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Adjustable Cuffless Smartphone Attachment (ACSA+) for Estimation of Blood Pressure Trends: A Pilot Study

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Abstract. Among the elderly, hypertension remains one of the prevalent health conditions, which requires monitoring and intervention strategies. Nevertheless, regular reporting of blood pressure (BP) from these individuals still poses multiple challenges. However, most people own cell phone and are engaged in phone conversations daily. Here, we propose an adjustable cuffless smartphone attachment (ACSA+) equipped with a PPG sensor for the estimation of BP during phone conversations. ACSA+ can be easily attached to the back of any modern cell phone. ACSA+ will help to continuously collect BP data and store it as a trend line.

Keywords. Cuffless blood pressure monitoring, wearable, PPG, blood pressure trends, elderly, hypertension, machine learning

1. Introduction

Wearables suggest various solutions for the estimation of BP [1]. Among wearable devices, a photoplethysmography (PPG) sensor is a frequent choice. PPG signals allow the monitoring of heart rate and oxygen saturation, and recently demonstrated a considerable performance in the estimation of BP [2]. Despite the benefits wearables can provide, their adoption by the elderly population remains a key challenge [3]. On the contrary, the ownership of personal phones by older adults is growing over the years. The elderly receive a median of two phone calls each day [4], which allows them to grip the cell phone twice a day, respectively. Therefore, the aim of this study is to utilize the time the older adults spend on holding their cell phones during a casual conversation to invisibly record their PPG signals and estimate BP.

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2. Methods

In this section, we describe the methods applied for the prototype and its environment development, framework, and machine learning (ML) models for BP estimation.

2.1. Prototype

The prototype was developed in the EasyEDA software [5]. The three main components were included: microcontroller, PPG sensor, and accelerometer. The prototype has a finger-oriented shape and can be easily attached to the back of a smartphone.

2.2. Framework

After the contact between the hand of the user and ACSA+ is established, the microcontroller activates, and the PPG signal starts being recorded (Figure 1). As the next step, the raw PPG signal departs to the cloud server with the help of Wi-Fi technology. The data from the accelerometer departs to the cloud simultaneously with raw PPG signals. From the following data, the ML model estimates BP and builds a trend.

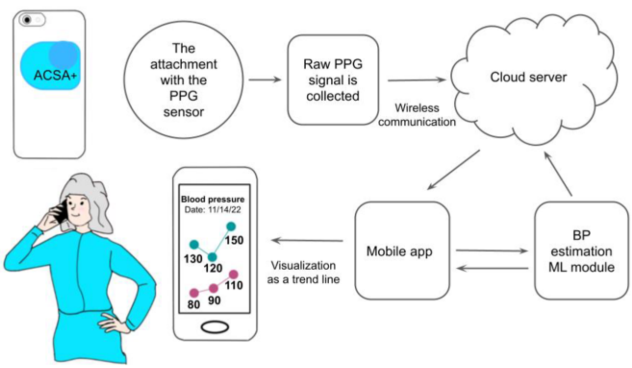

Figure 1. The framework of the study.

2.3. Dataset for developing ML model

MIMIC datasets are commonly extracted by researchers for ML estimations of BP as they contain the simultaneous recording of arterial BP (ABP) and PPG signals [6,7]. For this study, we utilized the MIMIC IV Waveform database which comprised 200 records from 198 patients.

2.4. Feature extraction

The good-quality recordings of ABP and PPG were extracted from the MIMIC IV Waveform Database (Figure 2) using WFDB package [8]. To extract the features, we utilized the tutorial in PhysioNet [9]. The signals were synchronized and filtered to remove the low and high pass frequencies. From the ABP signal, two variables, using the peakdetect algorithm [10], were extracted: SBP and DBP, which correspond to the highest value in systole and the lowest value in diastole. From the PPG signal, seven features were extracted based on the PPG waveform contour [11], including the pulse wave duration; systolic phase; diastolic phase; the time delay between systolic and diastolic peaks; the distance from the onset to the tip of signal; the distance from the tip to the peak of the diastole; the ratio of the diastolic time over the systolic time.

2.5. ML model

For predicting BP values from seven features, Random Forest Regression and XGBoost Regression models were implemented. The data was divided into 50% train and 50% test sets. As the next step, we will integrate the best-performing model into ACSA+ and utilize it for predicting SBP and DBP values from newly recorded PPG data.

