
CamBP: A Camera-Based, Non-Contact Blood Pressure Monitor

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Abstract

Convenient monitoring of vital signs, particularly blood pressure (BP), is critical to improve the effectiveness of health-care and prevent chronic diseases. This study presents a user-friendly, low-cost, real-time, and non-contact technique for BP measurement based on the detection of photoplethysmography (PPG) using a regular webcam. Leveraging features extracted from photoplethysmograph, an individual's BP can be estimated using a neural network. Experiments were performed on 20 human participants during three different daytime slots given the influence of background illumination. Compared against the systolic blood pressure and diastolic blood pressure readings collected from a commercially available BP monitor, the proposed technique achieves an average error rate of 9.62% (Systolic BP) and 11.63% (Diastolic BP) for the afternoon session, and 8.4% (Systolic BP) and 11.18% (Diastolic BP) for the evening session. The proposed technique can be easily extended to the camera on any mobile device and thus be widely used in a pervasive manner.

Author Keywords

Blood pressure; photoplethysmography; PPG; camera.

ACM Classification Keywords

C.3 [Special-Purpose and Application-Based Systems]:
Real-time and embedded systems; J.3 [Life and Medical

Sciences]: Health

Introduction

Non-contact monitoring of vital signs, such as heart rate (HR), heart rate variability (HRV), BP, and respiration rate (RR), is a promising and proven technique to improve the assessment quality for patients. BP is highly correlated with cardiovascular health and remote estimation of BP can provide an easy and efficient way to monitor cardiovascular health. Today, hypertension is a major health issue and it is reported that 62% of cerebrovascular diseases and 49% of ischemic heart diseases are due to prolonged high blood pressure, according to the World Health Organization (WHO) [8]. Nowadays, the risk of hypertension is not only limited to old-aged patients but also affects much younger population [11]. In the same report by WHO, it is indicated that timely treatment of hypertension can reduce the risk of stroke by 40% [8], stressing the need of a user-friendly, affordable, and accurate BP self-monitoring system that can be easily accessed by anyone, at any time and place.

Conventional BP measurement usually uses auscultatory [1], oscillometry, tonometry [12], and volume clamping techniques [6]. Auscultatory and oscillometry require externally applied cuff pressure to detect the changes in BP. Although these methods have been long used in clinical settings, they require well-trained manual assistance which limits their usage by individuals. Volume clamping method uses a finger cuff and an inflatable bladder with a plethysmograph sensor to measure finger arterial pressure [6]. Tonometry is another non-invasive technique to measure pulse pressure [12] by placing a pressure sensor on the radial artery.

Photoplethysmography (PPG)

According to U. S. National Library of Medicine, photoplethysmograph can be defined as a technique for measuring blood volume changes in various parts of body [3]. Each time the heart muscle contracts, blood is ejected from the ventricles and a pulse of pressure is transmitted through the circulatory system. So, photoplethysmograph provides a descriptive analysis of blood flow through superficial arterial structure and thus can potentially be used to infer and estimate relevant vital signs. Transmission-mode PPG method measures the changes in transmitted light due to the varying blood volume; and for reflectance-mode photoplethysmograph, the probe is placed on the same side as the light source and it measures pulsatile changes in the reflected light. Laser Doppler method and Radar Vital Signs Monitor (RVSM) were proposed for monitoring Pphotoplethysmograph [7, 16]. However, they work only when the subject is in the rest state. A conventional technique of measuring photoplethysmograph is to use the pulse oximeter, which contains the dedicated light source. This technique is non-invasive, but it needs the contact with the subject to take the measurements.

