Estimation of Blood Pressure Levels from Reflective Photoplethysmograph using Smart Phones

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Abstract— **As part of preventive healthcare, there is a need to regularly monitor blood pressure (BP) of cardiac patients and elderly people. Mobile Healthcare, measuring human vitals like heart rate, Spo2 and blood pressure with smart phones using the Photoplethysmography technique is becoming widely popular. But, for estimating the BP, multiple smart phone sensors or additional hardware is required, which causes uneasiness for patients to use it, individually. In this paper, we present a methodology to estimate the systolic and diastolic BP levels by only using PPG signals captured with smart phones, which adds to the affordability, usability and portability of the system. Initially, a training model (Linear Regression Model or SVM Model) for various known levels of BP is created using a set of PPG features. This model is later used to estimate the BP levels from the features of the newly captured PPG signals. Experiments are performed on benchmark hospital dataset and data captured from smart phones in our lab. Results indicate that by additionally adding information of height, weight and age play a vital role in increasing the accuracy of the estimation of BP levels.**

I. Introduction

With the increase in elderly population [1], the need for regular healthcare at home has gone up. Periodic initial screening of certain vital parameters is the aim for such healthcare. These parameters include heart-rate, blood pressure, electrocardiogram (ECG), hemoglobin, blood oxygen level, blood glucose level etc. There are portable devices available for measuring such parameters [2]-[5] however; they turn out to be expensive for home usage.

Hertzman [6] in 1938 developed a low cost optical technique to measure the blood flow by sensing the surface of the skin. This is called photoplethysmography. With the popularity of smart phones having light emitting diode (LED) flash and camera, reflective PPG [7] has gained popularity. In this method fingertip is placed on top of the smart phone camera with the LED flash "ON". The intensity of the reflected light follows the pulsating nature of the blood flow [8]. The period of the PPG signal captured by the camera provides the heart rate. The blood flow is a major complex function of the heart function and the structure of arteries and veins [9]. Hence, in this paper, we investigate the relationship of the shape of the PPG waveform (Fig. 2) with the BP of an individual. This is aimed towards a ubiquitous, low cost solution for estimating the BP levels from the PPG signals captured from smart phones.

Recently there have been work done on estimating BP from the sensor signals captured from smart phones [10], [11]. Zhang *et. al* [10] have the ECG and the PPG waveform to derive the BP. This is based on a principle of pulse wave transition, where the the time is measure between the peak of the ECG and the trough of the PPG. Chandrasekaran *et. al* [11] have used two sensor signals - PPG and audio sound of the heard beat. The audio sound can be either captured by the smart phones or a diaphragm, an additional hardware connected to the smart phone. However, these two sensor signals need to be synchronized for the processing, where a linear regression based model is created to estimate the diastolic and systolic BP using the time difference between the peak of the PPG signals and the peak of the audio wave.

In order to get rid of multiple sensors, we extract the time domain features from the PPG signals for estimating the BP levels. A good amount of PPG features are given in [12], of which we have used some and added some extra new features. In preventive healthcare, the aim of estimating BP is not to get an exact BP value, but to get an idea about the levels, whether it is normal or abnormal. Hence the entire range of systolic and diastolic BP values is partitioned into five levels – very high, high, normal, low and very low [13]. These levels are then used as ground truth to create models with the help of PPG features. We have used two types of machine learning – one using linear regression [14] based prediction and the other using classification, SVM [15]. Experiments are performed on two types of datasets – a standard PPG dataset captured from patients in hospitals where the PPG signal is noise free and the PPG dataset captured in our lab using a smart phone.

In this paper, we highlight that the measurements of BP are done using mobile phone camera only and no external sensors are needed. This adds to the affordability, usability and portability of the system, which not only eases the measurement for elderly patients, but also has use cases in Wellness systems, where instant BP can be measured while exercising.

The novelty of this paper lies in the following –

a. A machine learning based approach to estimate systolic and diastolic BP levels by only using the PPG signals.

b. Investigating the usefulness of height, weight and age information in the estimation accuracy.

