Unobtrusive Measurement of Blood Pressure During Lifestyle Interventions

Ariane Morassi Sasso, Suparno Datta, Bjarne Pfitzner, Lin Zhou, Nico Steckhan, Erwin Boettinger, Bert Arnrich
Digital Health Center, Hasso Plattner Institute, Potsdam, Germany
ariane.morassi-sasso@hpi.de

ABSTRACT

Hypertension is one of the most prevalent chronic diseases worldwide. Early diagnosis of this condition can prevent the incidence of stroke and also, cardiovascular diseases (CVDs) such as myocardial infarction and heart failure. Lifestyle interventions, such as intermittent fasting (IF), aim to lower blood pressure (BP) levels and increase the health of patients with cardiometabolic conditions. However, for monitoring BP, we still rely on a cuff that slows the flow of blood, which is both uncomfortable and makes continuous monitoring implausible. Recent research has shown that BP can be estimated using comfortable sensors such as the photoplethysmography (PPG) and the electrocardiography (ECG). Features that can be used for the estimation of BP are systolic upstroke time (SUT) and diastolic time (DT) extracted from the PPG signal, and pulse arrival and transit time (PAT/PTT) derived from the combination of ECG and PPG signals. In this paper we present: (1) a study design to collect continuous physiological signals, before and after a 7-days intermittent fasting (IF) intervention from both cardiometabolic and non-hypertensive patients using wearable devices and (2) initial results for predicting continuous blood pressure from the PPG and ECG signals using statistical and machine learning methods.

CCS CONCEPTS

• **Applied computing** → **Health informatics**; • **Computing methodologies** → *Machine learning*; • **Hardware** → *Sensor devices and platforms.*

ACM Reference Format:
Ariane Morassi Sasso, Suparno Datta, Bjarne Pfitzner, Lin Zhou, Nico Steckhan, Erwin Boettinger, Bert Arnrich. 2018. Unobtrusive Measurement of Blood Pressure During Lifestyle Interventions. In *PervasiveHealth '19: Proceedings of the 13th EAI International Conference on Pervasive Computing Technologies for Healthcare, May 20-23, 2019, Trento, Italy.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

1.1 The Burden of High Blood Pressure

According to the World Health Organization (WHO) [12], in 2008, the prevalence of hypertension (i.e. high blood pressure) for adults above 25 years was approximately 40% worldwide. In 2010, the Global Burden of Disease study analysed data from 187 countries and stated that high BP was the risk factor that achieved the highest global disease burden (i. e. proportion of deaths) due to its relation to diverse outcomes such as stroke and cardiovascular diseases (CVDs) [11]. Moreover, hypertension in its early stage has usually no symptoms and can stay undiagnosed in many people [17].

Lewington et al. [9] performed a meta-analysis to understand the impacts of high BP which involved 61 prospective observational studies (from Europe, North America, Australia and Asia) with more than 900 000 participants that had no vascular disease at baseline. After analysing the data, they could notice that at ages varying from 40 to 69, an increase of 20 mmHg in systolic blood pressure (SBP) or 10 mmHg in diastolic blood pressure (DBP) is associated with at least a twofold increase in the mortality by stroke and vascular diseases such as ischaemic heart disease (IHD). Conversely, they show evidence that by lowering SBP and DBP the death rate by stroke and CVDs would decrease considerably in middle age.

Therefore, there is a need for making the diagnosis of hypertension more comfortable in order to identify health risks earlier. The goal is to measure BP continuously and comfortably since the current standard way involves an inflatable cuff that makes long-term monitoring difficult. For managing hypertension and consequently lowering BP, guidelines indicate lifestyle interventions, such as introducing a healthier diet and more exercise to a person's life [1].

1.2 Blood Pressure Estimation

The current standard way of collecting BP involves a device with a cuff that controls the flow of blood by inflating and deflating. According to the American Heart Association (AHA), for a proper diagnosis of high BP in the office (i.e. clinic), the physician should take an average of $\geqslant$ 2 measurements in at least two different encounters [15]. However, this does not eliminate "white coat hypertension" (i.e. elevated BP in the doctor's office) and for that there is a need for other types of measurements that can be done outside.

One option is the home blood pressure monitoring (HBPM), that is done by the patient using a validated device during a period of time (e.g. 3 days). The other is the ambulatory blood pressure monitoring (ABPM), which is done automatically by a device during pre-programmed intervals (e.g. 15 or 30 mins) for a period that is usually 24 hours [16]. According to a meta-analysis by Hodgkinson et al. [7] that is considered to achieve a more precise diagnosis of hypertension than the office BP measurement or the HBPM.

