of S_1 and S_2 heart sounds on murmur PCG signal

4 Experimental Dataset

We created a corpus of CAD and non CAD subjects to conduct our experiments. A total of 11 healthy individuals, aged between 24 ± 2 years, having no known cardiovascular disease and 4 patients (aged 56 ± 11 years) being treated for non cardiovascular diseases in a large urban hospital in Kolkata, India participated as non CAD subjects. Another 10 angiography-proven patients (aged 61 ± 12 years), were selected from the same hospital as CAD subjects. According to their consultant physicians, out of 10 CAD subjects, 2 subjects had a marginal 30% blockage and the rest having a blockage of 70% or higher.

Heart sound was collected using our in-house digital stethoscope [14], which is a low cost replacement of a commercial digital stethoscope. The metal earpiece of a clinical stethoscope is removed and its tube ends are inserted into a 3-D printed rectangular cavity. In order to hear the heart sound, the microphone of a



(a) In-house Digital Stethoscope (b) Sample PCG Waveform

Fig. 7. Digital stethoscope with a sample PCG waveform

3.5 mm jack audio headset is placed inside the cavity with both ends coming out from the enclosure through small grooves. The enclosure is then sealed to form an air-tight cavity. The dimension of the cavity is chosen so that it does not produce any acoustic distortion till 500 Hz to preserve the properties of heart sound. The microphone jack is connected to a Nexus 5 Android phone, for recording and storage purpose. Figure 7(a) shows a labelled diagram of the digital stethoscope. Figure 7(b) on the other hand shows a sample PCG waveform recorded using the device.

5 Experimental Results and Discussion

For an exhaustive performance analysis on a limited dataset, we performed Leave One Out Cross Validation (LOOCV) to report our results. According to LOOCV technique, to test each of N entries present in the dataset, the remaining $N-1$ entries are used to train the classifier, and the same is repeated for N times, making N different training-testing scenarios.

First we tested the performance of our proposed methodology on the freely available dataset in [11]. Being a very clean dataset, We got the confusion matrix shown in Table 1 with 100% detection accuracy. However as we move on to the dataset captured using our in-house digital stethoscope, containing some noisy PCG signal, the performance of the proposed methodology drops. The confusion matrix is shown in Table 2. Results show that, the proposed methodology can detect the non CAD subjects more accurately compared to CAD patients. A detailed observation further reveals that, out of 4 false negative cases (actually CAD but predicted as non CAD), the proposed classifier failed to detect 2 borderline CAD patients, having 30% blockage (mentioned in Sect. 4). Inclusion of more such patients might be required in the training set in order to correctly detect such cases. The only false positive (actually non CAD but detected as CAD) occurrence, was a male subject who was being treated in the hospital for asthma related disease. It is remained to be seen, whether the PCG signal of a asthmatic patient contains any signature similar to a CAD patient.

Table 1. Confusion matrix on dataset [11]

Predicted	Actual	
	CAD	Non-CAD
CAD	2	0
Non-CAD	0	2

Table 2. Confusion matrix on our dataset

Predicted	Actual	
	CAD	Non-CAD
CAD	6	1
Non-CAD	4	14

Sensitivity and specificity are popularly used for measuring the performance of a binary classifier. In our application, sensitivity or true positive rate measures the fraction of CAD patients being correctly identified whereas specificity or true negative rate measures the fraction of non CAD subjects being correctly identified by the classifier. For an ideal system both sensitivity and specificity should be closer to 1. In our case the overall sensitivity and specificity of detecting CAD patients are found to be 0.6 and 0.93 respectively, with an overall 80% classification accuracy. A high specificity of the classifier indicates that, there is a very little chance of declaring a non CAD patients as CAD, which helps the doctor to prescribe lesser number of invasive medical tests to angina patients. However, due to low sensitivity, there is a high chance that a CAD patient might be classified as non CAD. This needs a significant improvement in order to realize the screening system.

6 Conclusion and Future Work

In this paper we propose a non invasive methodology to classify CAD patients. The proposed methodology extracts time and frequency domain features from PCG signal to perform the task. Results show that, in spite of performing well on a clean dataset, the sensitivity of the proposed algorithm still needs improvement before actual system deployment. Results also show that if PPG and PCG signals are available simultaneously at an equal sampling rate, a transfer function can be formed to detect CAD patients. Our future work will focus on cleaning of the noisy PCG data, as well as fusion of PCG signal with other non-invasive biomedical signals (PPG, ECG etc.) to boost up the overall confidence score of the system. Also we are experimenting the feasibility of estimating the percentage blockage in coronary artery of a cardiac patient in a non invasive manner, enhancing the proposed methodology.

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