Cuff-Less PPG based Continuous Blood Pressure Monitoring – A Smartphone based Approach

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Abstract— **Cuff-less estimation of systolic (SBP) and diastolic (DBP) blood pressure is an efficient approach for non-invasive and continuous monitoring of an individual's vitals. Although pulse transit time (PTT) based approaches have been successful in estimating the systolic and diastolic blood pressures to a reasonable degree of accuracy, there is still scope for improvement in terms of accuracies. Moreover, PTT approach requires data from sensors placed at two different locations along with individual calibration of physiological parameters for deriving correct estimation of systolic and diastolic blood pressure (BP) and hence is not suitable for smartphone deployment. Heart Rate Variability is one of the extensively used non-invasive parameters to assess cardiovascular autonomic nervous system and is known to be associated with SBP and DBP indirectly. In this work, we propose a novel method to extract a comprehensive set of features by combining PPG signal based and Heart Rate Variability (HRV) related features using a single PPG sensor. Further, these features are fed into a DBP feedback based combinatorial neural network model to arrive at a common weighted average output of DBP and subsequently SBP. Our results show that using this current approach, an accuracy of ±6.8 mmHg for SBP and ±4.7 mmHg for DBP is achievable on 1,750,000 pulses extracted from a public database (comprising 3000 people). Since most of the smartphones are now equipped with PPG sensor, a mobile based cuff-less BP estimation will enable the user to monitor their BP as a vital parameter on demand. This will open new avenues towards development of pervasive and continuous BP monitoring systems leading to an early detection and prevention of cardiovascular diseases.**

I. Introduction

Hypertension is known to be one of the silent health disorders with potentially fatal outcome [1]. Symptoms of hypertension are often not detectable until late stages of the disease. Consequently, most individuals are not aware of the disease progression leading to conditions such as cardiovascular diseases, renal dysfunctions etc. Although regular blood pressure (BP) checkup at clinics is expected after a certain age, it is often not possible due to fast paced urban lifestyle. Also, it has been found that 20% of the patients register higher BP at doctor's clinic compared to home settings [2]. Home monitoring of BP offers advantage in terms of providing familiar environment to the hypertension patients. Evidence suggests periodic and continuous monitoring of BP can help in early detection of hypertension [3] thereby reducing mortality. With growing usage of smartphones equipped with PPG sensor, cuff-less BP measurement using a smartphone seems a possibility.

Blood pressure gives a measure of peripheral resistance in blood vessel and is closely related to cardiac function. The upper limit is defined as systolic blood pressure (SBP) while lower limit is defined as diastolic blood pressure (DBP). Sphygmomanometers are the most commonly used devices to accurately measure BP. Although it is still considered the gold standard for measuring BP, it is mostly confined to clinical set up with medical/paramedical staff operating these devices. The method requires the user to inflate the cuff beyond a certain mercury level and auscultate to record the point correctly. This method needs proper training and is not ideal for self-use and continuous monitoring of BP. Therefore, a smartphone based cuff-less BP estimation solution is the need of the hour.

Several studies have been reported to check the feasibility of cuff-less BP monitoring through PPG sensor data [4, 5, 6, 7, 8]. Most of these PPG studies can be further classified into pure PPG signal based [3, 4] or hybrid approaches comprising both PPG and ECG signals [5, 6, 7, 8, 9]. Using two PPG sensors located at a known distance, McCombie et al [5] have estimated pulse wave velocity (PWV) to derive BP. Specifically they have utilized the relationship between BP and elasticity of arterial blood vessels (Moens-Kortweg equation). Zhang et al., have used the linear relationship between pulse wave transfer time (PWTT) and BP to correctly estimate BP [6]. Poon and Zhang et al [8] have computed PTT by placing the PPG and ECG sensors on finger tips whereas Jeong et al [9], have estimated PTT by placing the PPG sensor in ear lobe and ECG sensor on chest. BP estimation using PTT based approach is more cumbersome as it requires data from two sensors positioned at different locations on human body and is also prone to errors as calibration of individual physiological parameters is required. Till date, there have been very few attempts to measure BP directly using a single PPG sensor without estimating PWV or PTT. In a study published in 2003 [4], the authors, using a single PPG sensor based method have reported good accuracies although in a very small dataset (15 subjects). The method was based on efficient extraction of temporal features from PPG signal and a subsequent linear model built over it for estimation of BP [4]. In another similar study published in 2015 using a machine learning based model on 4254 pulses, error rates of ±8.45mmHg for DBP and ±16.17mmHg for SBP was reported [3]. Here we attempt to improve accuracies on a larger dataset (3000 subjects with 1,750,000 pulses) by proposing a method using a single PPG sensor that considers (a) HRV based features derived from 10 peak interval in addition to raw PPG sensor data (b) additional Non-Linear PPG derived features (c) a combination of different ANNs to estimate accurately DBP and SBP (d) a feedback of DBP output to derive the SBP.

