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Learning-Based Model for Central Blood Pressure Estimation using Feature Extracted from ECG and PPG signals

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***Abstract*— Pre-detection of hypertension mostly considers the measurement of Brachial Artery Blood Pressure (BABP). Although being a standard vital, it is still considered a poor alternative for Central Blood Pressure (CBP). However, CBP is measured invasively during the process of cardiac catheterization (Cath). Though cuff-less techniques to estimate BABP are widely employed, CBP estimation has not been explored yet. Moreover, to best of our knowledge intermittent CBP estimation has not been proposed earlier. Therefore, we present a cuff-less and beat-by-beat CBP estimation technique using linear regression analysis on features extracted from continuous Electrocardiogram (ECG) and Photoplethysmograph (PPG) signals. Unlike for BABP estimation, 30 supplementary features to conventional pulse transit time such as ST-interval, P-systolic peak interval, etc., were extracted to enhance CBP accuracy. This extraction was done using Haar wavelet along with modulus maxima. Feature selection has been done using the wrapper technique and reduced using principal component analysis. Segregation of each beat was achieved with the help of constraints developed based on iteration and backtracing. This model estimates Systolic CBP with a validation error of 0.109 ± 2.37 mmHg and Diastolic CBP with an error of 0.031 ± 2.102 mmHg for 33 Cath lab patients.**

I. INTRODUCTION

According to the World Health Organization (WHO) fact sheets, an estimated 1.13 billion people worldwide, that is two-third of the world population have hypertension [1]. Prior diagnosis and treatment of hypertension can be done if Blood Pressure (BP) is monitored continuously. Therefore, Brachial Artery Blood Pressure (BABP) has been considered as a standard vital for monitoring. However, in the blood circulatory system, blood is supplied to crucial organs through major arteries that are more exposed to aorta rather than the brachial artery. Since it is one of the second level branches to the aorta, BABP acts as a poor surrogate for blood pressure estimation. As a result, Central Blood Pressure (CBP), i.e. the force with which blood is pumped out of the heart, has to be monitored ideally [2], [3]. CBP is usually 10 - 50 mmHg lower than BABP due to the amplification of pressure wave as shown in Figure 1. The pressure wave is the sum of the incident wave and reflected wave as it travels down from highly elastic arteries to stiffer ones. The incident wave is generated by the left ventricle, whereas reflected wave is due to impedance mismatch at multiple peripheral sites such as bifurcations and small muscular arteries and arterioles.

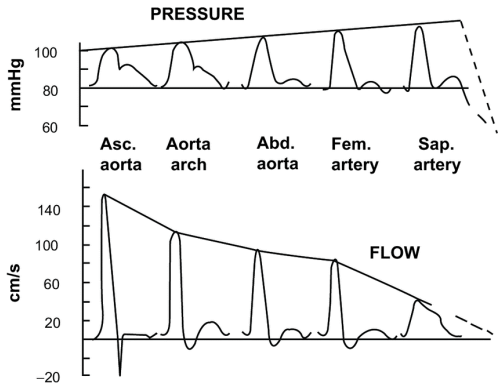

Fig. 1. Pressure waveform along arterial tree [3].

Conventionally, CBP is measured using the invasive insertion of a catheter through radial or femoral artery during the process of cardiac catheterizing [4]. As the procedure deals with invasion into the artery, it involves high sanitation requirements and excellent performing skills. Currently, this procedure has been used as a gold standard for continuous CBP monitoring. However, as expected it's usage is limited to ICUs and operation theatres.

Lately, few oscillometric CBP monitoring techniques have been proposed [5]–[7]. However, due to non-invasive reference from tonometry based Sphygmocor, these methods suffer limitations. Moreover, the cuff based BP meters cause pain, discomfort and tissue damage limiting the frequency of measurements. Hence, it is evident that a cuff-less BP estimation technique is required for continuous CBP monitoring.

Literature suggests that cuff-less methods for estimation of BP have been extensively used for the brachial artery [8]–[15]. For this BABP estimation, Pulse Transit Time (PTT) calculated from Electrocardiogram (ECG) and Photoplethysmograph (PPG) signals have been used. However, to the best of our knowledge, the cuff-less estimation technique has not been proposed for CBP.

