Cuff-Less BP Stratification based on Bio-Signals processing using Machine Learning : An Investigative Study

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***Abstract*—Cuff-Less Blood Pressure Stratification using Signal Processing with Machine Learning has gained immense attraction in the past decade among the research community. Blood Pressure, one of the most vital parameter of the human body representing overall well being of an individual. Most of the cardiovascular and cerebrovascular diseases (CCVD) including Hypertension are highly correlated to Blood Pressure. Existing BP measurement approaches are highly inconvenient and intermittent and do not allow continuous measurement of BP. Continuous BP measurement could prove to be significant indicator to most of the medicinal conditions and will lead to breakthrough achievement in the field of medical science. Cuff-Less Blood Pressure estimation hopefully can enable continuous blood pressure measurements in the time to come. A Plethora of methods for Cuff-Less BP Stratification have been experimented out by using Vital Bio-Signals such PTT based, nPTT based, Machine Learning and Deep Learning based. Most of these methods leading to satisfactory beliefs that Cuff-Less BP estimation could be possible to the utmost accuracy for the diagnosis of most of the CCVD diseases as well as to monitor the overall well being of humans. However, most of the approaches still needs improvements, needs to be tested on a larger population with varying demographic features and real time application. This paper presents an investigative study of existing Cuff-Less BP Estimation approaches and discusses the merits and opportunities for improvements of the Cuff-Less BP Estimation methods.**

Keywords—Machine Learning, Signal Processing, Blood Pressure, Cuff-Less BP, CCVD.

I. Introduction

Hypertension, a companion to Braunwald's heart disease is a giant and a silent killer [1]. 9.4 million People die annually due to hypertension as per the statistics of the World Health Organization (WHO) reported in 2014 [2]. According to 2008's survey, 29.2 percent of men and 24.8 percent of women suffer from the high blood pressure problem [3]. Hypertension is a condition of the human system in which the Systolic Blood Pressure (SBP) goes to 140 mm Hg or higher and Diastolic Blood Pressure (DBP) goes to 90mm Hg or higher. Gradual progression of Hypertension is observed due to variety of environmental, behavioral and genetic situations [4]. Lifestyles parameters such as diets, physical activity, alcohol consumption and obesity have major impact on our blood pressure [4]. Blood Pressure being such an important indicator of human body is measured traditionally using Cuff band wrapped around the arms of the subject, the nurse inflates the cuff and then takes measurements as the Cuff starts to deflate the first sound is SBP and after it fades the pressure is DBP. BP is measured in ICU by inserting a catheter into the arteries of the patient which is highly accurate. But these traditional methods of BP measurements are highly inconvenient to patients apart from being taken at discrete time intervals. Continuous BP measurements are difficult with these legacy systems. Hence, there is need for development of approach for continuous and convenient BP estimation which will be great assist to medical practitioners.

Kortis-Moeg Equation [5- 9] opened a new door in the paradigm of Cuff-Less BP estimation in 1981 by finding the correlation ship between BP and PTT. PTT defined as a time interval between the activation of pulse by heart and it reaches to the distal point. Many linear models have been developed to estimate BP using PTT parameter, but most of them remains in question due to their relatively low accuracy and widespread real time mass testing absence. Most of these models required personalized calibration as well [7], [10], [11], [12]. As illustrative example these calibrations are needed due to the periodic alignment of the estimated BP curve and the actual BP.

Mohammad Kachuee et. al.[5] shown that the relationship between PTT and BP is not exactly linear as was postulated in the earlier studies [13]. They have illustrated this fact with some non-linear algorithms.

Research was also carried out to apply machine learning based decision making systems to estimate BP in the Cuff-Less manner. This has opened a new door in the research of Cuff-Less BP estimation paradigm. Most of the machine

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Table-1: Blood Pressure Classes [14]

Blood Pressure Category	SBP Range	DBP Range
Hypotension	*Less than 90*	*Less than 60*
Normal	*90-119*	*60-79*
Prehypertension	*120-139*	*80-89*
Stage 1 Hypertension	*140-159*	*90-99*
Stage 2 Hypertension	*160-179*	*100-109*
Hypertensive Emergency	*>=180*	*>=110*

learning based estimation methods achieved satisfactory results but limited to a small number of test subjects and less variety of normal, hypotensive and hypertensive subjects, so also age, gender, weight, height and other demographic features were not considered to a large extent[5]. Machine Learning has been gaining popularity in most of the state-of-the art applications [44], [46], [47], [50], [51], and [52].

