A Fusion Approach for Non-invasive Detection of Coronary Artery Disease

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ABSTRACT

Coronary Artery Disease (CAD) kills millions of people every year across the world. In this paper, we present a novel idea of a low cost, non-invasive screening system for early detection of CAD patients by fusion of phonocardiogram (PCG) and photoplethysmogram (PPG) signals. Two sets of time and frequency features are extracted from both the signals. Support Vector Machine (SVM) is used to classify each subject separately based on both the feature sets. Finally, the outcomes of the two classifiers are fused at the decision level, depending upon the maximum absolute distance of the test datapoints form their respective SVM hyperplane. We created a corpus of 25 subjects, containing 10 CAD and 15 non CAD subjects using low cost non-medical grade devices. Results show that either of PCG or PPG based classifiers yields sensitivity and specificity scores close to 0.6 and 0.8 respectively in identifying CAD. Whereas, a significant improvement in both sensitivity (0.8) as well as specificity (0.93) can be simultaneously achieved by incorporating the proposed fusion approach.

ACM Classification Keywords

D.4.7 Software Engineering: Organization and Design - Pervasive Health, Ubiquitous System

Author Keywords

Preventive healthcare, Coronary Artery Disease, Non-invasive, Classification

INTRODUCTION

Coronary Artery Disease (CAD) is a common heart disease and also a leading cause of death. CAD is formed due to deposition of cholesterol and other fatty materials over time on the inner walls of coronary arteries, thus restricting the normal blood flow, causing chest pain and heart attack. In spite of numerous works, an early non-invasive detection of CAD is an open research area till date.

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Researchers found that certain non-invasive biomedical markers can identify CAD. The most commonly used marker for the same is Heart Rate Variability (HRV) [5]. HRV of a CAD patient is generally lesser compared to a normal person [8]. However, the gold standard technique for measuring HRV for a long duration, from the successive RR intervals of ECG is largely obtrusive and often impractical. Analysis of heart sound signal or phonocardiogram (PCG) can also be found in literature ([7], [2]) as an alternative approach. Research reveals that, the spectral energy of diastolic heart sound above 130 Hz is higher for a CAD patient compared to a non CAD subject [2]. However, PCG signal is extremely vulnerable to ambient noise and thus an accurate segregation of diastolic heart sound may not always be trivial. Moreover, many people have a faint heart sound, making them further difficult to process. Hence, accurate estimation of CAD from a single physiological signal is still an unsolved problem.
Photoplethysmogram (PPG) is a simple low cost non-invasive technique that measures the instantaneous blood flow in capillaries. Time, frequency and morphological features of PPG are widely used to estimate several physiological parameters including heart rate, blood pressure, HRV etc with commending accuracy. In this paper we propose a novel approach for classification of CAD patients using both PCG and PPG. For the ease of deployment, PPG is used for extracting HRV related features instead of ECG. It is to be noted that, HRV related features can also be derived from PCG. However, acquisition of heart sound for a prolonged duration using a digital stethoscope is uncomfortable for a user. Two separate classifiers are created based on PCG and PPG features. Finally we present a fusion approach to combine the outcomes of the two classifiers for an improved accuracy.

EXPERIMENTAL DATASET

Our experimental dataset includes CAD patients with ranging percentages of heart blockage while non CAD population consists of both healthy subjects as well as non cardiac patients. Initially, 11 healthy subjects aged between 22-25 years with no prior history of cardiovascular diseases were selected as non CAD subjects. 4 more patients, aged between 45-68 years, being treated in an urban hospital in India for non cardiovascular diseases, were also included in the dataset. Finally, 10 angiography-proven CAD patients, aged between 38-82 years were selected from the same hospital. Thus the corpus had grown into a total of 25 subjects, including 15 non CAD and 10 CAD subjects. 2 out of 10 CAD patients had marginal heart blockage of 30% while the rest had a blockage of 80%. We obtained the necessary approval from the hospital ethics committee along with written consent from individual subject before collection of data.

We used our in-house low-cost digital stethoscope for collection of heart sounds. This device [1] comprises an acoustically designed 3D printed cavity that can be attached to a smart phone for digitalizing and storing heart sounds. PCG was captured from each subject for a minute at a sampling rate of 8000 Hz in an uncontrolled environment of the catheterization laboratory of the hospital. This was done purposefully to make our system robust enough to deal with the background noise present in the signal. Subsequently, PPG was collected from the right hand index finger using a commercial pulse oximeter at 60 Hz. The duration of each PPG recording was fixed for five minutes so that information regarding HRV can be preserved in the measurement.