PPG and Blood Pressure

Several studies have shown the advantages of BP measuring techniques based on the features extracted from photoplethysmograph waveforms over traditional BP techniques. Nitzan *et al.* [13] used photoplethysmograph signals simultaneously recorded from fingers of both hands to estimate the BP values. However, this study still uses cuff-based technique and measures the pressure when photoplethysmograph signal reappears. Another study [9] used cardiac stimulus involving dopamine and epinephrine on 6 dogs to show the correlation between photoplethysmograph and hemodynamic changes. Photoplethysmograph amplitude has been used to monitor BP during sleep by uti-

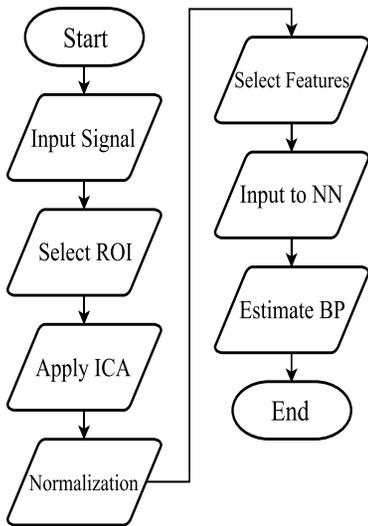


Figure 1: Processing flow for BP estimation

$$R_i = \frac{\sum_x^H \sum_y^W v_i(x, y, 1)}{W \times H}$$

Equation 1: RGB Calculations

lizing an electrocardiograph along with a transmission type transducer to measure different features [4]. Some studies have used a single photoplethysmograph waveform for the estimation of BP [2, 5] by establishing a linear correlation between BP and features such as systolic amplitude, time duration between each peak. Kurylyak *et al.* have used the systolic upstroke time, diastolic time, width of 2/3 and 1/2 pulse height from photoplethysmograph waveform to estimate BP [10]. Another work by Xing *et al.* has described a normalization technique and features which were extracted by a fast Fourier transform [19]. However, most of these existing models are proposed for specific test data or scenarios, and only gives constant coefficients resulted from the high probability for specific test groups. So far the main concerns for accurate BP monitoring system include: easy acquisition and sufficient precision, availability of an inexpensive and easy-to-use device, lack of trained manpower, awareness of the limitations of existing methods.

In order to overcome these challenges, we have proposed the use of neural network (NN) for estimation of BP. Very few studies are available for estimating BP using NN. Linear regression model and Support Vector Machine (SVM) model were used for BP estimation [18], which however, only indicate whether BP is in a specific range or not, instead of the specific BP values. The use of linear auto-regression [5] showed a relationship between BP and photoplethysmograph, which however required a rather large set of training data. To maximize the usability and affordability of the proposed system, we have used the common webcam for acquiring photoplethysmograph waveform. To the best of our knowledge, this is the first method of its kind to measure BP in real time and based on an inexpensive webcam.

Theory and Experimental Setup

Svaasand *et al.* [17] demonstrated that photoplethysmograph signals can be remotely measured on the human face with normal ambient light as the source and with a digital camera. Recently, scientists from MIT have developed a robust method for computation of blood volume pulse from color video recordings of the human face [15]. The basic principle behind photoplethysmograph measurement by using a camera is that, with each cardiac event, the change in blood volume in superficial arterial blood vessels (e.g., facial blood vessels) affects the wavelength of the incident surrounding light. These changes indicate the time period for cardiovascular events which can be monitored by recording a video of arterial region and extracting the red, green, and blue (RGB) traces from each frame [14]. Figure 1 shows the processing flow for estimating BP values. Input signal is acquired by a webcam and further processed with custom built software in MATLAB.

Face Detection and Region of Interest

The Viola-Jones detection algorithm is used for face detection, and for keeping track of the moving face. The Kanade-Lucas-Tomasi (KLT) feature extraction and tracking algorithm is implemented, which detects a face in the first frame and then uses the set of features across the video frames to keep track of the face. The forehead region is selected as the region of interest (ROI) because it is least affected by facial activities, like talking and eye blinking.