The main objective of this work is to develop a cuff-less

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BP monitoring solution that helps a smartphone user to continuously monitor BP. With this objective in mind, we have designed and developed a PPG based method for estimation of accurate DBP and SBP deployable on smartphones. Main features of the smartphone application are (a) Raw PPG sensor data acquisition and processing (b) extracting PPG based Linear, Non-Linear and HRV features (c) Estimation of DBP and SBP in a smartphone using a pre-trained Neural Network model. Such a non-invasive PPG based BP estimation system could help users in continuous monitoring and tracking of their BP leading to early detection of hypertensive condition.

II. METHODOLOGY

The proposed method of cuff-less BP estimation described below is based on machine learnt approach with elaborate training, validation and testing rather than a rule based or a pulse transit time approach. The proposed method can be divided into the following steps: a) Obtaining a database with adequate sample size representative of entire population; b) Preprocessing the BP and PPG signal to remove unwanted noise and invalid signals to create windows of data; c) Feature extraction from the pre-processed and windowed PPG sensor data; d) Post processing of the obtained features to acquire a clean features dataset; and e) Machine learning to train the regression model, validate and test the data over their respective sets. Each of the above mentioned points are described below in detail.

A. Data Acquisition

i) Cuff-Less Blood Pressure Estimation data set from UCI Machine Learning Repository [3] has been employed as the reference database in this work. This database is derived from Multi-parameter Intelligent Monitoring in Intensive Care (MIMIC) II database [10] of the Physionet Organization. The MIMIC dataset has been collected over thousands of people across different age groups at a sampling frequency of 125 Hz with at least 8-bit accuracy. We have extracted PPG and arterial BP signals of 3000 people for our study from this database.

ii) Samsung Galaxy Note5 was used for collection of data from PPG sensor at 100 Hz which is interpolated using cubic spline method to 125 Hz for testing and deployment of developed solution on smartphone.

B. Pre-Processing

A considerable part of the filtered PPG & BP signals obtained from the database are still distorted due to various artifacts present in the data. In order to extract reliable features, pre-processing of the data is required.

Pan-Tompkins peak detection algorithm [11] has been used to extract peaks and valleys of BP and PPG signals and the entire data is divided into windows between consecutive valleys. Following steps are implemented on each of the obtained 1,701,600 windows to ensure consistency of:

i) Windows with inconsistent and erratic blood pressure and heart rate values are removed. In order to remove phase lag in collected data, the processed PPG and BP signals are synchronized with each other and used for feature extraction.

ii) Windows obtained are normalized using min-max scaling in the magnitude range of 0.5 to 1.5 so as to calibrate smartphone PPG sensor with the sensor used in database.

C. Feature Extraction

In this paper, in addition to various features based upon the PPG and APG signal, we have used Heart-Rate variability based features to improve the BP estimation. The systolic and diastolic pressures for each window are calculated by simply finding out the peak (for systolic) and the following valley (for diastolic) of the BP waveform.

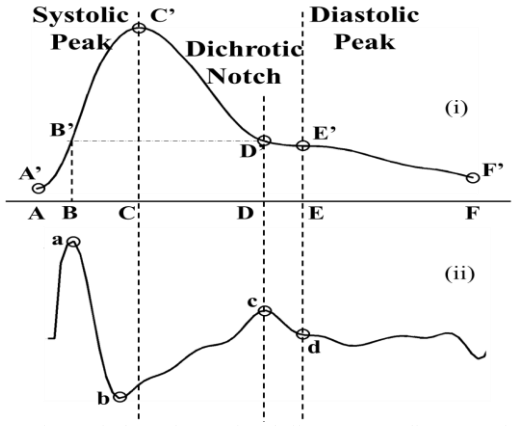

Figure 1. (i) A Window of PPG signal (ii) Corresponding APG signal

Feature extraction procedure is explained in this section:

i) Feature extraction is done on a window of PPG data from which 8 features are extracted from the magnitude and temporal variation information contained in the signal.