PROPOSED METHODOLOGY

Figure 1 depicts our proposed methodology. A detailed description of different steps is provided subsequently.

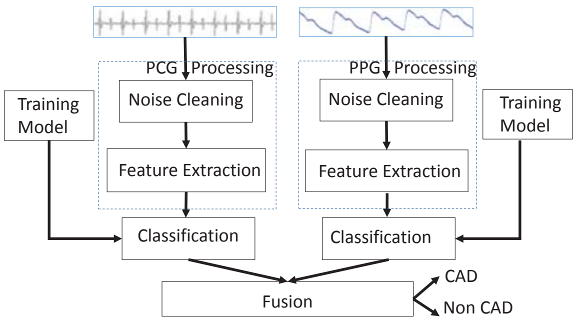


Figure 1: Proposed System Architecture

PCG Signal Processing

Raw PCG signal is extremely vulnerable to ambient noise in audible range. Even in a constrained quiet environment, the frictional noise generated at the contact region of human body and stethoscope corrupts the signal heavily. Segregation of fundamental heart sounds (S1, S2) from a noisy PCG is a tricky task. We applied the logistic regression based HSMM algorithm, developed by Springer *et al* [3] for segregating heart sounds on one very clean signal and one partially noisy signal, taken from our dataset. Figure 2 demonstrates that the performance of the algorithm degrades on noisy signal. Thus, instead of segregating the fundamental heart sounds, we decided to take a window based approach.

The relevant information regarding heart sound is typically stored below 500 Hz [2]. A low pass filter is used to remove all the frequency components above 500 Hz.

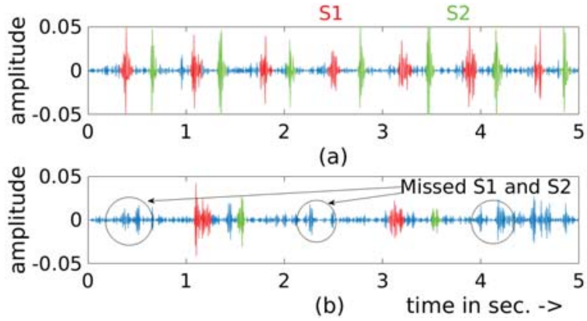


Figure 2: SoA Technique for identifying S1, S2 Regions on (a) Clean and (b) Noisy PCG

Subsequently, the signal is broken into small overlapping windows to retain the temporal information corresponding to individual heart beat. Since the heart rate of a stable cardiac patient does not go below 30 bpm, a window length of 2 seconds duration ensures the presence of at least one complete heart beat in every window. Time and frequency domain features are extracted from each window.

Table 1: Ranges of PCG Features in our Dataset

Feature name	CAD Range *mean* ± *std*	Non CAD Range *mean* ± *std*
Mean spectral power ratio between 0-100 Hz and 100-150 Hz	0.041 ± 0.017	0.031 ± 0.012
Mean spectral centroid $(\sum_{\omega=1}^{N} \omega * S_k(\omega) / \sum_{\omega=1}^{N} \omega)$	563 ± 60	589 ± 88
Mean spectral roll-off $(0.85 * \sum_{\omega=1}^{N} S_k(\omega))$	2486 ± 1660	2882 ± 1512
Mean spectral flux $(\lvert\lvert S_k(\omega) - S_{k-1}(\omega)\rvert\rvert)$	98.21 ± 55.28	113.22 ± 49.82
Mean kurtosis of all time window	18.53 ± 5	30.79 ± 13.95

Table 1 indicates that CAD patients typically possess a high value of spectral power ratio but reduced spectral centroid, roll-off, flux and time domain kurtosis values compared to a non CAD subject. For extracting frequency domain features, we compute the Short Time Fourier Transform (STFT) of each window to get the spectrum. In Table 1, for k^{th} time window $W_k(t)$, we assume N and $S_k(w)$ to be the length of the window and the corresponding spectral power amplitude respectively for representing the features.

