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Computerized approach for cardiovascular risk level detection using photoplethysmography signals

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A B S T R A C T

Cardiovascular disease (CVD) is the leading cause of death globally. In order to decrease the medical cost for treating the heart related pathologies, this paper proposes a computer-aided diagnostic system to classify various risk level of cardiovascular disease utilizing inexpensive and non-obtrusive diagnostic tool called photoplethysmography (PPG). In this study, features such as singular value decomposition (SVD), statistical features and wavelets (Haar, Daubechies, and Symlet) are extracted from the photoplethysmography signals. These feature vectors are then applied to the softmax discriminant classifier (SDC) and Gaussian mixture model classifier (GMM) for classification of various risk phases of CVDs. The classification performance of the proposed model incorporating SDC with SVD and statistical feature vectors increases with sensitivity of 97.24%, specificity of 99.09% and an accuracy of 97.88%.The method presented in this paper assist cardiologists to validate their diagnosis.

1. Introduction

Cardiovascular disease (CVD) is becoming one of the life threatening diseases in most of the countries. Likely 29.2% or 16.7 million of total world-wide deaths resulted from the different forms of CVD [1]. Many forms of CVD can be preventable by taking prime actions on risk factors like smoking, unhealthy food and lack of physical activity. The problems due to non-communicable diseases likely to be increased over the next decades significantly in low and middle income countries [2,3].To increase the life expectancy of the people and to cut down the medical cost, PPG has been emerging as a promising technique for the early screening of heart related problems [4,5]. The PPG signals are pulsatile in nature and from the PPG waveforms relevant features of the blood flow activities can be identified and can be used to measure the cardiac output [6,7]. PPG has been widely acknowledged by both the International Standard Organization (ISO) and European committee for measurement of oxygen saturation level. A high quality PPG signal can be easily recorded when the fingers are placed on the PPG device [8–11]. PPG signal require only less hardware and becomes more accessible when compared to current electrocardiogram (ECG) monitoring systems [12].

Allen examined photoplethysmography signals and has validated its latent ability for use in clinical measurements in a wide range especially for the valuation of the cardiovascular system [13]. Gil et al. measured the pulse rate variability (PRV) from the PPG signals as a substitute measurement of the non-stationary heart rate variability (HRV). Indices of time-varying analysis derived from the PRV showed no static differences with the indices derived from HRV. Thus for assessing the changes in the autonomic modulation of heart rate, PRV can be measured [14]. Kenji Takanawa et al. measured second derivative of the PPG waveform for the assessment of vascular aging [15]. Gonzalez et al. computed fourth derivative from the acquired PPG signal and computed the photoplethysmographic augmentation index for cardiovascular assessments. Techniques like Artificial Neural Networks (ANN), Support Vector Machine (SVM), Genetic Algorithm (GA), Extreme Learning Machine (ELM) and K-Nearest Neighbor (KNN) have been used in the PPG signal classification [16].

Soltane et al. adopted multilayer perceptron neural network employing Back Propagation (BP) algorithm to classify PPG signals as normal or pathological and its performance is compared with that of GMM classifier. Recordings of PPG signal are taken from 2 groups of volunteers consisting of 48 patients (11 pathologies and 37 normal having age between 21 and 64) [17]. Rohan Baid et al. proposed a model for extracting features known as an Auto-regressive exogenous input (ARX) linear parametric model which characterizes the circulatory system and adopted SVM for

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assessing the CVD risk level. SVM classifies the signal depending on the four selection policies [18]. Polania et al. carried out a technique for detecting and classifying cardiac arrhythmias through morphological analysis of PPG signals. Methods starts with preprocessing stage followed by extracting discriminative features based on time-domain signal processing, Fourier analysis, and non-linear dynamics of the heart rate variability. Arrhythmia classification is performed using SVM [19].

Shobitha et al. classified the PPG signals as healthy or at risk of CVD using ELM and its performance is compared with other supervised learning algorithms such as SVM and back propagation algorithm. These algorithms are tested for 30 pathological and 30 healthy signals which are obtained from Biomedical Research Lab. Also, ELM uses only less feature vectors as inputs to detect the risk of CVD and thus reducing the computation time [20]. Hosseini et al. proposed finger PPG obtained before and after hypermia to differentiate between subjects with normal-to-mild and serious coronary artery disease. PPG and ECG signals were recorded for 37 patients. Many time-domain features were examined using K-nearest neighbor classifier and the better results have been obtained for combination of features like pulse transit time, rising time, and crest time [21].