Recently, several Deep Learning based approaches are applied for the Cuff-Less BP Estimation and they too landed with improvements in terms of accuracy, applicability to large number of subjects in real time and testing with bodily movements such as before, during or after exercise. Deep Learning is also applicable in several Heart Disease Detection Systems [60].

Table-I below [14] shows the different Blood Pressure Classes for Systolic and Diastolic BP Value Ranges.

For the evaluation of the stratified BP Values following two standards are used extensively in the literature [5] globally:-

1. **The British Hypertension Society (BHS) standard:-**

The BP measuring devices are graded by BHS depending on their cumulative percentile errors under 3 threshold values 5, 10 and 15 mmHg.

2. **The Advancement of Medical Instrumentation (AAMI) criterion:-**

The BP measuring devices should have the STD and ME values less than 8 mmHg and 5 mmHg respectively.

II. LITERATURE SURVEY

P. Shaltis et.al. [11] in the year 2005 presented the opportunities and limitations of use of PPG signals for continuous BP estimation. The paper postulated that the relationship between PPG Signal and the ABP (Arterial Blood Pressure) is fundamentally non-stationary; however it could be useful for short duration continuous BP estimation that too with no need for recalibration.

Federico S. Cattivelli et.al. [07] proposed an adaptive calibration approach utilizing both ECG and PPG Signals. They used PAT and Heart Rate measurements as primary parameters in their work; however their method was based on recalibrations. The proposed method demonstrated much less accuracy for SBP in accordance with standards.

The work carried out by Q. Liu et.al. [15] was one of its kind in the initial experiments of BP Stratification after doing Exercise on Normal Subjects. They systematically carried out Time-Frequency analysis of following parameters: PTT, Heart Rate and SBP especially in terms of their variability.

Mohamad Forouzanfar et. al. [16] carried out an experiment wherein only ECG signal was used but it was recorded simultaneously with Oscillometric BP.

Maryam Moghadam et. al. [17], used model based approach for BP Estimation interestingly during exercise. The approach was based on Fuzzy Algorithm function which utilized 75 subjects data who were working on treadmill.

Satya Narayan Shukla et. al. [18] proposed PPG Signal processing based approach using standard MIMIC dataset. They compared the results obtained by applying Multi Task Gaussian Processes (MTGPs) with Artificial Neural Networks (ANN).

Saif Ahmad et. al. [19] presented an approach quite similar with Mohamad Forouzanfar et. al. [16] in which ECG and Oscillometric BP was recorded at a time.

The major drawback of both [16], [19] these methods is that manual adjustment of cuff deflation is required.

Shi Chao Gao et.al. [20] Demonstrated the use of Cell Phone to collect the data which could prove to be the most convenient option for Cuff-Less BP stratification.

In cheol Jeong, and Joseph Finkelstein [21] presented use of ECG and PPG for Non Invasive BP estimation during exercise. They recorded the data however of only 5 subjects which included 3 Female and 2 Male participants.

Xiaochuan He et. al. [22] proposed polynomial regression for BP estimation utilizing both ECG and PPG signals. More complex noisy situations were not considered in this study. This in turn restricts the real time use of this and many similar systems [49].

Ali Jadooei and Shulgin V.I. [23] proposed adaptive Kalman filter for BP Estimation based on PTT computed from simultaneous recordings of ECG and PPG signals. Calibration was required in this study.

Niranjan Kumar et.al. [24] proposed 2nd order curve-fitting regression model using both ECG and PPG Signals.

Mohamad Kachuee et.al. [3] proposed use of Machine Learning based approach for Cuff-Less BP Estimation by utilizing both PPG and ECG signals based on PTT. This method was advantageous in terms of that it's calibration-free, however with limited accuracy.

ANDREAS PATZAK et.al.[25] carried out comparison of continuous BP measurements obtained using PTT based approach with intra-arterial values.

Sarvesh Kumar et.al. [26] established new relationship between Diastolic BP and PTTt as well as between Systolic BP and PTTb. Unfortunately the study was limited to only 4 subjects and remained a question of its applicability to large participants as future work.

Artur Polinski et.al. [27] developed custom ECG Module and tested the applicability of Ex-Gaussian Model. In this work, Different approximations produced different results and the polynomial approximation produced worst results.

Amirhossein Esmaili [28] proposed the use of 3 signals namely ECG, PPG and PCG and it was unique in its own terms of utilizing 3 signals. They used exercise based calibration.