ii) Further feature extraction is done on the second derivative of the PPG waveform called the Acceleration Plethysmogram (APG) waveform [12]. APG signal is filtered using FFT technique to remove high frequency noise from which 19 features are extracted. APG signal is used for identifying certain relevant points such as dichrotic notch, diastolic point etc. on the PPG curve as well as for extracting magnitude information at those points. Time variation information of APG is also used for feature extraction. Such features of APG have been shown to contain age and the arterial characteristic information [12] of an individual which in turn affects the blood pressure to give more robustness to the training model.

iii) Novel set of non-linear cardiac cycle time ratio based features are added based on statistical significance and correlation with target BP values, 8 such features are extracted. Physiological significance of these non-linear feature lies in the fact that time spent in each component of cardiac cycle (atrial contraction, relaxation, ventricular contraction, relaxation) affects the blood volume and the force with which it is pushed into peripheral blood vessels. Peripheral arterial pressure in turn affects the SBP and DBP.

iv) Heart Rate Variability (HRV) based features [13] are extracted by considering 10 consecutive peak interval of PPG data from which 11 features are extracted. HRV is a result of time spent in each component of cardiac cycle eg., if the aortic valve opens prematurely the pulse peak will arrive earlier and if aortic valve closes late, the peak pulse

TABLE 1. FEATURE DESCRIPTIONS

I. A. PPG signal magnitude features [Fig. 1]
1: Mean value of the window
2: Variance value of the window
3: Skewness value of the window
4: Kurtosis value of the window
I.B. PPG signal temporal features [Fig. 1]
5: Length of window (AF)
6: Difference of location of peak and first valley with respect to the length of window (AC/AF)
7: Difference of peak and first valley with respect to time (AC)
8: Difference of peak and second valley with respect to time (CF)
II. APG signal derived features [Fig. 1]
9: Location of dichrotic notch with respect to the length of window (AD/AF)
10: Location of dichrotic notch with respect to time (AD)
11: PPG signal value at dichrotic notch (D')
12: Difference of location of peak and dichrotic notch with respect to the length of window (CD/AF)
13: Difference of peak and dichrotic notch with respect to time (CD)
14: Difference of location of second valley and dichrotic notch with respect to the length of window (DF/AF)
15: Difference of location of second valley and dichrotic notch with respect to time (DF)
16: Difference of location of pre-dichrotic notch and dichrotic notch with respect to the length of window (BD/AF)
17: Ratio of area under the curve of PPG signal from dichrotic notch to second valley & the area under curve from first valley to dichrotic notch
18: Location of diastolic point on PPG signal with respect to the length of window (AE/AF)
19: Location of diastolic point on PPG signal with respect to time (AE)
20: APG signal value at the diastolic point in the window (d)
21: PPG signal value at the diastolic point in the window (E')
22: Ratio of APG signal value at the diastolic point to the peak value of APG signal in the window (d/a)
23: Ratio of APG signal value at the dichrotic notch to the peak value of APG signal in the window (c/a) [12]
24: Ratio of APG signal value at the first valley to the peak value of APG signal in the window (b/a) [12]
25: Area under the curve of PPG till the peak of PPG signal (S2) [3]
26: Area under the curve of PPG from the peak of PPG signal to the diastolic point (S3) [3] in the window
27: Area under the curve of PPG from diastolic point to the second valley of PPG (S4) [3] in the window
III. Non-Linear(NL) derived features
28: Ratio of feature no. 5 to feature no. 1
29: Ratio of feature no. 6 to feature no. 8
30: Ratio of feature no. 7 to feature no. 8
31: Ratio of feature no. 1 to the square root of feature no. 2 (μ/σ)
32: Ratio of feature no. 12 to feature no. 8
33: Ratio of feature no. 14 to feature no. 8
34: Ratio of feature no. 13 to feature no. 16
35: Ratio of feature no. 15 to feature no. 16

arrival will be delayed. This will result in higher/lower blood pressure and this variation can potentially be captured by our proposed approach. HRV has also been shown to have implicit information of autonomic nervous system and respiration [14] which has a direct effect on blood pressure of an individual.

The summary table of all the features is given in Table 1.

TABLE 1.(CONTD.) FEATURE DESCRIPTIONS

IV. Heart Rate Variability(HRV) based features [13]
36: Root mean square of successive difference (RMSSD)
37: No. of pairs of successive RR intervals that differ by 50ms (PRR50)
38: No. of pairs of successive RR intervals that differ by 20ms (PRR50)
39: Mean of RR interval
40: Standard Deviation of RR interval
41: Ratio of standard deviation to mean (Coefficient of variation)
42: Standard deviation of successive differences of RR intervals
43: Standard deviation of long diagonal axis in Poincarè plot
44: Low frequency power of RR intervals
45: High frequency power of RR intervals
46: Ratio of low frequency power to high frequency power

D. Post-Processing

Features and blood pressure values are averaged over 10 peak windows from which HRV features are calculated. Post processing of all the features described in Table 1 is done by assigning a maximum and a minimum threshold for filtering out any erroneous value which may have crept in despite the filtering described. Feature values outside the range of $\mu \pm 5\sigma$ (heuristically determined) for a particular feature calculated over the entire dataset are removed.

