Non Invasive Cardiovascular Health Assessment in Post-adolescent Age Group Using Augmentation Index

Sai Karun, Suhan S. Nath, Kunal Bharathi, Manjunath Gaonkar, and B. Niranjana Krupa

Abstract

This paper presents a non-invasive method of classifying a subject's health into either one of two classes depending on the condition of the subjects' cardiovascular health. Novelty of the work lies in segregating the subjects who had good cardiovascular health and the subjects who were at risk. In the proposed work, VPG signals and other general information such as weight, height, BP were collected from 38 individuals in the post-adolescent age group. Furthermore, a signal from a person who was known to have good cardio vascular health was collected. This signal became the reference that was used to compare with other signals. After the initial pre-processing, the PPG and APG were obtained from the VPG. Then a total of 7 features of the wave contour from the APG and PPG signals were extracted. Based on the Augmentation Index the signals were classified into two classes using SVM and ELM classifiers. Where one class represented healthy individuals and the other class represents the individuals at risk of CVD. The average values of the extracted features were used and the final accuracy obtained was also an average value. The accuracy obtained using ELM classifier with K-fold cross validation was 77%. Whereas the efficiency achieved using SVM was 94.59%. Hence the proposed method can be used to assess the vascular health analysing PPG signals in the post-adolescent age group.

Keywords

Cardiovascular diseases • Photoplethysmogram (PPG) • Velocity photoplethysmogram (VPG) • Acceleration photoplethysmogram (APG) • Extreme learning machine (ELM) • Support vector machines (SVM)

1 Introduction

Cardiovascular diseases (CVD) are identified as one of the leading causes of death in the world today, accounting for 17.3 Million cases in 2013. CVDs are the diseases involving the heart or blood vessels. CVDs are the single largest cause of death worldwide [1]. The trends indicate the seriousness and danger that CVDs pose. The current tests that indicate whether a person has CVD is time consuming and very expensive. PPG is an optical method that is non-invasive and is used to detect flow of blood and changes in volume in peripheral vessels and smaller arteries at various locations in the body [2]. Light travelling through biological tissue can be absorbed by various substances. Almost all the changes in blood flow are mainly observed in the arteries and arterioles. The changes in the blood flow volume in the microvascular bed of tissue is detected using PPG sensor via reflection from or transmission through the tissue [3].

The peaks and valleys which are needed for analysis may not be very clear in a few PPG signals [4]. As a result, the Velocity Photo Plethysmogram (VPG), the first derivative of PPG is used. In the original PPG, sometimes there is a difficulty in detecting small changes in the phase of the

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inflections. So as an alternative the second derivative of the PPG signal is obtained which is also known as the Acceleration Photo Plethysmogram (APG). Even though the clinical significance of PPG has been documented there remains a lack of documentation on how healthy a person is in a young age group. Recent studies have found that 230,600 heart attack hospitalizations between 2001 and 2010 have occurred for patients between the ages 30 and 54 [5]. Another study also shows 10% of all heart attacks occur before the age of 45 [6]. So it becomes vital to identify people who are at risk of CVDs so as to prevent it. Post-adolescent age group consists of people in between 19 and 25 years. Thus, this investigation, is aimed at identifying people who are not healthy as others in the post-adolescent age group. Identification of healthy and unhealthy in the proposed work is done based on the Augmentation Index (AI) calculated from the APG signal [7].

An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. ELM theories show that the hidden neurons are important but can be randomly generated and independent from applications. ELMs, which can be biologically inspired, offer significant advantages such as fast learning speed, ease of implementation, and minimal human intervention.

In this study, algorithms have been developed to extract various features and using these features healthy and unhealthy classes in the post adolescent age group based on AI using ELM and SVM classifiers have been identified.

