Using Cuffless Non-Invasive Methods for Blood Pressure Estimation: Description of the Selected Solutions

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Abstract. Blood pressure is a crucial vital sign used as an indicator of patient's medical state. However, the standard methods of measuring blood pressure continuously are not convenient enough in order to be used versatilely. Critical and life threatening situations such as civil disasters require measuring blood pressure as fast and as accurately as possible without the need of manual calibration. In this paper, we introduce several existing blood pressure estimation techniques using machine learning and deep learning algorithms based on ECG and/or PPG signals acquired from a wearable sensor.

Keywords: cuffless blood pressure · ECG · PPG · machine learning · deep learning

1 Introduction

Blood pressure is one of the most important vital signs indicating patient's medical condition with the remaining signs being heart rate (HR), respiratory rate (RR), blood oxygen level (SpO2) and body temperature.

Assessment of these vital signs is important both in clinical settings and patient's home environment. However, there are serious situations such as civil disasters, accidents or wars which usually bring numerous victims whose medical condition must be assessed as soon as possible. Such situations with the number of victims exceeding the number of medical personnel require new ways of assessing and monitoring patient's medical state in order to prioritize victims based on their medical condition in the triage process.

Based on the importance of blood pressure there is a substantial need for a novel non-invasive methods of blood pressure assessment in standard clinical settings as well as in critical situations as described above.

In this paper, we present description of the selected solutions regarding non-invasive blood pressure approaches using data gathered from wearable biosensors and machine learning (ML) and deep learning (DL) methods.The selection was based on discussion among authors during work on diploma thesis of the first author. No formal method was used for selection of the papers (e.g. Preferred Reporting Items for Systematic Reviews and Meta-Analyses - PRISMA). This paper therefore represents the preliminary work on the topic and will be extended in the next two years as a part of the research in NATO project - Smart Patch for Life Support Systems (G5825 SP4LIFE).

This work is structured as follows: Section 2 describes the background of the topic in terms of physiology and briefly introduces existing methods to measure and assess BP. Section 3 introduces and compares selected BP estimation techniques based on the underlying ML/DL approach used. Finally, Section 4 concludes the analysis and suggests possible next steps for the future research.

2 Background

2.1 Physiology of Blood Pressure

Blood pressure (BP) is defined as the force created by blood pushing against the walls of arteries [1]. It is measured in millimeters of mercury ($mmHg$). The value of BP is usually represented as two separate numbers [2]:

- i systolic blood pressure (SBP) refers to the maximum pressure in the arteries when the heart contracts in order to deliver blood to the body
- ii diastolic blood pressure (DBP) represents the lowest pressure in the arteries between heart beats in the phase of heart muscle relaxation

With regard to BP, pulse wave velocity (PWV) is the measure by which the pulse wave propagates from heart to entire body through arteries [3]. Pulse transit time (PTT) represents the time needed for the pulse wave to propagate from heart chambers to body and is inversely proportional to BP [4].

Finally, using SBP and DBP we can obtain the value of mean arterial pressure (MAP) which represents the mean BP value during one heart cycle [5] using Formula 1

$$MAP = DBP + 1/3 * (SBP - DBP) \tag{1}$$

2.2 Comparison of Blood Pressure Measurement Methods

Given the importance of BP and other vital signs, it is crucial to measure them promptly and accurately. However, standard methods of measuring BP are rather inconvenient either because of patient discomfort and increased risk (i.e. invasive intra-arterial measuring) or do not provide continuous measurement (i.e. auscultatory or palpatory methods using inflatable cuff) [1]. Moreover, the values of BP are not stable and may fluctuate during the day meaning that a single isolated BP measurement may not carry important information [1]. Thus, there is an increasing demand for a non-invasive and continuous way of BP measurement without the need to use an inflatable cuff.

The increasing popularity of affordable wearable medical devices such as smartwatches, patches for glucose monitoring or ECG sensors offer the opportunity to gather vital signs in a convenient and easy way. Given the availability of low-cost wearable biosensors, their usage in massive disasters might make the triage process more effective and provide necessary help to more victims.