In this paper, we propose a non-invasive, cuff-less and beat-by-beat CBP estimation technique, which is calibrated against the gold standard invasive BP data of 33 patients obtained from Cath Lab. Section II discuss the process of data collection, feature extraction, and regression analysis. Results obtained thereafter are discussed in section III and

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the paper is concluded in section IV.

II. Method

A. Collection of Clinical Data

The study was conducted on 33 Cath lab patients in Care Hospital, Hyderabad, admitted for various cardiac procedures. The study is approved by the ethics committee of Care Hospital. Patients scheduled for the procedure were approached and informed consent was obtained from them. The patient data for 19/14 male to female ratio and aged 60 ± 10 years has been collected.

B. Study Protocol

This study involves the measurement of cuff based BABP before and after the catheterizing procedure, collection of ECG & PPG data and recording CBP during the Cath procedure. Cuff based BABP was recorded using Omron HEM-7130 BP Monitor. It is to observe the variation of BABP from CBP. CBP was recorded manually from the monitor present in the console room adjacent to the lab as shown in Fig. 2. Simultaneous digital ECG and PPG data were collected using the Vios Medical System (VMS). VMS is a Food and Drug Administration (FDA) [16] approved physiological signal monitoring device.

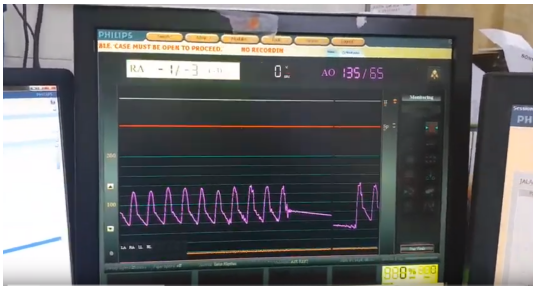


Fig. 2. CBP monitor at Cath lab.

C. Feature Extraction

VMS provides ECG data with a sampling rate of 200 samples/sec and PPG data at 75 samples/sec. To extract features such as PTT, we require simultaneous and equally sampled data. Therefore, data sets are interpolated to obtain the data rate of 1200 samples/sec. For training and validation, two data sets of around 1.5 minutes each are considered. Using the timestamps present within the data, the synchronicity is maintained between the training data and the reference CBP. 1.5 minutes of data is considered to obtain features averaged over the time duration of of the presence of catheter within the Aorta, to perform statistical analysis. Further, Wavelet Transformation (WT) is performed on the signals to get rid of the noise and also to extract information from various frequency components of the signals. WT provides both frequency and time domain information, hence it is appropriate for the process of feature extraction [9]. Haar wavelet has been used due to less complexity and its ability to detect sudden changes. An algorithm has been developed using Matlab as discussed in Fig. 3.

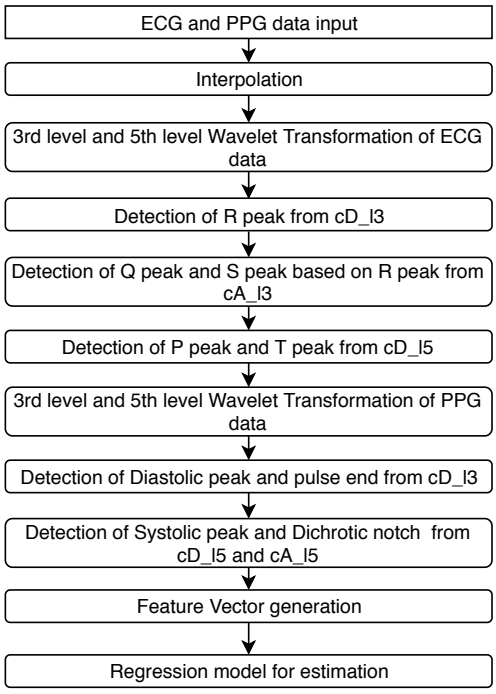


Fig. 3. Algorithm for feature extraction from ECG and PPG signal data.