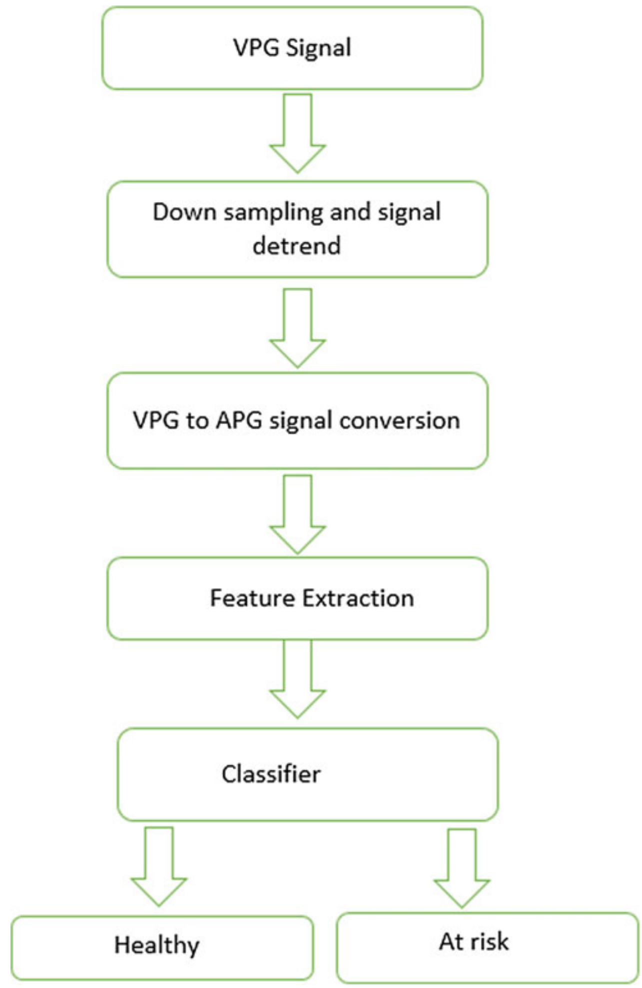

Fig. 1 Flow of the proposed work

2 Methodology

This section provides a detailed explanation of data acquisition, signal preprocessing, feature extraction and classification. Below illustrates the flow diagram of the work that was carried out (Fig. 1).

2.1 Dataset Overview and Acquisition

The dataset used in the current work consists of 36 VPG signals consisting of both genders were recorded using the pulse sensor [8]. In accordance with the declaration of Helsinki, informed consent was obtained from all the subjects. These signals were recorded for a duration of 2 min and sampled at a frequency of 50 Hz.

Before the signal was collected, it was verified whether the subjects satisfied a few inclusion criteria. Subjects were both non-diabetic and non-hypertensive, hadn't consumed food or caffeine based products six hours prior, alcohol products twenty-four hours, hadn't smoked two hours and hadn't exercised two hours prior to the recording [9].

As the procured signals had to be compared with a base/reference, a PPG signal was collected from an athlete who was known to have good cardiovascular health. The athlete belonged to the same post-adolescent age group. The Pulse Sensor was placed on the right hand index finger of the subject [10] while they were made to sit in upright position [11]. The VPG was obtained from the sensor.

Omron Blood Pressure Monitor, HEM-7120 was used to find the Blood pressure of the subject. This was noted before the VPG signals were recorded. The weight of each subject was measured using a digital weighing machine. Different demographic data such as height, weight, blood pressure, type of diet, etc. was collected. From their height and weight, Body Mass Index of each individual was calculated in kg/m^2. Information such as blood pressure, smoking status and alcohol consumption can give an indication of the cardiovascular health. A protocol was developed and followed during data acquisition to ensure that the data was uniform.

2.2 Preprocessing

In this section, unwanted artifacts, baseline wandering etc. were removed from the signal to make it suitable for feature extraction. The signal was first down sampled by a factor of 975, then, the signal was detrended to remove the trend from it. Next, the signal was split into 4 windows where each window consist of 1500 samples each which corresponds to 30 s, now one window was selected and the VPG signal was passed through a FIR bandpass filter to get the first derivative of VPG called the APG signal. A filter with Order 50, lower and upper cut-off frequencies of 0.1 and 10 Hz respectively. These filter specifications have been derived based on the power spectral density of VPG. Finally each cycle was extracted from the selected APG window.