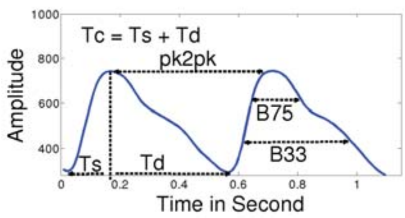


Figure 3: Sample PPG Signal, indicating some of its Features

PPG signal Processing

A PPG signal also contains several noise components. The low frequency noise is because of the respiratory rate of the subject (typically 14 -18 times/minute). Several high frequency noise components are also there due to motion artifacts and circuit noise of the sensor device. To mitigate those, raw PPG is fed into a bandpass filter having cut-off frequencies of 0.5 Hz and 10 Hz. Figure 3 shows 2 complete cycles of a sample PPG signal, indicating some of its features. Table 2 details different features used for classification along with their ranges for CAD and non CAD subjects. Out of these, feature 1, 2, 3, 5, 7, 9 and 11 are related to HRV and the rest are related to pulse shape. Some of the features described here are detailed in our earlier waork [6], while the rest are new features proposed in this paper.

Table 2: Ranges of PPG Features in our dataset

Feature name	CAD Range *mean* ± *std*	Non CAD Range *mean* ± *std*
Spectral power of NN intervals in 0-0.04 Hz	0.99 ± 0.2	1.32 ± 0.3
Spectral power of NN intervals in 0.04-0.15 Hz	0.05 ± 0.02	0.08 ± 0.01
Spectral power of NN intervals in 0.15-0.4 Hz	0.006 ± 0.001	0.008 ± 0.001
Mean of pulse duration (T_c) in seconds	0.77 ± 0.14	0.85 ± 0.14
Std of pulse duration (T_c)	0.07 ± 0.05	0.09 ± 0.05
Mean of relative crest time (T_s/T_c)	0.29 ± 0.03	0.27 ± 0.03
Std of relative crest time (T_s/T_c)	0.02 ± 0.01	0.03 ± 0.01
Mean of relative diastolic time (T_d/T_c)	0.71 ± 0.04	0.73 ± 0.03
std of relative diastolic time (T_d/T_c)	0.03 ± 0.01	0.04 ± 0.02
Mean of time ratio (T_d/T_s)	2.49 ± 0.49	2.81 ± 0.53
std of of time ratio time (T_d/T_s)	0.35 ± 0.25	0.43 ± 0.19

Classification

Support Vector Machine (SVM) is used for classification. We explored both linear and non-linear SVMs and found that, non-linear SVM with a Radial Basis Function (RBF) kernel produces the optimum performance for both PCG and PPG features.

Fusion of PPG and PCG Classifiers

SVM separates two classes in a multidimensional feature space by fitting an optimal separating hyperplane to the training samples by maximizing the margin between the hyperplane and the closest training samples (support vectors). For a given sample, higher the distance to the hyperplane, the more reliable the output class label is. In our fusion approach, if there is a classification mismatch between PCG and PPG based classifiers for a test case, the classifier producing higher absolute distance of the test data-point form its separating hyperplane is considered as the reliable source for final decision making.

EXPERIMENTAL RESULTS

For an exhaustive validation on a relatively smaller dataset, we used Leave One Out Cross Validation (LOOCV) approach for reporting the results. Performance analysis was done in terms of sensitivity (Se) and specificity (Sp) of identifying CAD and overall accuracy is measured as $Acc = (Se + Sp)/2$.

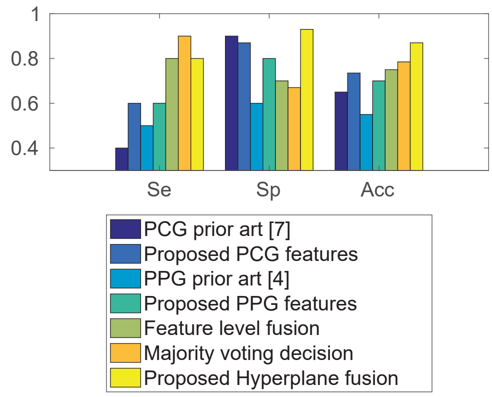
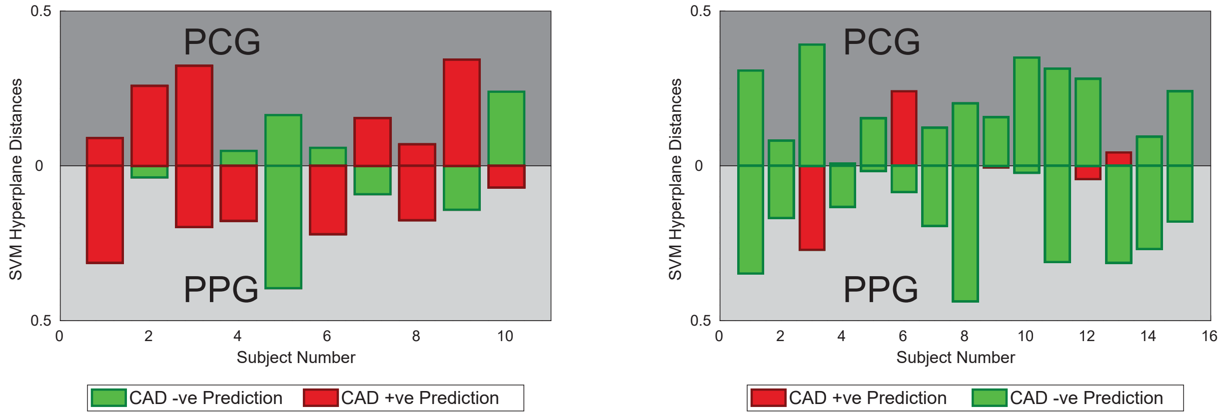