The paper is organized as follows. Section II gives the proposed approach. Section III provides the results followed by conclusion in Section IV.

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II. Proposed Approach

The proposed method of BP estimation is shown in Fig. 1. There are two phases – training and testing. Initially the PPG features are extracted in both the phases. After that in the training phase, a model is created using the ground truth information of the BP levels. This model is used for estimating the BP level in the testing phase.

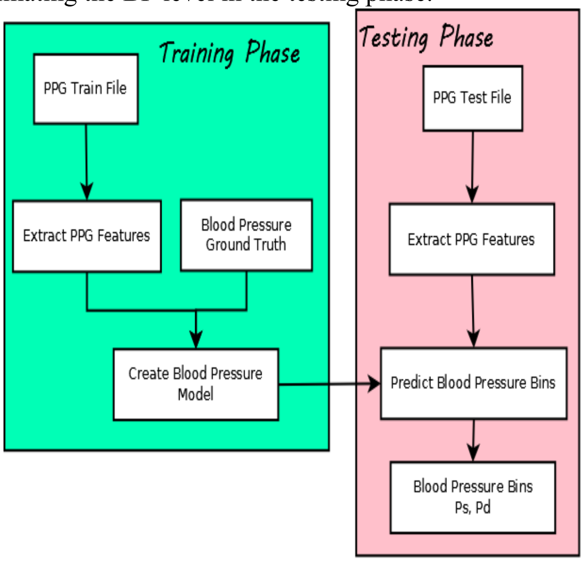

Fig. 1. Flowchart of Proposed Approach for Blood Pressure Estimation

A. *Feature Extraction*

A PPG signal, P, is used to extract features, as shown in Fig. 2. Fourteen time domain features are extracted based on the proposal in [12].

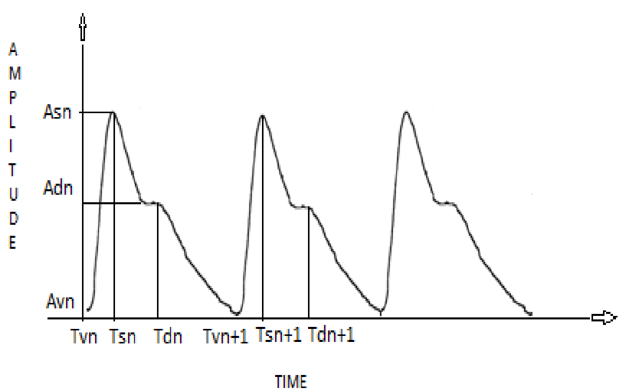

Fig. 2. PPG Signal for Feature Extraction

As a first step, from every cycle of the PPG signal, the Systolic Peak (Tsn, Vsn), the Valley Point (Tvn, Avn) and the Dicrotic Notch (Tdn, Adn) points is computed. These are then used to compute the 14 features as shown in Table I. The peaks and valley points are detected using a simple peak detection code and the Dicrotic notch is calculated by searching for the first local maxima in the first derivative of the PPG signal between systolic peak and its immediate next valley point. In Table 1, the features and the equations used to calculate them are shown.

TABLE I
FEATURES EXTRACTED FROM PPG

Feature	Feature Name	Description
1	Valley Amplitude	Avn
2	Systolic Peak Amplitude	Asn
3	Dicrotic Notch Amplitude	Adn
4	Systolic Area	$Sys\_Ar=\Sigma_{Tsn}^{Tdn}\ P$
5	Dicrotic Notch Area	$Dia\_Ar=\Sigma_{Tdn}^{Tvn+1}\ P$
6	Total Area	$Tot\_Ar=Sys\_Ar+Dia\_Ar$
7	Ratio of Area	$Ratio\_Ar=Dia\_Ar/Sys\_Ar$
8	Peak Interval	$Pk\_Int=Tsn_{+1}-Tsn$
9	Pulse Height	$Pl\_Ht=Asn-Avn$
10	Pulse Interval	$Pl\_Int=Tvn_{+1}-Tvn$
11	Crest Time	$Cr\_Ti=Tsn-Tvn$
12	Delta Time	$Dt\_Ti=Tdn-Tsn$
13	Augmentation Index	$AI=(Adn-Avn)/(Asn-Avn)$
14	Reflection Index	$RI=1-AI$

B. *BP Model Creation*

For BP analysis, it is seen that estimating the BP bins (Table II), is sufficient for measuring human vitals rather than the exact BP values for (systolic pressure) Ps and diastolic pressure (Pd). Thus in this paper, BP bins are predicted for the test PPG signals, rather than the exact BP values. The bin formation shown in Table II is only suggestive; it can be tuned to specific demographic needs.