Majority of solutions presented in current literature use electrocardiography (ECG) signals and/or photoplethysmography (PPG) signals measured by wearable sensors. ECG measures electrical activity of the heart which results in heart muscle contraction [6]. The resulting ECG graph used to depict the ECG signal contains certain characteristics which are often extracted from the signal and used as input predictors. The characteristics are described below, for more details see [6, 7]:

- P wave which represents the electrical activation of heart valves
- QRS complex representing the electrical activation of heart chambers; prolongated QRS complexes may indicate a serious underlying health issue
- ST segment which is usually used in myocardial ischemia detection
- QT interval whose length is inversely proportional to HR; given this relationship it is necessary to use corrected QT interval (QT_c) which is adjusted to HR value using Bazett's formula (see Formula 2)
- RR interval represents distance between two QRS complexes

$$QT_c = \frac{QT}{\sqrt{RR}} \tag{2}$$

PPG uses small optical sensor with infra-red light and measures the change of color in the skin tissue as the blood flows through the arteries after each heartbeat [8]. Most frequently, PPG is measured using a pulse oximeter placed on a fingertip and can be also used to measure SpO2, heart rate or respiratory rate. The characteristics of PPG signal comprise (for more details see [8]):

- peak of the systolic phase
- peak of the diastolic phase
- dicrotic notch which corresponds to closing of the aortic valve
- pulse width
- systolic phase amplitude (x)

– diastolic phase amplitude (y)

Some of the BP estimation methods use ECG as well as PPG signals measured synchronously in order to estimate the BP value. Extracted features of the signals are then used as input values to the regression model.

2.3 Evaluating the Performance of Blood Pressure Estimation Models

With regard to the clinical importance of BP, certain criteria must be met in order to evaluate the predictive accuracy of a given model. Therefore, there have been few attempts to establish an international standard for BP estimation assessment, e.g. the first standard published by Association for the Advancement of Medical Instrumentation (AAMI) in 1987 [9]. Since then, there have been several attempts to unify different standards. Finally, the AAMI/ESH/ISO standard issued in 2018 is considered an internationally accepted BP estimation assessment standard. According to the AAMI/ESH/ISO standard [9], several conditions must be met in order to consider a certain measurement method acceptable:

i Measuring device is considered acceptable if the obtained values reach tolerable error ($<=\ 10\,mmHg$) in $>= 85\%$ cases

ii Average difference between reference values and obtained values must be $<=\ 5\,mmHg$ and standard deviations $<=\ 8\,mmHg$. Both criterias apply to SBP as well as DBP.

iii Reporting the number of estimations where the absolute difference between reference values and obtained values are $<=\ 5\,mmHg$, $10\,mmHg$, $15\,mmHg$ together with a corresponding Bland-Altman plot.

3 Non-invasive Blood Pressure Assessment

As presented in [10], the task of BP assessment using ML/DL techniques can be perceived in two different ways. The first technique views the problem as a classification task - that is assigning a discrete category (class) to an individual based on the acquired BP values. The discrete categories in this case are usually stages which denote how low (hypotension) or how high BP (hypertension) an individual has. There are several different scales for stage classification, however, the most widely used is shown in Table 1. Table was created based on information regarding the classification of blood pressure for adults in [11].

The second approach uses various regression technique in order to estimate the continuous value of BP and/or its two components (SBP and DBP).

In the rest of the paper, we will primarily focus on existing solutions which use regression techniques in order to estimate BP values.

Table 1. Blood pressure classification [11]

Blood pressure classes			
Class	SBP [mmHg]	Logic function	DBP [mmHg]
Normal BP (normotension)	<120	AND	<80
Pre-hypertension	120-139	OR	80-89
Stage I. hypertension	140-159	OR	90-99
Stage II. hypertension	>= 160	OR	>= 100

3.1 Blood Pressure Estimation using Machine Learning Methods

Traditional methods of ML such as linear regression, support vector regression (SVR), decision trees (DT) or random forest (RF) have been extensively explored in BP estimation problems.

Authors [4, 12] used simple linear regression algorithm to estimate BP based on PTT and PWV values calculated using certain points of both ECG and PPG signals measured synchronously.