For all practical purposes, systolic pressure values < 80mmHg and diastolic pressure values > 120mmHg are removed. To ensure that blood pressure did not change considerably over this 10 peak window, all windows of systolic and diastolic pressures having standard deviation greater than 5mmHg are removed.

Finally, after combining consecutive 10 windows and post processing we remove 9% of data and obtain 151,487 (Total peaks/10 – erroneous values) blocks of data with 46 features averaged over 10 windows along with average target SBP and DBP values.

E. Machine Learning Model

The entire dataset consisting of 151,487 blocks is divided into two sets randomly in 80:20 ratios. The smaller set is the test set. The larger set is further divided into training and validation set in 80:20 ratios randomly three times. Separate models for systolic and diastolic pressures are used for training. The larger set is used to train and validate three Artificial Neural Network (ANN) regression model for each systolic and diastolic pressures, as detailed in Fig. 2 using Levenberg-Macquardt algorithm.

Diastolic model was trained using 46 features as described in Table 1. Since the dataset consists of 3000 individuals with 1,750,000 pulses, the 4 hidden layers network gives the best representation of the BP variation of the underlying human population without under or overfitting. Hence, three separate models with 4 hidden layers and different combination of neurons are used as described in Table 2. For training the Systolic model, we have used an additional feature of Diastolic pressure along with 46 other features as described in Table 1. Diastolic pressure is a unique feature having a very high correlation of 0.53 with Systolic pressure and hence has potential to improve the accuracy of Systolic pressure. 47 features are hence used to train the systolic model as described in Table 2

The final output is determined by combining the weighted outputs of the three models. The weights are calculated so as to minimize the standard deviation of the error and are reported in Table 2.

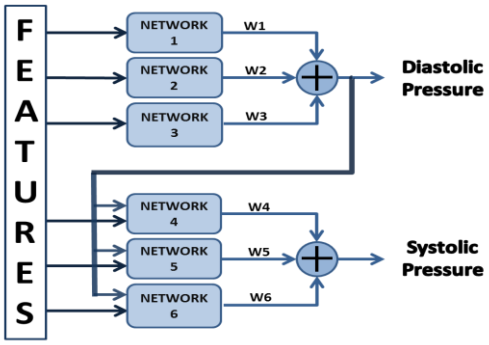

Figure 2. Combinatorial Neural Network Model

III. RESULTS

TABLE 2. MODEL PARAMETERS

Diastolic Model		Systolic Model	
Hidden Layers (No. of Neurons) (Input → Output)	**Weights**	**Hidden Layers (No. of Neurons) (Input → Output)**	**Weights**
50,40,20,10	0.34	50,25,35,20	0.31
50,20,30,20	0.21	50,35,25,15	0.38
50,30,30,20	0.45	50,30,30,20	0.31

TABLE 3. FEATURE BASED RESULTS COMPARISON

Feature sets	**Mean Error (mmHg)**		**Error Standard Deviation (mmHg)**		**Mean Absolute error (mmHg)**	
	Sys.	**Dia.**	**Sys**	**Dia.**	**Sys.**	**Dia.**
PPG+APG (Previous)	0.10	0.03	15.17	8.68	11.26	6.27
PPG+APG+NL+HRV (Proposed approach)	0.16	0.03	6.85	4.72	4.47	3.21

The Hidden layer network and weights of individual networks are shown in Table 2. We obtained the accuracies of SBP and DBP using both existing state of the art (using single PPG sensor) [3] and our proposed approach for comparison purposes as in Table 3. The results tabulated in Table 3 show a two-fold improvement in accuracy over previous studies by incorporating Non-Linear, HRV based features and a combination of ANNs with DBP feedback. The accuracies obtained using our proposed method is 0.03±4.72mmHg for DBP and 0.16±6.85mmHg for SBP. There is further scope of improvement in terms of accuracies if age and gender information are also provided in the database. The solution is deployed on smartphone and screenshots are shown in Fig 3.