Figure 4: Comparison between Different Approaches

Figure 4 shows a comparative analysis among different methodologies explored in this paper along with certain popular prior art techniques. Prior art [7] models the diastolic region of PCG using an autoregressive (AR) model for identifying CAD, whereas prior art [4] is a PPG based approach that considers relative crest time as the discriminative feature. It can be observed that both our PCG and PPG based classifiers outperform prior art [7] and [4]. However, the sensitivity scores obtained by either of them is largely unsatisfactory (0.6). We also performed a simple feature level fusion, where all 16 features (5 PCG features + 11 PPG features) are combined to form a composite feature set for classification. It is observed that in spite of an improvement in sensitivity (0.8), the specificity (0.7) falls, resulting in an overall accuracy score, similar to the earlier approaches. Subsequently, we applied a simple majority voting based fusion at decision level as a benchmark approach. Here a subject is declared as CAD, if either of the classifiers marks him/her as CAD. Although a very high sensitivity (0.9) is achieved in this approach, the specificity drops significantly (0.67), resulting in a minimum improvement in overall accuracy (0.79).

A significant improvement in both sensitivity (0.8) and specificity (0.93) can be simultaneously achieved by incorporating the proposed hyperplane based fusion approach, resulting in the maximum accuracy ($Acc = 0.87$) among all. Figure 5 provides a detailed outcome of the proposed fusion technique on the entire dataset. Here, we have shown the predicted labels by both the classifiers along with their absolute distance values from the SVM hyperplane to show the effect of fusion on an individual level. As shown in Figure 5(a), out of 10 CAD subjects,



(a) CAD subjects

(b) non CAD subjects

Figure 5: Subject Level Analysis of Hyperplane based Fusion Approach

there is a mismatch between PPG and PCG classifiers in 6 cases (Subject 2, 4, 6, 7, 9, 10). In 5 out of 6 such cases (except Subject 10), the proposed fusion technique yields the correct decision. However, in non CAD subjects, 5 out of 15 cases (Subject 3, 6, 9, 12 and 13 of Figure 5(b)) had this mismatch of decisions and the proposed fusion technique was able to correctly resolve 4 out of those 5 conflicts. A closer inspection further revealed that one of the two borderline CAD patients having 30% blockage (Subject 5 of Figure 5(a)) was missed by both PPG and PCG classifiers. A possible reason is that PPG and PCG features of those subjects are similar to a normal person rather than a severe CAD patients, hence they are often very difficult to be identified even by the doctors. The only false detected non CAD subject (Subject 6 of Figure 5(b)) was a patient being treated for asthma related issues. In spite of being detected correctly by the PPG classifier, the fusion algorithm fails in this case due to the strong confidence score provided by the PCG classifier for CAD. It remains to be seen whether, PCG features of an asthma patient contains any similarity of a CAD patient.

CONCLUSION

This paper describes a decision level fusion approach for classifying CAD patients using PCG and PPG signals. Initial, results show that compared to a single signal based approach, a higher sensitivity and specificity can be simultaneously achieved by fusing both the signals. Our present focus is to successfully validate the proposed methodology on a larger dataset to test its effectiveness. Our future work includes investigating other popular sensor fusion techniques along with incorporating other non-invasive biomedical markers like single lead ECG, thermal imaging sensor etc for an improved accuracy. Also we are analysing the feasibility of non-invasive estimation of heart blockage level of a cardiac patient as an extension of the current classification approach.

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