RGB Level Calculations

The required red channel values in region of interest are processed for computation of photoplethysmograph. In order to calculate the pixel values of each frame in real time, we have separated the red, green and blue planes using independent component analysis (ICA) and taken the average of all the pixels in the red plane. A moving window

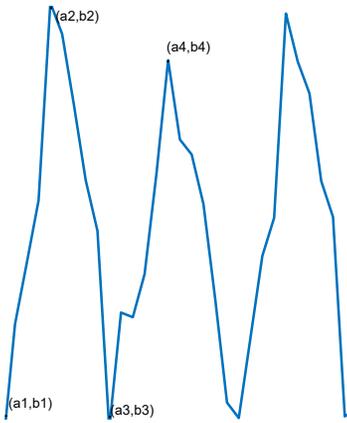


Figure 2: Photoplethysmograph waveform

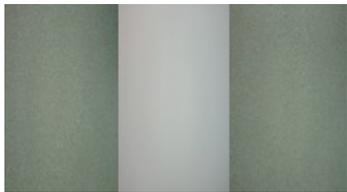


Figure 3: Light conditions (Morning, Afternoon, Evening)

method is used to extract the signal in real-time format. A 45s window is extracted with an increment of 1s. This is computationally efficient and can give substantial results. Equation 1 defines the red level for the i -th sample frame. In equation 1, W is the width of the region of interest in pixels, H is the height of the region of interest in pixels, and $v_i(x, y, 1)$ represents the light level of the red plane (index 1) at the (x, y) coordinates of frame i . The pixel values can be affected by surrounding light illumination. Normalization is performed to have zero mean and unit variance. We have used the following features from the photoplethysmograph wave from (as shown in Figure 2): Systolic Amplitude ($b2 - b1$), Pulse Interval ($a3 - a1$), Systolic Slope, Diastolic Slope, Peak Interval ($a4 - a2$), Crest Time ($a2 - a1$), and Delta Time ($a3 - a2$).

Neural Network Architecture

Neural network is one of the most widely used machine learning models to predict outputs of a non-linear complex function. It can be classified into two learning categories: supervised and unsupervised. Supervised learning model is inferred based on the labeled training data. For unsupervised learning algorithm, only the unlabeled data are used for training the model. In our model, a feed-forward neural network with one hidden layer is used for regression. In the training phase, the extracted PPG features were used as inputs, and the ground truth BP values measured by the commercially available BP monitor are treated as output labels. The NN model is optimized by using the gradient descent (GD) algorithm to minimize the cross-entropy cost function based on the true BP values and the predicted values.

We have used a common, inexpensive webcam (Logitech HD 720p) for video acquisition. Video signals were recorded at 30 frames per second with a pixel resolution of 480×640 . The experiments were conducted on 20 human subjects

(14 males, 6 females) between the ages of 21-45 without known blood pressure disease. A standard wrist BP monitor (i.e., Omron BP652) was used to collect BP measures as the ground truth. To observe the effect of changing surrounding light illumination, all experiments were conducted in the morning, afternoon, and evening sessions. Figure 3 shows the actual light conditions in real world deployment of this work. Morning session recording was used to train the neural network and the rest two sessions were used for testing purpose. The subjects were seated in front of a computer and their BP was measured after a rest period of 5 minutes. To validate our algorithm in more challenging real world conditions, we have asked subject to do small head movements that could be considered as normal work in front of computer screen, also each subject was measured three times, as per standards by AAMI and BHS. All the experimental protocols have been reviewed and approved by the Binghamton University Institutional Review Board (IRB).

Results

The time period for training session was 4 minutes when features were recorded along with BP readings. In the following sessions, the same data was used to estimate the BP values based on the input features. It takes about 45 seconds (based on the window length) to estimate the first promisingly accurate BP value on a DELL XPS computer. Figure 4 shows the Systolic BP and Diastolic BP readings obtained from the webcam and the standard BP monitor respectively, for both the afternoon and the evening sessions. The relative comparisons of systolic and diastolic BP measurements is shown in Figure 5 in terms of the error rate (%). The abbreviations STD. and Cam. in respective figures refer to the measurements from the standard BP monitoring device and from the webcam respectively. The correlation coefficients between the camera and contact device meth-

	SBP	DBP
Aft.	10.714%	4.054%
Eve.	-5.263%	-3.947%

Table 1: Minimum % Error Rate for Systolic BP (SBP) and Diastolic BP (DBP) for Afternoon (Aft.) and Evening (Eve.) sessions