2.3 Feature Extraction

A set of six features extracted from PPG, VPG and APG signals used in the work are presented below:

B/A Ratio. This ratio was determined from the Acceleration plethysmogram (second derivative of the PPG signal). The absolute values of the ‘a’ and ‘b’ waves of the APG were taken as ‘A’ and ‘B’ respectively [4].
P0/P1 Ratio. This ratio was determined from PPG and was calculated as the amplitude from the foot to the valley point (point where dichrotic notch is located) divided by the amplitude from the foot to the systolic peak [4].
ΔTBVP/T. ΔTBVP represents the absolute time delay between the diastolic and the systolic peaks and T represents the time period of the PPG signal [4]. The time factor to be multiplied to the samples was 0.02 s as the signal had a sampling frequency of 50 Hz.
Stiffness Index (S.I.). The assumption made here was that the path length was proportional to a person’s natural height, the stiffness index has been defined as S.I. (m/s) = Body Length/ΔTBVP.
ΔTBVP was found in the same way as mentioned above. The data from the demographics was used along with ΔTBVP to find the S.I. [4]. Area under the systolic peak. The area under the systolic peak was calculated as the area lying under the systolic peak and the foot of the wave [4].
Augmentation Index (A.I.). Augmentation Index was defined as the ratio of the amplitude of late systolic peak(Y) to the amplitude of the early systolic peak (X) [12] (A.I. = Y/X).

Augmentation index has been shown to be a sensitive indicator of arterial status and known to be a predictor of adverse cardiovascular events in a diverse patient population [7]. The early systolic peak maps to the B wave in the APG, similarly, the late systolic peak maps to the C wave in the APG [12].

Detection of A wave was done by finding the maximum peak, B wave was determined by inverting the APG and finding the maximum peak and C wave was obtained by finding out the next maximum peak in the APG (see Fig. 2).

ZC1, ZC2, ZC3 and ZC4 represent the four zero crossings of the APG wave respectively (see Fig. 3).