ECG signal signifies the electrical activity of the heart and it consists of P, Q, R, S and T waves. R peak is the highest peak in the ECG pulse and the QRS complex has a higher frequency in comparison to P and T waves. Hence, Q, R and S peaks are detected from third level detail coefficients i.e. cD_3 and P and T peaks are detected using fifth level detail and approximate coefficients i.e. cD_l5 and cA_l5 respectively as shown in Fig.4. The first R peak is detected by identifying the highest peak between the maximum and minimum values of cD_l3. Further, Q and S peaks are detected by performing maximum modulus analysis (MMA) about R peak. Hence, detection of Q peak and S peak relies on the precise detection of R peak. P peak is detected as the highest point in cA_l5 between maximum and minimum points in cD_l5 of the wave segment before Q peak. Similarly, T peak is detected from the wave segment beyond S peak.

PPG signal signifies the change in volume during blood flow using optics. It consists of systolic peak (SP), diastolic peak (DP), dicrotic notch (DN) and end of pulse (EB). DP and EB are obtained using cD_l3, whereas SP and DN are obtained by taking derivative and threshold comparison along with cA_l5. The detected points in PPG pulse are shown in Fig.4. DP is detected using a similar procedure as R peak. Further EB is detected after DP using cD_l3 and DN and SP is detected using cA_l5 and cD_l5 by observing zero crossings in the part of the wave segment before DP.

The above methodology is followed for wave-point detection in the physiological signal segment for each beat. Further, the challenge is to identify that signal segment such that all the wave-points in the segment are in order. To circumvent this, the first segment size is calculated as the

number of samples between two consecutive R peaks and DP's for ECG and PPG respectively. Afterwards, constraints have been developed while considering the basic behavior of each signal. Each beat is identified as a segment satisfying the constraints by the process of iteration and back-tracing. The constraints for the ECG signal are as follows:

- R peak should be detected.
- Difference between R peak and the center of the segment must be less than 10% of the segment size.
- Within the segment, the number of modulus maxima points (MMT) before and following the R peak should be greater than 2.

The presence of these MMT points ensures the presence of P and T waves within the segment. Further, to validate the presence of the above-mentioned PPG wave points, the segment should fulfill the following conditions.

- DP should be detected.
- Difference between DP and the center of the segment must be less than 10% of the segment size.
- Number of modulus maxima points (MMT) before and following DP should be greater than 3 and 2 respectively.

The presence of SP and previous beat's EB is ensured with the presence of 3 MMT points before DP. The presence of current EB is ensured by 2 MMT points following the DP. Hence, the presence of the entire beat within the segment is assured. If the above conditions are not satisfied, the segment is iterated by 10 samples.

Using these aforementioned wave points, the feature vector containing 30 features supplementary to PTT is generated for each patient.Some of these features have been shown in Fig.4. DP is back-traced to the most previous R peak to assure that features are calculated only among simultaneous ECG and PPG beats. The feature vector includes features calculated from ECG signal, from PPG signal and both ECG and PPG signal. These features are extracted beat-by-beat. To get rid of artifacts and incorrect detection, mean and standard deviation (SD) is calculated the values lying out of [mean - SD, mean + SD], are discarded.

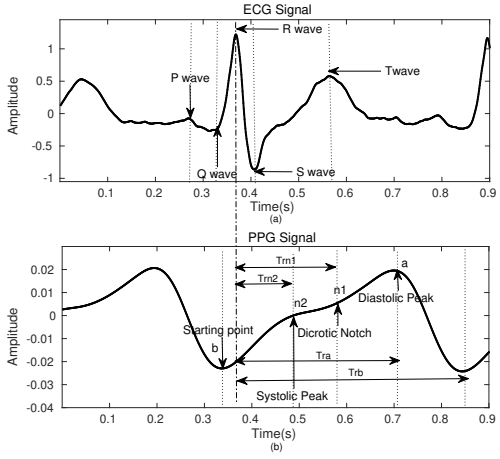


Fig. 4. Feature extraction from simultaneous ECG and PPG signal.