Yue Zhang et.al. [29] extracted features of only PPG Signals and evaluated the results by applying Decision Trees, KNN, Naive Bayes and SVM. They basically classified BP in different ranges of DBP and SBP. Here, poor accuracy for certain classes were observed. They considered 32 surgical cases and 6000 subjects which was sufficiently big number used for the validation of the proposed methodology.

Mohammad Kachuee et. al. [5] proposed ECG and PPG signals simultaneous processing based approach for continuous BP Estimation based on machine learning. They tested the results with AdaBoost, Decision Trees, RF and SVM. MIMIC Dataset was used for the experimentation purpose.

Yang Xu et.al. [30] proposed Adaptive Calibration method which was based on nPTT. They postulated that nPTT is better than PTT for BP estimation, however they could not come out with the reason for the same. Moreover the testing was conducted wherein the participants were in resting state.

Mark Butlin et.al. [31] presented an interesting work of calibration approach considering Variability of arterial stiffness. That too they tested it across different sites of measurements and individuals. Interestingly they carried out Study of Anatomical Site Variability and Individual Variability for BP and PTT relationship. Drawback of this method was that it required calibration.

Nicolas Bersano et.al. [32] presented Multiclass classification method using Features of PPG Signals. The classifier used was ANN. In this method preprocessing of PPG Signals were not necessary and without considering demographic features there results were promising. But they tested only 52 Healthy subjects.

Jishnu Dey et.al.[33] used Smartphones for collection of PPG Sensor data. This is the easy method since Smartphone is used for data collection. However, the accuracies were not acceptable as per the BHS Standard.

Hin-Wai Lui et.al. [34] Attempted to estimate BP using both Respiratory Rate and Heart Rate. It’s also BP-PTT based approach. This was used only 10 healthy subjects and calibration is still required here.

Jing Liu,,et.al. [35] were the first to attempt the use of Multi-wavelength PPG Sensor which interestingly covers all 3 layers of skin the enhances the accuracy of BP Prediction. However, this method used only 9 Subjects for experimentation.

Toan Huu Huynh et. al.[36] presented use of IPG and PPG signals which is quite a novel way of signal combination. They used IPG Sensor on wrist, and it’s basically PTT-IPG model. Significant hypothesis resulted from this work that states PTT does not fully correlate well with BP.

To summarize the major research gaps from the above literature survey indicates that:

- Proof-of-the concept Cuff-Less BP Estimation framework for Heterogeneous subjects and wider age ranges lacks in the existing literature.

- To validate the practicability and robustness of the existing methods and their improvements more real time sample collection is required.

- Accuracy of the existing methods needs improvement.

- Deep Learning research for optimization of vital signal features based BP Estimation is insufficient in present studies.

- SBP accuracy quite a low compared to DBP in most of the existing methods.

III. PROPOSED SYSTEM ARCHITECTURE

The Generalized System Architecture for Hypertension detection is depicted schamtically in Fig.1.

A. Input: In this Step Vital Bio-Signals such as ECG/PPG are acquared from the Subjects. The data set is formulated using the publically available UCI Machine Learning Dataset [3] developed by Mohammad Kacuhe et.al. The dataset contains 12,000 patient records organized in cell array of matrices. Each cell is one signal part such as Channel1 is PPG signal, Channel2 is ABP signal and Channel3 is ECG signal. The sampling frequency is 125Hz, unique for all 3 channels. PPG is fingertip, ABP is invasive and ECG is from another channel.

B. Signal Preprocessing: In this Step Noise, Jitter and other unwanted artifacts are removed and signal quality is enhanced. Only PPG signal is considered and ECG is not requied such that only single signal is sufficient to use and its usability is also good considering the number of wearble sensors requried to be used on the body.

C. Optimal Signal Feature Extraction: In this step Optimal Feature extraction is carried out such as Morphological and Physiological features of PPG signals. Both Time domain and frequency domain features are useful indicators for BP Stratification.

D. Machine Learning Algorithm: Hypertension class is detected based on the machine learning algorithm. Adaboost, Linear Regression and Decision Tree algorithms are studied. In our precious work we have applied Hybrid framwork and obtained satisfactory results[59].