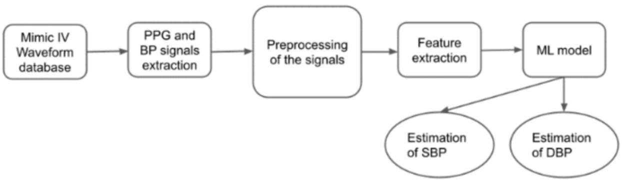

Figure 2. Workflow of BP estimation.

3. Results

The PPG signals from ACSA+ were recorded for demonstration purposes during different activities (Figure 3). The further step will be to compare the recordings obtained from the elderly group during phone conversation activity.

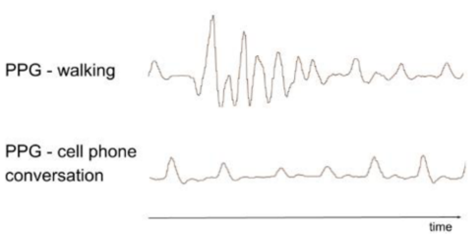

Figure 3. The demonstration of PPG signals recorded from ACSA+ during different activities.

From the MIMIC IV Waveform dataset, we extracted the 200 records of 198 patients. From 198 patients, only 57 patients satisfied the condition of the simultaneous presence of ABP and PPG signals and acceptable duration time. Of these 57 patients, only 9 patients had good and acceptable qualities of both signals, resulting in a total number of 920 waveforms extracted. The demographics of qualified patients revealed that 5 (56%) were identified as White, 1 (11%) as Asian, 1 (11%) as Black/African American, 1 (11%) as belonging to another ethnicity, and the ethnicity of 1 (11%) patient was unknown. Among the eligible participants, 6 (67%) were male and 3 (33%) were female. Figure 4 demonstrates the age distribution of the study participants, with a median age of 64 years old.

The waveforms (n=920) were preprocessed and features from them were extracted accordingly to the methods described above.

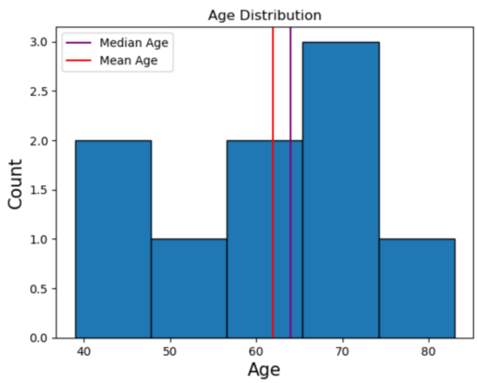

Figure 4. The age distribution of the patients.

The feature importance was also examined for the best-performing models. We discovered that the diastolic time and the ratio of the diastolic time over the systolic time are important features for both models. This result is in line with the previous works [11]. Then, two ML models were implemented to estimate SBP and DBP values (**Table 1**) and compared with AAMI standards.

Table 1. Performance of two models compared with AAMI standards for cuffless BP estimation.

ML model	Prediction task	MAE (mmHg)
Random Forest Regressor	SBP	5.96
	DBP	4.15
XGBoost Regressor	SBP	6.02
	DBP	4.32
AAMI standards	SBP	≤5
	DBP	≤5

4. Discussion

The Random Forest Regressor had an overall better performance for estimating SBP and DBP. However, the model still needs several improvements to comply with the global standards set by the AAMI for cuffless BP estimation. Some of the improvements might include adding other features such as pulse widths at different amplitudes [11], as well as the first and second derivatives of the signal, and time series features. Additionally, the upcoming release of the database is anticipated to include 10,000 new records, providing us with the opportunity to expand the patient sample size and improve the model's ability to generalize to the broader population.

It is evident that BP is a parameter that naturally varies during the day and night. Stress is known to temporarily increase BP, while there are limited studies on how phone conversation can influence the continuous measurements of BP. The context of the conversation might play a significant role, therefore, the questionnaire to evaluate how stressful the talk was for the participants will be a part of the follow-up study.

The developed device and framework originally focused on the elderly cohort. However, this study is not only limited to the elderly as it has the potential to be extended to a broader demographic cohort, including a younger adult population.

5. Conclusions

In this paper, we presented the prototype of ACSA+ for BP estimation. ACSA+ was developed for the elderly to record their PPG signals invisibly, while they are engaged in a phone conversation. The preliminary ML models were established and are expected to be improved and tested on ACSA+ recorded PPG signals from the elderly participants. Comparing ACSA+ with the gold standard of BP monitoring is a crucial follow-up work to establish the accuracy and reliability of the device for daily use. The contribution of this pilot study is that it presents a new framework for the invisible estimation of BP for the elderly.

Acknowledgement

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