D. Estimation using Regression Analysis

The feature vector obtained is high dimensional in comparison to the number of data sets. Also, it is observed experimentally that models with reduced features also perform almost equally well. Partial Least Square Regression (PLSR) technique has been used for training. PLSR is the combination of Principle Component Analysis (PCA) and Multi-linear regression. This technique is best known for training models with lower training data. Here, PCA calculates co-variance and reduces the feature dimension. As a resultant, 25 features each are selected for the estimation of SBP and DBP.

These features are used to perform a regression analysis to train the estimation model. The model has been trained using a Matlab regression learner and 5 cross-validations has been enabled to avoid over-fitting. The comparison between the performance of various regression models has been discussed in Table I. Linear Regression models have been chosen due to higher R^2 values and acceptable errors.

TABLE I

COMPARISON BETWEEN THE PERFORMANCE OF VARIOUS REGRESSION MODELS

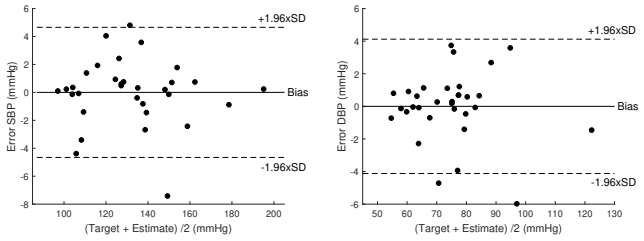
Regression Model		RMSE (mmHg)	R^2	MAE (mmHg)
SBP	Linear Regression	0.26	0.6	0.2
	Squared Exponential	0.17	0.24	0.13
	Exponential	0.16	0.28	0.13
DBP	Linear Regression	0.65	0.44	0.4
	Squared Exponential	0.18	0.02	0.14
	Exponential	0.18	0.13	0.13

III. RESULTS

The models for systolic and diastolic CBP were trained using the data of 33 patients. Due to the lesser amount of data, cross-validation has been enabled, but for validation, different data sets were required. To circumvent this need, ECG and PPG signal data for each patient were divided. One part of each patient was used for training, and others were used for testing. The results for testing have been demonstrated with the help of the Bland-Altman plot as shown in Fig. 5. The error obtained during the estimation of systolic CBP is 0.109 ± 2.37 mmHg whereas it 0.031 ± 2.102 mmHg for diastolic CBP estimation. Mean Absolute error is 1.6 mmHg and 1.41 mmHg for systolic and diastolic CBP estimation respectively. The performance of the models can be observed through the dispersion plot in Fig. 6. It can be inferred that outliers or maximum error are obtained for SBP and DBP exceeding 150 mmHg and 85 mmHg respectively.

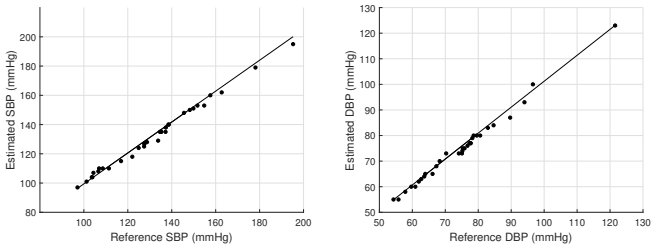
IV. CONCLUSION

The study involved data collection from 33 patients who were scheduled for cardiac procedures involving catheterization. Simultaneous ECG and PPG data were collected and the feature vector was generated by using Haar wavelet and MMA. The linear regression model was trained for



(a) (b)

Fig. 5. The Bland-Altman plot for (a) Systolic and (b) Diastolic CBP estimation



(a) (b)

Fig. 6. Dispersion plot for (a) Systolic and (b) Diastolic CBP estimation where line and dots represent the ideal and actual behavior of estimation

both systolic and diastolic CBP. As per the results obtained from the above study, it is concluded that the approach of estimating CBP using features extracted from ECG and PPG signals is a reliable one. The errors obtained are 0.109 ± 2.37 mmHg and 0.031 ± 2.102 mmHg for SBP and DBP respectively. The results can be further improved by training the model with more data. Also, if the data was present for the SBP and DBP exceeding 150 mmHg and 85 mmHg respectively, the sensitivity and robustness of the model can be further increased. Hence, this approach can be used for continuous CBP estimation and can act as a better alternative in comparison to BABP.