	SBP	DBP
Aft.	16.071%	-22.7%
Eve.	13.91%	-19.66%

Table 2: Maximum % Error Rate for Systolic BP (SBP) and Diastolic BP (DBP) for Afternoon (Aft.) and Evening (Eve.) sessions

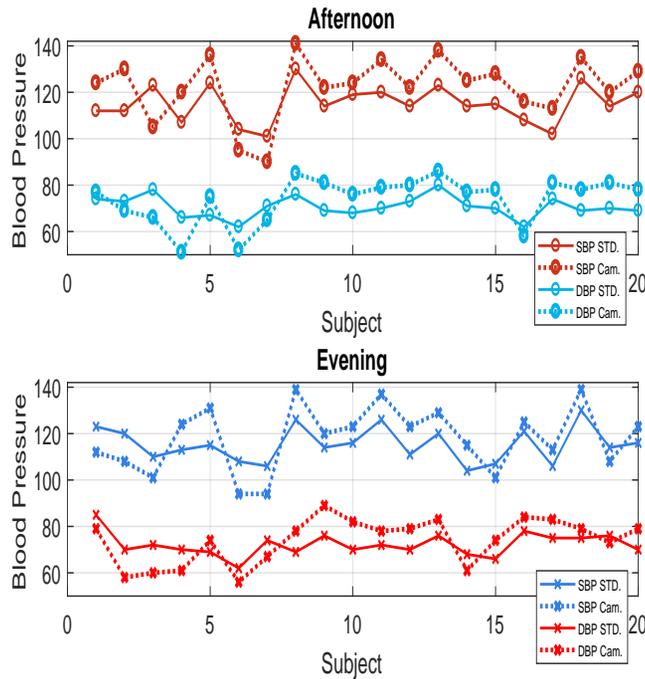


Figure 4: Systolic BP (SBP) and Diastolic BP (DBP) measurements for afternoon and evening sessions using standard (STD.) and Camera (Cam.) devices

ods are: for the afternoon session: Systolic BP=0.74, Diastolic BP=0.6; for the evening session: Systolic BP=0.72, Diastolic BP=0.53. The average errors are: for the afternoon session: Systolic BP=9.62%, Diastolic BP=11.63%, and for the evening session: Systolic BP=8.4%, Diastolic BP=11.18%. Table 1 shows the best obtained results (minimum % error) for the systolic and diastolic BPs. Maximum errors for the recorded results are shown in Table 2.

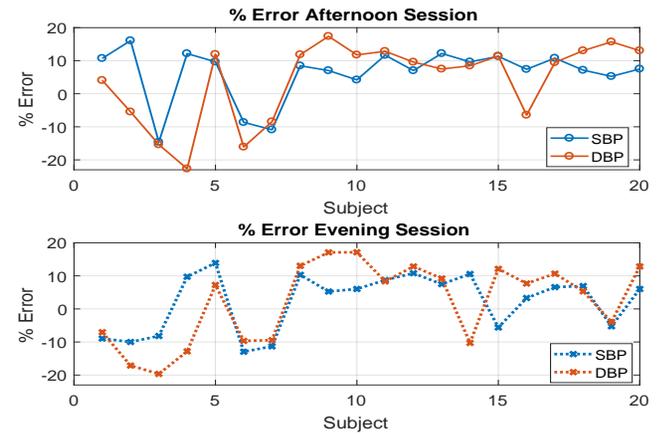


Figure 5: % Error Rate for Systolic BP (SBP) and Diastolic BP (DBP) measurements for afternoon and evening sessions using standard and Camera devices

Conclusion

In this study, we have demonstrated the estimation of blood pressure using a regular webcam. The experimental results show that BP measurements by a camera are highly correlated with the measurements by the standard devices. Although the results are affected by ambient light, this algorithm shows satisfactory accuracy, i.e., more than 85%, considering its superior ease of use and competitive cost over the conventional BP monitoring devices. It can be easily extended for continuous, real-time monitoring of BP in regular clinical practice and home environment. Ongoing research is focused on improving this method in terms of ease of use, accuracy and making it more robust for all light conditions. This method requires training data from individual subjects and frequent calibration which would be improved by exploring other machine learning approaches.

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