E. Hypertension Class Detection: Hypertension class caterogry as per Table-I is detected in this step.

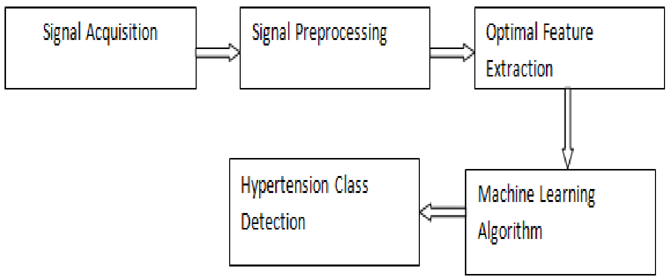

Fig. 1: Generalized System Architecture for Hypertension Class Detection

IV. FLOW OF THE SYSTEM WORK

A. Signal Aqusition

PPG Signals were extracted from the Data available on UCI repository for Cuff-Less Blood Pressure Estimation[5]. Fig.2 shows Sample PPG Signal. The 3 channels available in this dataset of 12,000 patient records contains PPG (channel1), ABP(Channel2) and ECG(Channel3) respectively. First 300ms time records of each signal are better useful for processing.

B. First Phase

Since the Signals are already cleaned up in the UCI Repository by Mohammad Kacuhe et.al.[5] Which were orginally captured from MIMIC database of Critical patients these are used for further work. The PPG signal is obtained by extracting the first row of each patient record available in the .csv file and the ABP reference signal is extracted using the second row of the each patient record from the same .csv file. The dataset contains 3 rows for each patient in cell array of matrices each row corresponding to one signal channel i.e. PPG, ABP and PPG respectively. Total 12,000 patient records available in 4 parts as Part_1, Part_2, Part_3 and Part_4 files each containing 3000 patient records.

C. Second Phase

The reference ground truth for this work was considered the captured ABP Signals. The Peak detection algorithm gives the detected High and Low peaks as SBP and DBP values as shown in Fig.3. The highest magnitude value corresponds to SBP value whereas the Valley corresponds to DBP value. One cycle is considered for each value computation. The output of this phase is detected SBP and DBP Values.

D. Display Result

Fig. 4 displays the class of Hypertension being detected. Since in most of the cases the category of Hypertension being detected is sufficient for most of the Cardiovascular diseases detection, treatment and prevention, the stratification of BP in different categories as illustrated in Table-I is normally sufficient to medical practitioners until and unless its emergency.

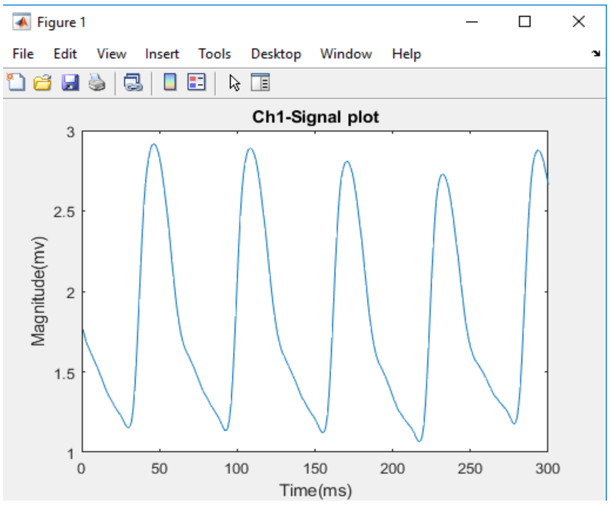

Fig. 2: Sample PPG Signal

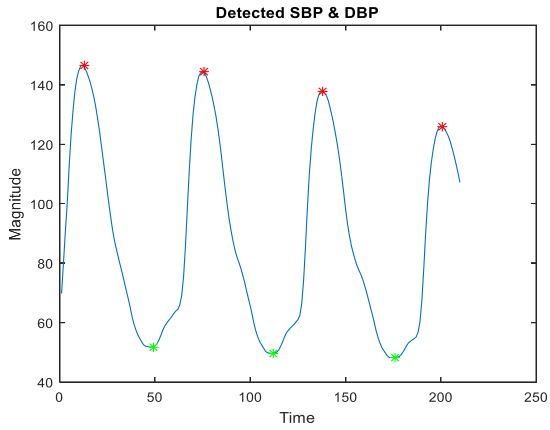

Fig. 3: Detected SBP and DBP Values from ABP Signal

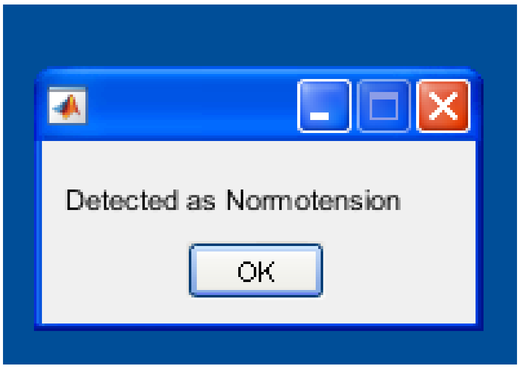

Fig. 4. Detected Class

Therefore in the BP estimation paradigm in medical science this novel concept of BP stratification in the cuff-less manner would be extremely helpful for continuous monitoring of BP.