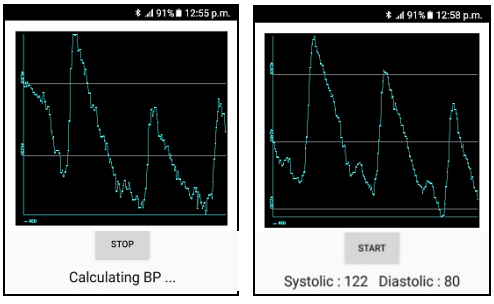

Figure 3. Screenshots of developed BP estimation application.

IV. CONCLUSION

We have developed a cuff-less BP monitoring solution that will enable smartphone users to continuously track their BP. The proposed solution employs HRV as an additional parameter to provide better physiological input for correct and accurate estimation of BP. Based on the present approach, we have recorded an accuracy of ±4.72mmHg for DBP and ±6.85mmHg for SBP for cuff less BP estimation which is significantly higher than previously reported studies over a larger dataset. The unique features of this proposed solution are (a) direct estimation of BP using single PPG sensor without approximating PTT (b) providing a feedback mechanism from DBP output for estimation of SBP as DBP is found to be highly correlated with SBP (c) a combinatorial ANN approach for optimizing the individual DBP and SBP output. We believe that such a portable smartphone based BP estimation system will enable on demand home monitoring of BP as an important vital, resulting in overall reduction in cardiovascular morbidity and mortality.

REFERENCES

[1] Gillespie C, Kuklina EV, Briss PA, Blair NA, Hong Y. "Vital signs: prevalence, treatment, and control of hypertension – United States, 1999–2002 and 2005–2008". *MMWR*. 2011; 60(04);103–108.

[2] Pickering TG, James GD, Boddie C, Harshfield GA, et al. "How common is white coat hypertension?" *JAMA*. l988; 259:225–228.

[3] M. Kachuee, M. M. Kiani, H. Mohammadzade, M. Shabany. "Cuff-Less High-Accuracy Calibration-Free Blood Pressure Estimation Using Pulse Transit Time," *IEEE International Symposium on Circuits and Systems (ISCAS'15)*, May. 24-27, 2015, pp. 1006-1009.

[4] X.F. Teng and Y.T. Zhang. "Continuous and noninvasive estimation of arterial blood pressure using a photoplethysmographic approach," *25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Sept. 17-21, pp. 3153–3156, 2003.

[5] D.B. McCombie, A.T. Reisner, HH. Asada. "Adaptive blood pressure estimation from wearable PPG sensors using peripheral artery pulse wave velocity measurements and multi-channel blind identification of local arterial dynamics", *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2006. EMBS '06*, Aug. 30- Sept. 3, 2006.

[6] Zhang, J. M., P. F. Wei, and Y. Li. "A LabVIEW based measure system for pulse wave transit time." *In Information Technology and Applications in Biomedicine, 2008. ITAB 2008. International Conference on*, pp. 477-480. IEEE, 2008.

[7] P. Fung, G. Dumont, C. Ries, C. Mott, M. Ansermino. "Continuous noninvasive blood pressure measurement by pulse transit time," *Engineering in Medicine and Biology Society, 2004. 26th Annual International Conference of the IEEE*, pp. 738-741, Sept. 1-5, 2004.

[8] C.C.Y. Poon, Y.T. Zhang. "Cuff-less and Noninvasive Measurements of Arterial Blood Pressure by Pulse Transit Time", *IEEE-EMBS (Engineering in Medicine and Biology Society), 27th Annual International Conference,* pp. 5877-5880, Jan. 17-18, 2005

[9] G-Y. Jeong, K-H. Yu, N-G. Kim, "Continuous Blood Pressure Monitoring using Pulse Wave Transit Time," *International Conference on Control, Automation and Systems*, pp. 834-837, 2005.

[10] Goldberger, Ary L., et al. "Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. 215–220, 2000.

[11] Pan, Jiapu, and Willis J. Tompkins. "A real-time QRS detection algorithm." *Biomedical Engineering, IEEE Transactions on 3* (1985), pp. 230-236.

[12] M. Elgendi. "On the analysis of fingertip photoplethysmogram signals," *Current cardiology reviews*, vol. 8, no. 1, p. 14, 2012.

[13] Peng, Rong-Chao, et al. "Extraction of heart rate variability from smartphone photoplethysmograms." *Computational and mathematical methods in medicine 2015* (2015).

[14] Task Force of the European Society of Cardiology, "Heart rate variability standards of measurement, physiological interpretation, and clinical use," *Circulation*, 1996; 93: 1043-1065.