The PPG features extracted are modeled in the training phase using either 1) Linear Regression Model, or 2) Support Vector Machine (SVM). The models created are used to then predict the BP bins of a PPG test signal in the testing phase, as depicted in Fig. 1.

TABLE II
BLOOD PRESSURE BIN LEVELS (IN MM HG)

BP Level	Pd	Ps
Very Low	<50	<70
Low	50-65	70-100
Normal	65-90	100-135
High	90-100	135-160
Very High	>100	>160

III. RESULTS

The development and experimentation of the discussed approach was done in Matlab and C, in PC environment. In this paper, two data sets were used to verify the above discussed approach of BP estimation.

A. Standard Dataset

Firstly, the approach was tested with The University of Queensland Vital Signs Dataset[1] [16], which contains patient vital data and signs that were recorded during 32 surgical cases ranging in duration from 13 minutes to 5 hours over a period of 4 weeks, at the Royal Adelaide Hospital. Pleth Data (PPG signal) from this data set was used to extract the features and the corresponding BP values were used to model the data.

From each of the above PPG Data Signal, 14 features for each cycle were extracted as explained in Section III.A. The number of feature vector set obtained from all the PPG data signals in the 32 cases was 49697, which was divided into training (50%) and testing (50%) sets based on the histogram analysis done on the Ps and Pd values.

The prediction accuracy into appropriate BP bins, based on the models created by Linear Regression and SVM on the above described features is shown in Table III.

TABLE III
COMPARISON OF BP DETECTION ACCURACY (%) FOR STANDARD DATASET

Standard Data Set: 14 features	Linear Regression	SVM
Ps bin	93.25	51.6
Pd bin	76.4	53.6

B. Smart Phone Dataset

The second data set comprised of PPG signals captured from 17 subjects using smart phone. The video signal for PPG was captured by placing a finger on the camera lens of a smart phone, iPhone4, with the flash ON. The BP ground truth data was collected using - ETCOMM Bluetooth Blood Pressure Monitor HC-502[2].

Fig. 3 shows the method of BP estimation for the second dataset. In order to remove the noise from the smart phone captured PPG signals a pre-processing is performed according to the method given in [17]. Here a finite state machine (FSM) is implemented to detect the consistency of the PPG signal and reject the noise. Thus 512 good PPG samples are obtained which are used for feature extraction. It is to be noted that the previous PPG dataset from Queensland is captured using medical grade instruments in hospitals; hence they are quite clean signals and do not need any preprocessing.