However, there are limitations to ABPM since it is usually expensive and uncomfortable. For that reason, researchers have been trying to diagnose hypertension using other sensors such as the photoplethysmography (PPG) and the electrocardiography (ECG),

PervasiveHealth '19, May 20–23, 2019, Trento, Italy

ACM ISBN 978-1-4503-9999-9/18/06…$15.00
https://doi.org/10.1145/1122445.1122456

DOI 10.4108/eai.20-5-2019.2283509

which can be easily integrated into wristbands, smartwatches, chest-bands and arm-bands [5, 6].

Therefore, as a first objective of this paper, we will describe a protocol for collecting continuous physiological signals from wearable devices that could be used to estimate blood pressure. In the next step, the protocol will be applied to a study with cardiometabolic and non-hypertensive patients going through a 7-day intermittent fasting (IF) intervention. Cardiometabolic patients are hypertensive patients who have at least two other risk factors (e.g abdominal obesity and high triglycerides) and that could benefit from lowering BP and continuous monitoring [14].

The second objective is to apply different methods to estimate BP using features extracted from PPG and ECG signals. There is evidence in literature that measures such as systolic upstroke time (SUT) and pulse arrival time (PAT) can be good predictors of systolic blood pressure (SBP) and diastolic blood pressure (DBP) [3, 8].

2 EXPERIMENTAL SETUP

2.1 Devices

For this experiment we selected the following devices: Faros^{TM} 180, a chest ECG from Bittium[1], Empatica[2]'s wristband E4 and Everion, an armband from Biovotion[3]. The sensors present in each device are described in Table 1 together with their sampling frequency range. For the blood pressure measurement, we used the OMRON EVOLV (HEM-7600T-E) and Mobil-O-Graph® NG. The PPG and ECG devices were chosen since they provide raw data and were used in other research studies. For the BP devices, we chose the ones that were either validated by the U. S. Food and Drug Administration (FDA), as OMRON EVOLV or according to the British and Irish Hypertension Society (BISH) and the European Society of Hypertension (ESH) as Mobil-o-Graph®.

Table 1: Devices and Sensors Specification
photoplethysmography (PPG), electrocardiography (ECG), accelerometer (ACC)

DEVICE	PPG	ACC	ECG
Everion	51.2 Hz	51.2 Hz	-
Empatica E4	64 Hz	32 Hz	-
Faros 180	-	10-400 Hz	100-1000 Hz

2.2 Experiment Design

We designed an experimental setup to collect data from subjects before and after a trigger that would increase their blood pressure values. The short version (a) involves 5 minutes (mins) of rest, 5 mins of biking (2.5 mins on a medium level of difficulty and 2.5 mins on a higher level) followed by 5 more mins of rest. The blood pressure is measured using a 1 min interval when at rest. The long version (b) involves 10 mins of resting, 10 mins of biking on a medical ergonomic bike (which increases its level of difficulty every 2 mins) and 10 mins of rest. The blood pressure is measured with an interval of 2 mins. As stated in the AHA and ESH guidelines, there is at least a 1 min interval between BP measurements and they are done with the subject relaxed, in silence and in the sitting position with his/her arms resting on his/her knees [15, 16].

Before each recording session, all of the devices are charged, and set up for data transmission. The blood pressure from both arms is measured, and the arm with higher BP is chosen. The Everion, Empatica E4 and the Faros^{TM} 180 devices are taken in both hands and shaken by the experimenter. This action aims at creating a distinct acceleration signal, which will later be used for synchronising the data streams of all devices.

The Everion and Empatica E4 devices are then attached to one arm of the subject, and the BP device to the other arm, so the measurements will not be influenced by the arm being constricted. The Faros^{TM} 180 device is attached to the chest of the subject using two electrodes.

At the start of data collection, the subject is asked to sit still with both hands resting on the knees and watching a relaxing video, meanwhile the blood pressure is measured multiple times. Then the subject is asked to ride an ergonomic bike for a short period of time. After biking, the subject is asked to sit down again, and the BP is measured the same number of times as in the first round.

A tagging app is used to manually tag all events (start of data collection, blood pressure measurement, start and end of biking, end of data collection). The labels are designed to help with the alignment of the different streams of data.