In this paper, an investigation on various risk groups of cardiovascular disease from PPG signal has been carried out. Statistical features, singular value decomposition and wavelets are extracted from the PPG signals and given to a simple but efficient classifier called softmax discriminant classifier (SDC). SDC takes nonlinear transformation of the distance between the training and testing samples and assigns the label information to the new testing sample. Then the performance of the SDC is compared with the Gaussian mixture model classifier (GMM). The performance of SDC and GMM are assessed using measures like sensitivity, specificity, accuracy, error rate, false alarm, precision and F-measure.

The paper is structured as follows: Section 2 explains in detail the methods for identifying the various risk stages of cardiac using PPG which includes feature extraction process, Softmax discriminant classifier and Gaussian mixture model classifier. Section 3 explains the results and discussions. The Section 4 of this paper gives conclusion followed by references.

2. Methods

In this study, classification of various risk levels of cardiovascular disease has been carried out. The input given to the proposed system is the photoplethysmography (PPG) signal. The PPG signal dataset has been sampled at a sampling rate of 300 Hz and the data sample length obtained from the PPG signal is 1,44,000 which has 720 segments in total. These segments are of equal intervals comprising of 200 samples per segment.

In the first stage, features extraction process is carried out using statistical analysis, singular value decomposition (SVD) and different types of wavelets from the PPG signal dataset. These extracted features are given as input to the SDC and GMM classifier. Finally classification of the PPG signal into normal and three different levels of abnormality are labelled. The illustration of the proposed CVD risk level detection system is shown in Fig. 1. Each block of Fig. 1 is explained briefly in the following sub-sections.

2.1. SVD and statistical features

In the context of machine learning or signal processing or pattern recognition, feature extraction aims to build features from the original data set which are instructive and non-redundant. Appropriate information will be obtained from the selected features and the expected task can be performed from this reduced dataset instead of the comprehensive original data. SVD and nine statistical features are extracted from the PPG signals are defined in Table 1.

The SVD provides a systematic way to determine the dominant patterns underlying in a high-dimensional system and also provides a low-rank approximation to high-dimensional data. The SVD results in numerically stable computation. By extracting above features, data has been compressed to 10 samples out of 200 samples per segment. Since there are 720 segments in the recorded PPG signal, data size has been reduced to 7200 samples from 1,44,000. Table 2 depicts the sample SVD and statistical features extracted from abnormal and normal PPG signal of Capnobase dataset.

2.2. Discrete wavelet transform

Discrete Wavelet Transform (DWT) uses a discrete set of wavelet scales and transformations obeying some defined rules [22]. Wavelet transform can be applied to PPG signal and convert that to wavelet parameters or coefficients. The acquired coefficients depict the behavior of the PPG signal. There are different types of wavelet transforms such as Daubechies, Haar, Symlets, Coiflets, Biorthogonal etc [23]. In this paper, db4, haar and sym8 wavelets are chosen based on their properties like symmetry, smoothness, orthogonality and symmetry for feature extraction.

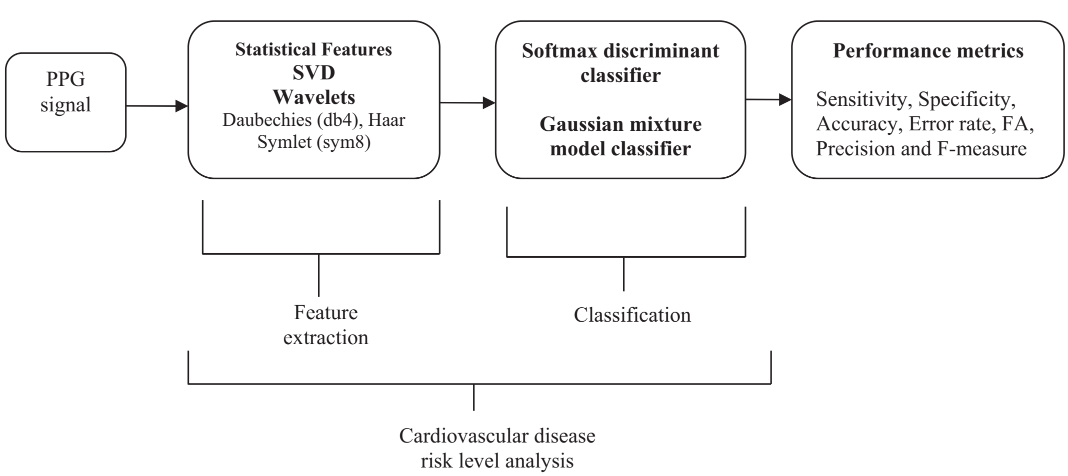

Fig. 1. Flow diagram of the proposed CVD risk levels detection system.