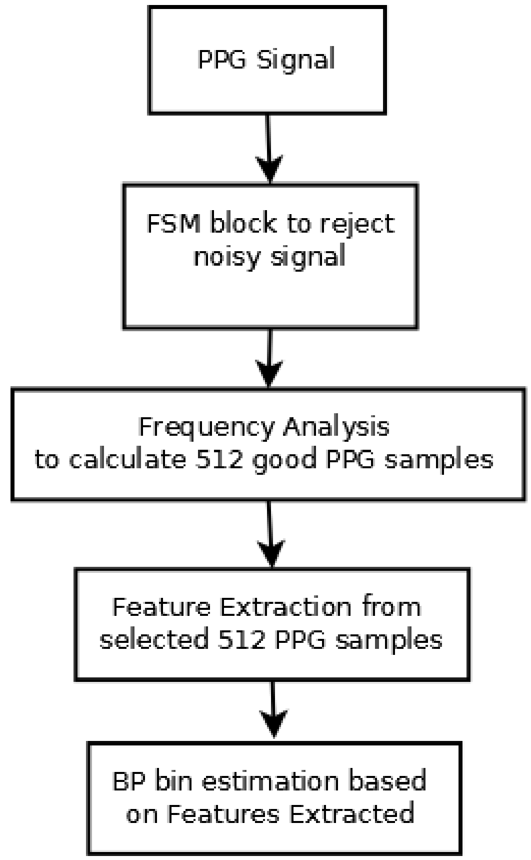

Fig. 3. Flowchart of Proposed Approach for Blood Pressure Estimation of 17 subjects from second dataset

In the case of smart phone dataset, 17 features were used for analysis. The first 14 features were as mentioned in Section III.A. In addition, the subject's height, weight and age were used, as it was experimentally seen that these three values added to the increase in prediction accuracy as shown Table IV.

TABLE IV
COMPARISON OF BP DETECTION ACCURACY (%) FOR SMARTPHONE DATASET WITH 17 SUBJECTS

Method	Linear Regression		SVM	
	Pd	Ps	Pd	Ps
14 features	80.3	82.1	85.8	87.3
17 features	99.7	98.7	99.29	100

[1] http://www.ncbi.nlm.nih.gov/pubmed/22190558
[2] http://www.etcomm.cn/en/products_hc-502b.html

TABLE V
COMPARISION ESTIMATED BP VALUES FOR 17 SUBJECTS USING LINEAR REGRESSION AND SVM

Subjects	Ground Truth		Linear Regression Estimation		SVM Estimation	
	Ps	Pd	Ps Bin	Pd Bin	Ps Bin	Pd Bin
1	130[3]	93[4]	3	3	3	4
2	127[3]	84[3]	3	3	3	3
3	116[3]	80[3]	4	3	3	3
4	119[3]	75[3]	3	3	3	3
5	116[3]	77[3]	3	3	3	3
6	140[4]	92[4]	4	3	4	4
7	107[3]	61[2]	3	2	3	2
8	123[3]	78[3]	3	3	3	3
9	148[4]	79[3]	3	3	4	3
10	144[4]	64[2]	4	3	4	2
11	120[3]	67[3]	3	3	3	3
12	112[3]	61[2]	3	3	3	2
13	120[3]	86[3]	4	3	3	3
14	94[2]	65[3]	3	3	2	3
15	103[3]	69[3]	3	3	3	3
16	130[3]	75[3]	3	3	3	3
17	113[3]	74[3]	3	2	3	3

C. *Derivation of the BP Bin*

For the purpose of experimentation and verification of the approach, 50% the feature vectors were used for training, using Linear Regression and SVM. Two models created were then tested with the remaining feature vectors to test the accuracy of the prediction models. For example, consider a PPG signal with ground truth Pd bin value of 3. The features extracted in every cycle of PPG signal and linear regression model is used to predict the BP values. The predicted values for every PPG cycle are shown in Fig. 4a.

To arrive at a single BP (Ps and Pd) value for a signal, histogram analysis is performed on all the predicted values of the signal. The histogram plot for the example is shown in Fig. 4b, where the maximum predicted Pd value is 3. This value of Pd is used as the estimated bin. In this case the Pd bin value of 3 matches the ground truth value. Similarly, for SVM the Ps and Pd bins are classified for every PPG cycle. Finally the histogram analysis is done to derive the maximum occurring bin as the estimated BP level.

The comparative results of the 2 models (linear regression and SVM) for the 17 subjects are shown in Table V, where the green cells show correctly predicted values. The columns for ground truths contain the BP values along with the bins in square bracket.