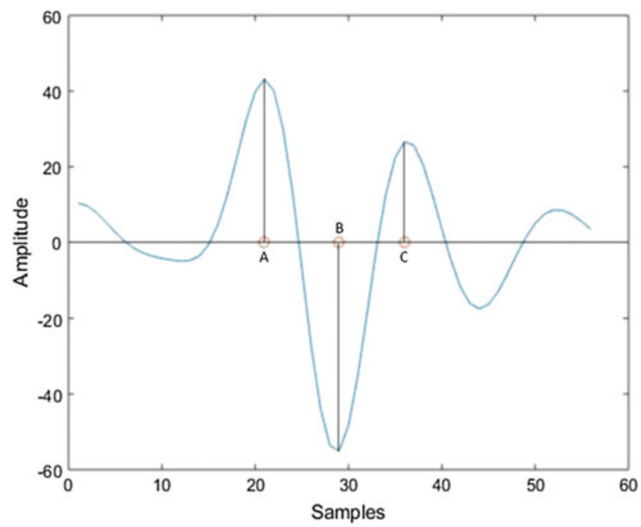

Fig. 2 A, B and C wave detection

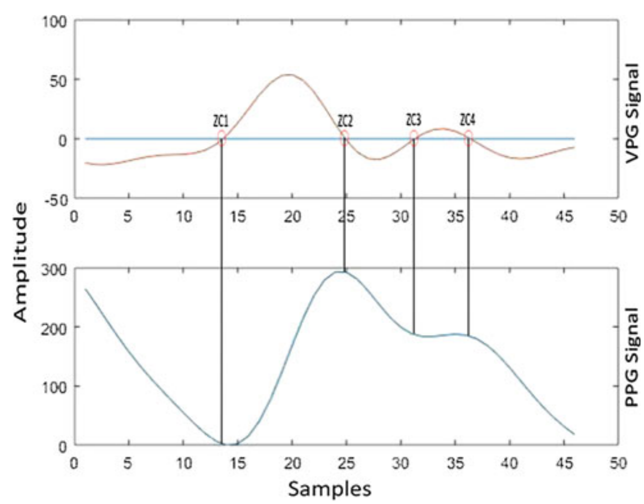

Fig. 3 Mapping of VPG on PPG

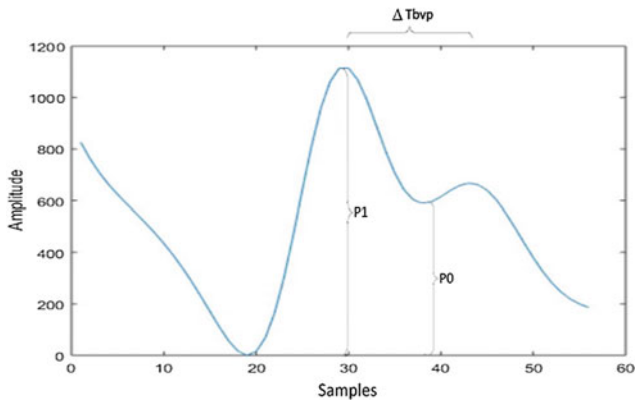

Fig. 4 Computation of ΔTBVP

P0 was obtained by determining the third zero crossing in the VPG signal and mapping it back to the PPG signal. P1 was obtained by calculating the Systolic peak amplitude in PPG. Diastolic peak required for the calculation of ΔTBVP was obtained by mapping the fourth zero crossing in VPG to PPG (see Fig. 4). Finally, for A.I. X and Y was obtained by adding the sample difference of A&B and sample difference of A&C to the starting point of systolic peak in the PPG signal, respectively.

Input feature set to classifier consist of following features, F = {B/A, P0/P1, ΔTBVP/T, S.I, Area under systolic curve, A.I.}.

2.4 Classification

The features extracted in the previous section was used to classify the samples into two classes. The dataset was divided into 2 classes based on the increase in A.I., one where the A.I. was between 0.70 and 0.919 and the other class where the A.I. was greater than 0.919. Classification has been performed using two machine learning algorithms; ELM and SVM.

Extreme Learning Machine (ELM). The ELM [13] for SLFNs indicates that hidden nodes can be randomly generated. The mapping of the input data to L-dimensional ELM random feature space, and the network output was

$$F_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \tag{1}$$

β = [β1, …, βL]′ represents the output weight matrix between the hidden nodes and the output nodes. For the better accuracy, K-fold cross validation was used and average efficiency was computed. Totally 25 samples were used for training and 13 for testing.

Support Vector Machines (SVM). SVM, a learning machine based on the principle of Structural Risk Minimization theory was used [14]. The SVM classification was performed with a Linear Kernel and four fold cross validation.