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REFERENCES

[1] "WHO Hypertension Fact Sheet [Online] https://www.who.int/news-room/fact-sheets/detail/hypertension."

[2] C. M. McEniery, J. R. Cockcroft, M. J. Roman, S. S. Franklin, and I. B. Wilkinson, "Central blood pressure: current evidence and clinical importance," *European heart journal*, vol. 35, no. 26, pp. 1719–1725, 2014.

[3] E. Agabiti-Rosei, G. Mancia, M. F. O'Rourke, M. J. Roman, M. E. Safar, H. Smulyan, J.-G. Wang, I. B. Wilkinson, B. Williams, and C. Vlachopoulos, "Central blood pressure measurements and antihypertensive therapy: a consensus document," *Hypertension*, vol. 50, no. 1, pp. 154–160, 2007.

[4] B. Gupta, "Invasive blood pressure monitoring," *Update in Anaethesia*, vol. 28, pp. 37–42, 2012.

[5] H.-M. Cheng, K.-L. Wang, Y.-H. Chen, S.-J. Lin, L.-C. Chen, S.-H. Sung, P. Y.-A. Ding, W.-C. Yu, J.-W. Chen, and C.-H. Chen, "Estimation of central systolic blood pressure using an oscillometric blood pressure monitor," *Hypertension Research*, vol. 33, no. 6, p. 592, 2010.

[6] R. E. Climie, M. G. Schultz, S. B. Nikolic, K. D. Ahuja, J. W. Fell, and J. E. Sharman, "Validity and reliability of central blood pressure estimated by upper arm oscillometric cuff pressure," *American journal of hypertension*, vol. 25, no. 4, pp. 414–420, 2012.

[7] T. Weber, S. Wassertheurer, M. Rammer, E. Maurer, B. Hametner, C. C. Mayer, J. Kropf, and B. Eber, "Validation of a brachial cuff-based method for estimating central systolic blood pressure," *Hypertension*, vol. 58, no. 5, pp. 825–832, 2011.

[8] M. Jain, N. Kumar, S. Deb, and A. Majumdar, "A sparse regression based approach for cuff-less blood pressure measurement," in *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 789–793, IEEE, 2016.

[9] A. M. Zakrzewski and B. W. Anthony, "Noninvasive blood pressure estimation using ultrasound and simple finite element models," *IEEE Tran. on Biomed. Engg. (TBME)*, vol. 65, no. 9, pp. 2011–2022, 2018.

[10] L. Wang, W. Zhou, Y. Xing, and X. Zhou, "A novel neural network model for blood pressure estimation using photoplethesmography without electrocardiogram," *J. healthcare Engg.*, vol. 2018, 2018.

[11] R. Banerjee, A. Ghose, A. D. Choudhury, A. Sinha, and A. Pal, "Noise cleaning and gaussian modeling of smart phone photoplethysmogram to improve blood pressure estimation," in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 967–971, IEEE, 2015.

[12] X.-R. Ding, Y.-T. Zhang, J. Liu, W.-X. Dai, and H. K. Tsang, "Continuous cuffless blood pressure estimation using pulse transit time and photoplethysmogram intensity ratio," *IEEE Tran. on Biomed. Engg. (TBME)*, vol. 63, no. 5, pp. 964–972, 2016.

[13] M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, "Cuffless blood pressure estimation algorithms for continuous health-care monitoring," *IEEE Tran. on Biomed. Engg. (TBME)*, vol. 64, no. 4, pp. 859–869, 2017.

[14] K. Duan, Z. Qian, M. Atef, and G. Wang, "A feature exploration methodology for learning based cuffless blood pressure measurement using photoplethysmography," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 6385–6388, IEEE, 2016.

[15] M. Singla, P. Sistla, and S. Azeemuddin, "Cuff-less blood pressure measurement using supplementary ecg and ppg features extracted through wavelet transformation," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 4628–4631, IEEE, 2019.

[16] S. Mazar and A. Patel, "Patient care and health information management systems and methods," Oct. 22 2015. US Patent App. 14/681,333.