Finally, the data is extracted from each device using different methods (e.g. direct USB connection, download from a mobile phone) and stored. The protocol aim is to get a range of BP values for each subject in order to see how different features from other signals, such as ECG and PPG, might correlate with blood pressure.

3 METHODS

3.1 Data Processing Procedures

Firstly, the data was plotted for initial manual inspection of errors. Secondly, quality checks were performed on the raw data extracted from each device in order to verify data completeness and noise.

3.1.1 PPG. The photoplethysmography (PPG) raw data from Empatica E4 was extracted and normalised. Only data with a 1 minute window around the time of blood pressure measurement was used for further processing. To eliminate motion artefacts induced by wrist movement, sections where the Euclidean norm of x-, y- and z-acceleration lies outside of an interval of 25% of the standard deviation around the sample mean for the current window were removed from consideration. For the remaining signal, the start of each PPG cycle was identified with a standard peak detection function.

All detected cycles in the current window were combined to a custom PPG waveform template (Figure 1), following a procedure described by Li and Clifford [10]. Individual cycles were then compared with the template using two signal quality indices (SQI): (1) direct linear correlation and (2) direct linear correlation between the cycle, re-sampled to match the template length, and the template. Only if both correlations lie above 0.8, the cycle is further processed to extract features as explained in Section 3.2.

3.1.2 ECG. The electrocardiography (ECG) raw data from Faros^{TM} 180 was very clean already, having only a limited amount of baseline

[1] https://www.bittium.com/products_services/medical/bittium_faros
[2] https://www.empatica.com/research/e4/
[3] https://www.biovotion.com/everion

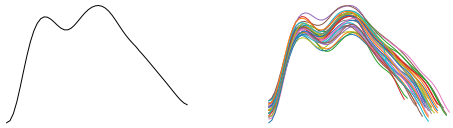

Figure 1: PPG Template (left) and Valid Cycles (right)

Table 2: Features Extracted from PPG

NAME	DESCRIPTION
SUT	Systolic Upstroke Time
DT	Diastolic Time
CP	Cardiac Period
DW_n	Diastolic Width at n% amplitude
$SW_n + DW_n$	Sum of Systolic Width and Diastolic Width at n% amplitude
DW_n / SW_n	Ratio between Systolic Width and Diastolic Width at n% amplitude

for $n \in \{10, 25, 33, 50, 66, 75\}$

drift and almost no noise. Thus we did not have to apply filters to pre-process the data and could immediately use the method proposed by Christov [2] to find the location of the R-peaks.

3.2 Estimate Blood Pressure from ECG/PPG

The features in Table 2 and Figure 2 were extracted from the clean Empatica E4 PPG cycles as explained by Kurylyak et al. [8]. The first step was to identify the first peak in the cycle, which corresponds to the systolic peak. Then for various percentages of the peak amplitude, we consider the time between systolic peak and end of the cycle (DW_n), start of the cycle and end of the cycle ($SW_n + DW_N$), and the ratio between the time in the cycle before and after the systolic peak (DW_n/SW_n). For every window, the mean and variance of each feature were computed and used as input for the different models.

In addition to the features from only the PPG, we extracted The pulse arrival time (PAT) from the combination of PPG and ECG. Defined as the time difference between the R-peak visible in the ECG signal and the systolic peak in the PPG signal. In context, the pulse arrival time (PAT) defines the time the blood takes to get pumped from the left ventricle to the wrist, where the PPG is measured. Higher values indicate stiffer veins, which is suspected to be correlated with blood pressure [13].

3.3 Machine Learning Models

Previous works show that machine learning algorithms perform well in predicting BP from features derived from PPG and ECG [6, 8]. We have employed in our experiment two popular machine learning algorithms: Generalised Linear Models (GLM) with Elastic Net [18] regularisation and Gradient Boosting Machines (GBM) [4] to predict the systolic and diastolic blood pressure (see Section 4.2).