V. DISCUSSION AND OPPORTUNITIES

Although several different techniques for Cuff-Less Blood Pressure estimation have been investigated and evaluated on a limited subset of subjects by different researchers, most of the existing methods still needs robust testing on a large scale with different physiological conditions such as hypertensive or normal, noisy data such as complex noise due to muscular contraction and sound of other body organs and its effect, demographic features such as geographical location and aging, anatomical studies such as arterial stiffness, effect of noise due to respiration and other body organs, different body postures and movements such as testing pre-exercise, post-exercise and during exercise on real time data. Early studies mostly based on PTT and regression analysis on series data opened new doors for the possibilities of Blood Pressure Stratification using Bio-Signals processing. Most of the earlier methods focused on simultaneous processing of ECG and PPG signals captured simultaneously, however they lacked in terms of accuracy, performance issues and real time temporal data testing. Adherence to AIIMI and BHS standards which are internationally accepted standards by both SBP and DBP values also remained inconsistent in most of these studies.

Dealing with real time data and efficient noise handling, optimum feature selection and application of an appropriate machine learning strategy still remains open subjects for research. The need for calibration also remained a challenge in most of the demonstrated techniques. Several studies were carried out to reduce the calibration as one time calibration or without calibrations as well. Calibration needed to be done for each individual which is again a hectic and difficult task and lacks the generality of the BP Stratification methods.

Use of Machine Learning algorithms for BP estimation proved to be more satisfactory compared with the earlier strategies. Blood Pressure estimation using vital signals such as ECG, PPG based on machine learning methods is possible and it had been demonstrated by many prevailing methods. However, it is still not been generalized covering wider age ranges, heterogeneous subjects, not extensively tested before, during and after exercise.

The existing research efforts still needs calibration and they are based on some sort of Cuff-based methods. We are still not completely Cuff-Free. This research has to go a long way to make it a complete Cuff-Free BP Estimation. The meaning of Cuff-Free is we even won't use Cuff based measurements for gold standard as ground truth.

Recently Deep Learning based techniques such as CNN and RNN have been evaluated for BP Stratification and achieved significant milestones in this direction but still leaving some gaps for further work and improvements in terms of efficient and proof-of-the concept models.

Apart from normal Blood Pressure estimation other important parameters such as age, gender, diseased conditions, cardiac contractility, left ventricular ejection period, large artery compliance and level of sympathetic activity, work and home environment needs more attention.

Parameters which affect the Arterial Stiffness which could be considered in near future research [31]:

1. Severity of Inflammatory diseases
2. Severity of Cardiovascular diseases
3. Duration of Inflammatory diseases
4. Duration of Cardiovascular diseases
5. Insulin related values like resistance to insulin and level of insulin
6. Smoking habits
7. Alcohol Consumption
8. Level of Cholesterol
9. Race
10. Gender
11. Effect of different antihypertensive medications
12. Resting BP

Use of minimum number of signals (Preferable single signal), easy methods of signal capturing, minimum processing delay and enhanced performance and accuracy are desirable characteristics of BP Stratification process in the future work.

Further performance optimization, secure transmission and storage efficiency can be achieved in such BP Stratification systems using Cloud Storage and Large-scale computer intensive servers [42], [43], [45], [48].

Future Work of this system could include the Big Data Analysis in continuous monitoring of this system which will make use of large number of Samples from varied use base from all categories such as Normal, Hypotensive and Hypertensive users as well as those suffering with different Cardiovascular diseases. The proposed system is still not completely Cuff-Free and the gold standard for computing the accuracy is still Cuff-based technique which is a major limitation of many existing and similar systems.

VI. Conclusion

This paper presented an elaborate investigative study of the Cuff-Less Blood Pressure Stratification techniques. Early PPT based methods exploring linear relationship with BP provided enough assurance for the exploration of BP stratification based on bio-signal processing. Machine Learning based methods provided satisfactory results and recently deep learning based techniques strived to achieve better accuracy and performance levels however still remained candidate for further research in terms of many issues which are discussed in sufficient details in this paper. Exploration of efficient noise-handling mechanisms, optimum feature selection and better machine learning algorithm selection still needs more work in future. We foresee a future where accurate and continuous Cuff-Less BP estimation would be a possibility in real time. We are still in the stage of Cuff-Less and not Cuff-Free because gold-standards for comparison are still Cuff based.

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