Given the context of our study (i.e. BP estimation in critical life threatening situations), the estimation method should be versatile enough to handle noisy signals or signals measured in unexpected conditions. Motion artifact may contribute to less accurate estimations. The effect of motion artifacts on BP estimation accuracy was examined by Ghosh et al. [13]. However, the proposed BP estimation method based on PTT calculation from ECG/PPG signals was only proved to be acceptable in seated position (with error of $0.07 \pm 5.8\, mmHg$ for SBP and $-2.1 \pm 7.3\, mmHg$ for DBP), while the errors were significantly higher for non-stationary positions.

Chen et al. [14] used SVR alongside with genetic algorithms for model parameters optimization to estimate BP values using PPG wave features and PTT. Experimental results were promising and compliant with the AAMI standard (see 2.3) - the estimation error for SBP was $3.27 \pm 5.52 mmHg$ and $1.16 \pm 1.97 mmHg$ for DBP.

Both classification as well as regression approach were combined by Simjanoska et al. [15] in a stacking ML design which combines individual classifiers to a single metaclassifier. As opposed to other approaches, the only source of information used was ECG signal and signal complexity analysis was performed instead of morphological features extraction. Without calibration, the experimental results showed a mean absolute error (MAE) of 8.64 mmHg for SBP, 18.20 mmHg for DBP, and 13.52 mmHg for the MAP prediction. In case of probability distribution-based calibration, the achieved errors decreased to 7.72 mmHg, 9.45 mmHg and 8.13 mmHg for SBP, DBP and MAP respectively.

3.2 Blood Pressure Estimation using Deep Learning Methods

Selected DL methods, especially neural networks (NNs) have been recently used in BP estimation as well.

Paviglianiti et al. [16] proposed a feed-forward fully-connected neural network ABPNet based on multi-layer perceptrons (MLP). Data used in the training phase originate from the Multi-parameter Intelligent Monitoring for Intensive Care (MIMIC) Physionet [17, 18] database and comprise synchronously measured ECG, PPG as well as invasively measured BP. The initial BP estimation results (for SBP, the Pearson correlation coefficient was $\rho = 0.97$ and for DBP $\rho = 0.93$) conform to the AAMI standard described in 2.3.

A novel convolutional neural network (CNN) called Deep-BP for BP estimation using ECG and PPG signals was proposed in [19] by Yan et al. Deep-BP is capable of extracting features from ECG/PPG associated with BP and estimating a BP value. In evaluation both with and without calibration process, Deep-BP showed promising and highly accurate results.

In comparison to the aforementioned methods, Miao et al. [20] trained Res-LSTM network based on a fusion of a residual network and long short-term memory network using one-channel ECG only. Experimentally obtained results (estimation error of $0.07 \pm 7.77 mmHg$ for MAP and $0.01 \pm 6.29 mmHg$ for DBP) conform to the AAMI standard (see 2.3).

4 Discussion

Continuous non-invasive blood pressure estimation using ML/DL algorithms and wearable ECG/PPG sensors is an increasingly popular research area. In this paper, we presented the background and introduced selected BP estimation approaches.

Nevertheless, there are several challenges which need to be addressed and which are also part of our future research. First of all, the importance of BP as a vital sign requires the estimation accuracy to be as high as possible. Even though the estimation model is required to provide as accurate results as possible, the model must be able to generalize enough so that it is not prone to overfitting. Generalization is related to the problem of manual calibration process during which the model coefficients are estimated using a dedicated portion of data, e.g. previously measured data from an individual patient. In the context of our scenario, i.e. critical life threatening situations which require fast responses, it is not desirable nor feasible to use manual calibration for every single individual. Thus, the topic of eliminating manual calibration is one of the key research questions we are dealing with. Finally, it is important that the method for non-invasive continuous BP estimation in disastrous settings requires as few input data as possible because multiple sensors/devices may not be available at hand.