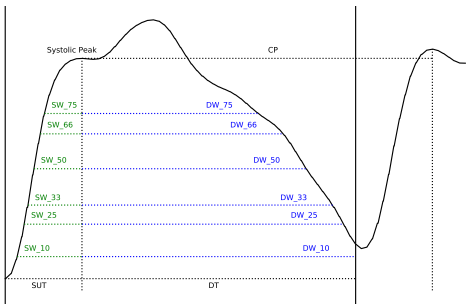

Figure 2: Features Extracted from PPG

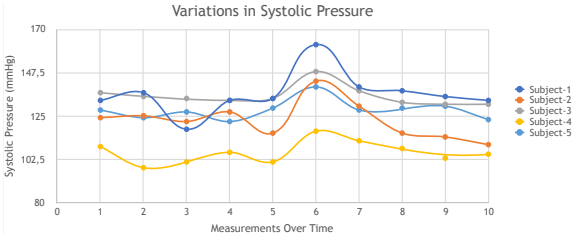

Figure 3: Variation of Systolic blood pressure (SBP) Before and After Exercising

4 RESULTS

4.1 Blood Pressure Measurement

4.1.1 Data Collection. Data from 5 healthy subjects (3 men and 2 woman) was collected using the shorter version of the protocol, Empatica E4, Everion, Faros^{TM} 180 and OMRON EVOLV.

4.1.2 Accuracy of OMRON EVOLV. To check the OMRON EVOLV accuracy, its measurements were compared to those from a manual sphygmomanometer on five healthy subjects, and the mean absolute error (MAE) reported was 6.0 mmHg for diastolic blood pressure (DBP) and 5.1 mmHg for systolic blood pressure (SBP).

4.1.3 Evolution of blood pressure. Figure 3 shows the variation of SBP for each subject. The first 5 measurements were made before exercising and the subsequent ones after biking. We can notice that there is an elevation in the BP right after biking and a decrease to the baseline values afterwards.

4.2 Blood Pressure Estimation PPG and ECG

4.2.1 Problem Setting. Data from 5 healthy subjects was collected using the shorter version of the protocol described in Section 2.2. We started with 50 blood pressure measurements (10 for every participant). After removing the sections of the signals corrupted by motion artefacts we ended up with 35 observations. We used the data from one subject with 9 observations to validate the model and 26 observations from the rest of the subjects to train it. We observed a high correlation between the derived features, which hampered the performance of the models. To tackle that, we randomly removed one out of every two columns which shared a correlation

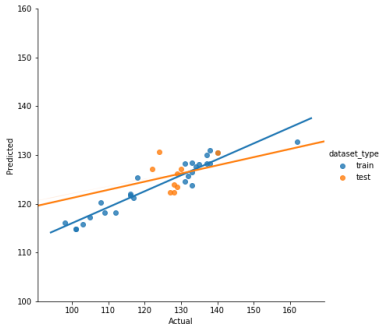

Figure 4: Predict x Actual Systolic blood pressure (SBP) Gradient Boosting Machines (GBM)

Table 3: Model Performance

Blood Pressure	Model	MAE(mmHg)	RMSE(mmHg)
SBP	GBM	4.05	4.77
SBP	GLM	6.09	7.13
DBP	GBM	10.05	11.1
DBP	GLM	10.79	11.82

higher than 0.95. Finally, we ended up with 14 features which were used as input for the machine learning algorithms.

4.2.2 Evaluation. A comprehensive model evaluation on the test dataset is shown in Table 3. The metrics we used to evaluate the models were Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Figure 4 shows a scatter plot of the predicted and actual SBP values with corresponding regression lines.

5 DISCUSSION AND CONCLUSION

In this paper we could show that features derived from the photoplethysmography (PPG) signal have potential to be used as estimators for blood pressure since our MAE for systolic blood pressure (4.05) was lower than the best one reported by Esmaili et al. [3] (4.71) using non-linear equations and it is closer to the one found by Kurylyak et al. [8] (3.8) using neural networks. Moreover, even without doing an extensive search on the hyperparameters of GBM it already produces decent prediction results.

As shown in Table 3, the estimation errors of diastolic blood pressure (DBP) are clearly higher compared to the estimation errors of systolic blood pressure (SBP). We need larger sample sizes in order to further investigate this effect and to perform a meaningful comparison of our estimation performance with traditional blood measure devices.

As next steps, firstly we will execute the short and long protocols in a new group of healthy subjects for testing Mobil-o-Graph®. Secondly, we will train and test models again with new data such as the one made available by Esmaili et al. [3][4] and we intend to test new features from both the ECG and PPG signals.

Thirdly, we plan to add electrodermal activity (EDA) features in the models in order to have a better prediction, since there is evidence in literature that they might be connected to hypertension and both Empatica E4 and Everion include this sensor [5]. Lastly, the protocol will be executed in the intermittent fasting (IF) study with cardiometabolic and non-hypertensive patients.

[4]https://www.kaggle.com/mkachuee/noninvasivebp/home

ACKNOWLEDGMENTS

We would like to thank *D4L data4life gGmbH* for offering a platform to securely store the data and manage the study.

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