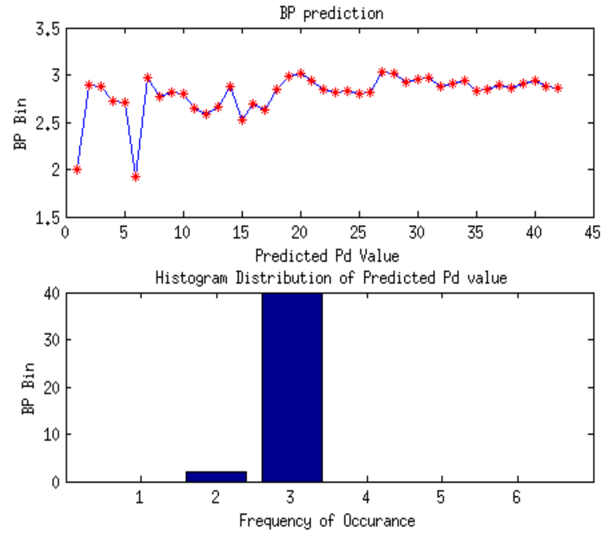

Fig. 4. (a) Predicted BP (Pd bin) for each PPG cycle of a complete PPG signal captured from a smart phone, (b) Histogram Analysis of the Pd bins.

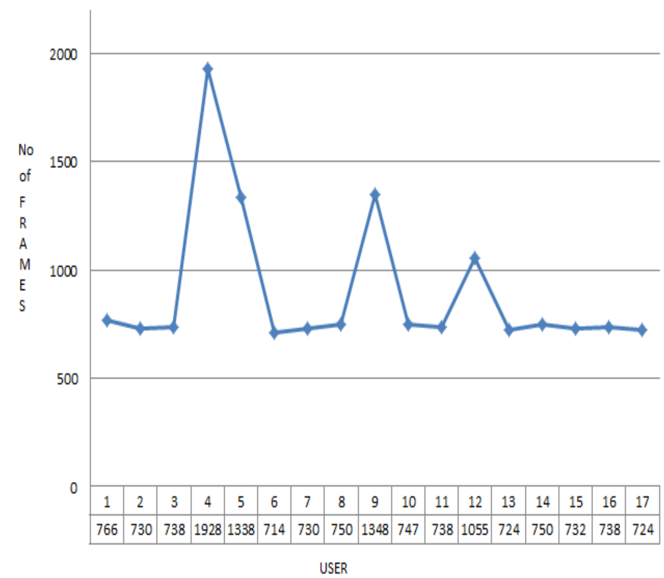

Fig. 5. No of Video Frames captured for each of the 17 subjects, before BP estimation.

D. *Measurement Time*

The captured video signal is checked for consistency with adjacent frames as discussed in [17]. In this paper, 14 consecutive blocks of 64 frames each are checked for consistency before the BP estimation phase.

Fig. 5 indicates the number of frames captured for each of the 17 subjects, before the system moved to the BP estimation phase. The variation in the number of captured frames for different subjects is due to the improper placement or excess pressure of the subject's finger on the camera lens. This led to signal loss and a feedback was given to reposition the fingers. In general, after several measurements and feedbacks, the subjects get a good idea on how to position the finger.

In fact, data collection takes 99.99% of the measurement time. The ideal minimum time required for data capture would be 64*14 frames at 30 fps which is a little less than 30 seconds. The estimation of the BP values is almost instantaneous, after obtaining consistent good samples, as basic mathematical functions is required for feature extraction and a simple matrix multiplication operation is performed using the extracted features and pre-trained model. These are computed in less than a second on iPhone4 which has high processing speed and memory.

VI. Conclusion

In this paper authors have presented the usage of only Photoplethysmograph signals to estimate the Blood Pressure range of a person using a smart phone. For this purpose, time domain features of the PPG signals were extracted and regression and classification models were used to predict the right BP bins. The above methods were tested with a standard data set as well as PPG signals from a Smart Phone. The tip of the index finger of the subject was placed on the smart phone, while covering both the flash and the camera, with the flash in "ON" mode. Linear Regression performs well for noise free signals of standard data set with 14 features. As we incorporate 3 additional features of height, weight and age to the 14 features, results clearly indicate that SVM performs better for signals captured on smart phone. As a further step, a feature selection study needs to be performed. This will help us understand which features are important for estimating BP. Moreover, in future, the smart phone solution needs to be ported to Android platforms and tested for many more subjects. Frequency domain PPG features also need to be explored.

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