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References

1. Rehman, S., L. Nelson, V. Blood Pressure Measurement. Available from: https://www.ncbi.nlm.nih.gov/books/NBK482189/
2. Shahoud JS, Sanvictores T, Aeddula NR. Physiology, Arterial Pressure Regulation. [Updated 2021 Sep 6]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2022 Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK538509/
3. Kim, H. L., & Kim, S. H. (2019). Pulse Wave Velocity in Atherosclerosis. In Frontiers in Cardiovascular Medicine. https://doi.org/10.3389/fcvm.2019.00041
4. Yoon, Y., Cho, J. H., & Yoon, G. (2009). Non-constrained blood pressure monitoring using ECG and PPG for personal healthcare. Journal of Medical Systems. https://doi.org/10.1007/s10916-008-9186-0
5. Homan, T., Bordes, S., Cichowski, E. Physiology, Pulse Pressure. Available from: https://www.ncbi.nlm.nih.gov/books/NBK482408/
6. Sattar Y, Chhabra L. Electrocardiogram. [Updated 2021 Jul 31]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2022 Jan-. Available from: https://www.ncbi.nlm.nih.gov/books/NBK549803/
7. Cascino, T., J.Shea, M. Electrocardiography - Cardiovascular Disorders - MSD Manual Professional Edition. Available from: https://www.msdmanuals.com/professional/cardiovascular-disorders/cardiovascular-tests-and-procedures/electrocardiography
8. Elgendi, M. (2012). On the Analysis of Fingertip Photoplethysmogram Signals. Current Cardiology Reviews. https://doi.org/10.2174/157340312801215782
9. Stergiou, G. S., Alpert, B. S., Mieke, S., Wang, J., & O'Brien, E. (2018). Validation protocols for blood pressure measuring devices in the 21st century. Journal of Clinical Hypertension. https://doi.org/10.1111/jch.13294
10. Martinez-Ríos, E., Montesinos, L., Alfaro-Ponce, M., & Pecchia, L. (2021). A review of machine learning in hypertension detection and blood pressure estimation based on clinical and physiological data. In Biomedical Signal Processing and Control. https://doi.org/10.1016/j.bspc.2021.102813
11. Chobanian, A. V., Bakris, G. L., Black, H. R., Cushman, W. C., Green, L. A., Izzo, J. L., Jones, D. W., Materson, B. J., Oparil, S., Wright, J. T., & Roccella, E. J. (2003). Seventh report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure. In Hypertension. https://doi.org/10.1161/01.HYP.0000107251.49515.c2
12. Goli, S., & Jayanthi, T. (2014). Cuff less Continuous Non-Invasive Blood Pressure Measurement Using Pulse Transit Time Measurement. International Journal of Recent Development in Engineering and Technology.
13. Ghosh, S., Banerjee, A., Ray, N., Wood, P. W., Boulanger, P., & Padwal, R. (2016). Continuous blood pressure prediction from pulse transit time using ECG and PPG signals. 2016 IEEE Healthcare Innovation Point-of-Care Technologies Conference, HI-POCT 2016. https://doi.org/10.1109/HIC.2016.7797728
14. Chen, S., Ji, Z., Wu, H., & Xu, Y. (2019). A non-invasive continuous blood pressure estimation approach based on machine learning. Sensors (Switzerland). https://doi.org/10.3390/s19112585
15. Simjanoska, M., Gjoreski, M., Gams, M., & Bogdanova, A. M. (2018). Non-invasive blood pressure estimation from ECG using machine learning techniques. Sensors (Switzerland). https://doi.org/10.3390/s18041160

16. Paviglianiti, A., Randazzo, V., Pasero, E., & Vallan, A. (2020). Noninvasive Arterial Blood Pressure Estimation using ABPNet and VITAL-ECG. I2MTC 2020 - International Instrumentation and Measurement Technology Conference, Proceedings. https://doi.org/10.1109/I2MTC43012.2020.9129361
17. Moody, G. B., & Mark, R. G. (1996). A database to support development and evaluation of intelligent intensive care monitoring. Computers in Cardiology. https://doi.org/10.1109/cic.1996.542622
18. Moody, G. B. (2000). PhysioNet: Research Resource for Complex Physiologic Signals. Circulation.
19. Yan, C., Li, Z., Zhao, W., Hu, J., Jia, D., Wang, H., & You, T. (2019). Novel Deep Convolutional Neural Network for Cuff-less Blood Pressure Measurement Using ECG and PPG Signals. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS. https://doi.org/10.1109/EMBC.2019.8857108
20. Miao, F., Wen, B., Hu, Z., Fortino, G., Wang, X. P., Liu, Z. D., Tang, M., & Li, Y. (2020). Continuous blood pressure measurement from one-channel electrocardiogram signal using deep-learning techniques. Artificial Intelligence in Medicine. https://doi.org/10.1016/j.artmed.2020.101919