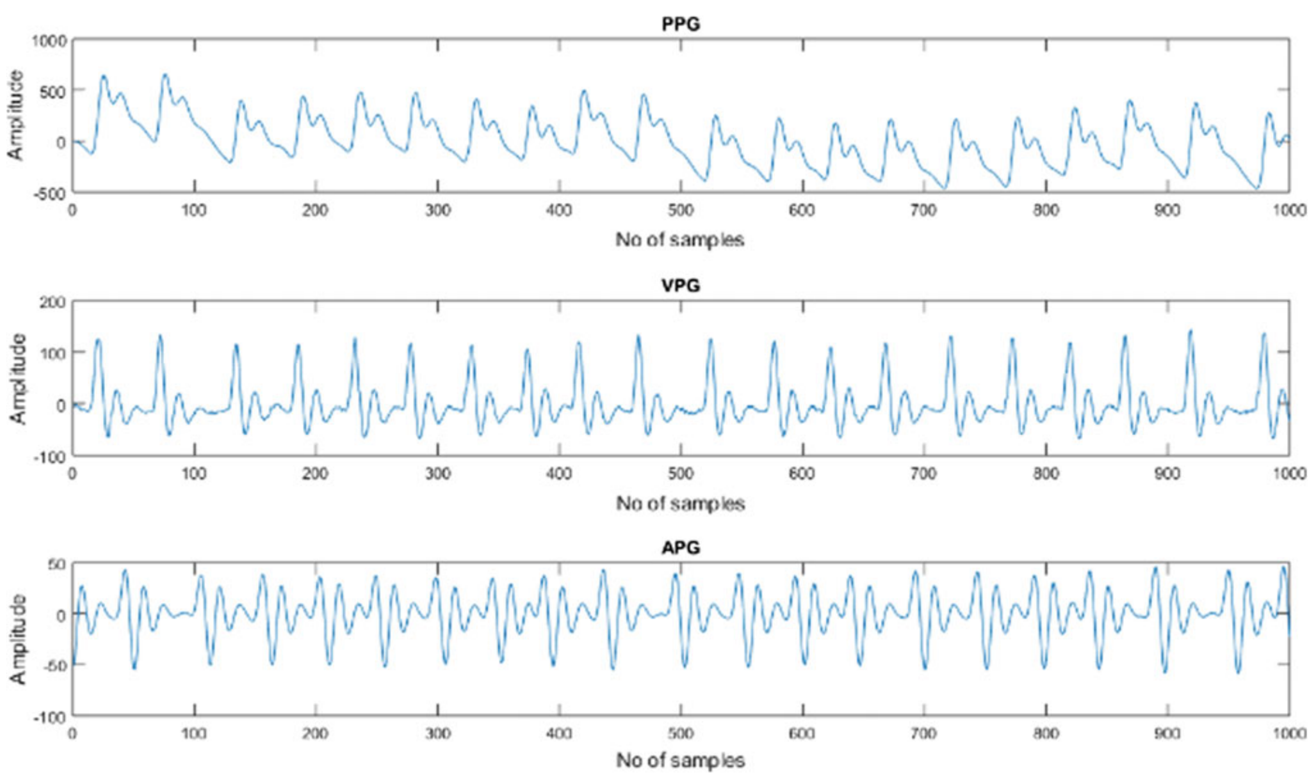

Fig. 5 Preprocessed PPG, VPG and APG signals

3 Results and Discussion

The detailed performance of the feature extraction and classification is discussed in this section. Also, the role of pre-processing is indicated by presenting the necessary plots.

Firstly, the signal was down sampled, after which the DC shift in the signal was removed. This signal is then divided into four windows, each of 30 s. Next, the signal is passed through a band pass filter so as to differentiate the input signal. Finally, the signal is segmented in a way that individual segments of a signal were obtained. The preprocessed PPG, VPG and APG are obtained respectively (see Fig. 5).

Using the formulae previously discussed, features for all 38 signals have been extracted and documented. A binary classification using Augmentation Index is performed on the set of features. Firstly, an ELM classifier with 23 neurons and a sigmoidal activation function is used for classification. This resulted in an average k-fold cross validation accuracy of 77%, for a *k*-value of four.

Later the same features set was given as input to an SVM classifier with linear kernel which yielded a 4-fold cross validation accuracy of 94.59%. It was observed that SVM was more successful in classifying the data than ELM.

4 Conclusion

In this paper, a novel method has been presented to identify unhealthy or subjects who are at risk of developing CVDs in a young age group. Augmentation index which is a major indicator of heart diseases was used to segregate data. Using popular machine learning algorithms the recorded data was classified and accuracies were compared. An accuracy of 77% was achieved using ELM with cross validation. Upon using SVM with cross validation an accuracy of 94.59% was achieved.

Both the algorithms effectively were able to distinguish unhealthy set of subjects and healthy set, but looking at the accuracy achieved it is evident that SVM performed better than ELM. By combining both signal processing and machine learning techniques, this paper proves that it is possible to effectively evaluate the cardiovascular health and is also able to distinguish unhealthy and healthy set of subjects from a young age group. However, it is necessary to test the proposed system on data belonging to subjects of other age groups and come up with an age index.

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