Arterial Blood Pressure Stratification with Wrist Photoplethysmography: Laboratory vs. Real World

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Abstract

Photoplethysmography (PPG) has recently gained attention for monitoring the cardiovascular system with wearable sensors. One of the most critical challenges is estimating blood pressure (BP) from PPG. Several attempts have been made in this direction, primarily based on laboratory recordings. Real-world recordings can provide more complete information about cardiovascular health by monitoring physiological changes throughout the day. In this work, we analyzed PPG morphological features obtained during laboratory and real-world sessions to evaluate their ability to discriminate between low- vs high-BP individuals. All features presented different behaviors when comparing laboratory and real-world sessions. Some showed statistically significant differences between subjects with low and high BP, based on the type of session and the hour of the day. This study underlines the differences between laboratory and real-world recordings to estimate BP from PPG.

1. Introduction

Photoplethysmography (PPG) is an optical technique able to detect changes in the blood volume occurring at each heartbeat [1].

The PPG signal is a quasi-periodic waveform, with each cycle referred to as a PPG pulse. Within each PPG pulse, several key fiducial points can be identified: the onset, marking the start of the pulse; the systolic peak, representing the maximum blood volume during systole; the dicrotic notch, a local minimum corresponding to the closure of the aortic valve; the diastolic peak, indicating the second maximum associated with diastole and pulse wave reflection in the periphery; and the offset, signifying the end of the pulse [2]. Additionally, the first and second derivatives of the PPG pulse (Figure 1) provide additional fiducial points that can yield valuable information about cardiovascular health [3].

Beyond heart rate estimation, which is the primary application of PPG sensors, the morphology of the PPG signal provides critical insights into various physiological conditions, such as arterial stiffness [4], microcirculation [5], and aging [6].

The potential of PPG sensors to revolutionize healthcare lies in their cost-effectiveness and ability to be easily integrated into wearable devices, enabling continuous and ubiquitous monitoring. One of the most promising applications of PPG is in estimating blood pressure (BP) using wearable sensors, which could potentially replace the obtrusive gold-standard instruments currently used for BP measurement, such as brachial cuff-based methods. This has been the focus of several studies, both in research [7] and in commercial solutions [8]. However, most of these studies are based mainly on laboratory recordings. Real-world recordings offer the advantage of monitoring physiological changes throughout the day and night, potentially providing more comprehensive insights on cardiovascular health.

In this paper, we aimed to compare PPG morphological features obtained in a controlled laboratory environment

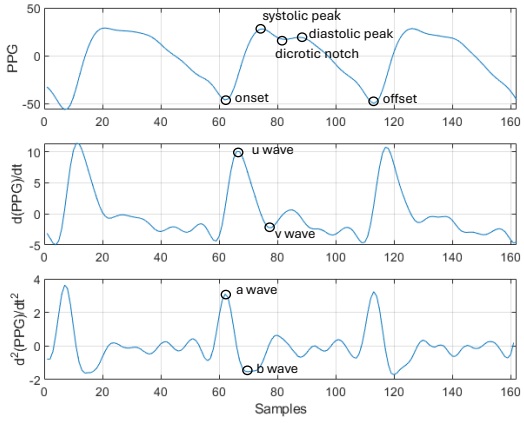

Figure 1. PPG and its first and second derivatives with highlighted fiducial points. Sampling frequency = 64 Hz.

with those obtained in the real world, differentiating between wakefulness and sleep time and examining the behavior of PPG features as a function of the subjects' BP values.

2. Materials and Methods

2.1. Dataset

Data from thirty-nine healthy subjects were used for this analysis in the context of a broader clinical study, conducted according to the declaration of Helsinki and approved by the Local Ethical Committee (Area Vasta Emilia Centro, Bologna, Italy; approval n° 712/2018/Sper/AOUBo). The Empatica E4 wristband (Empatica srl, Milan, Italy), a wearable medical device, was employed to record PPG and tri-axial accelerometer data at 64 Hz and 32 Hz, respectively. The Mobil-O-Graph 24h-PWA (IEM GmbH, Aachen, Germany), an oscillometric BP monitor, was used to record systolic and diastolic BP. Each participant underwent two different monitoring sessions:

- In-lab: the participant was asked to stay still and relax for 5 minutes. Then, a 2.5-minute recording was made with the Empatica E4 wristband to record the PPG, followed by a triple-measurement recording session with the Mobil-O-Graph 24h-PWA, consisting of three consecutive measurements of BP. The mean of these three measurements has been used for further analysis, thereby increasing the reliability of the BP measures.
- Real-world: after one hour from the in-lab session, each participant was asked to wear the Empatica E4 wristband for 24 hours, conducting their normal activities of daily living, and instructed to remove the device when showering.

2.2. Signal processing

The PPG signal, both for in-lab and real-world sessions, was pre-processed by applying a second-order Butterworth band-pass filter (cut-off frequencies [0.5-12] Hz), and subsequently divided into PPG pulses by applying the algorithm proposed by Elgendi et al. [9] to detect PPG systolic feet. In addition, recordings from real-world sessions were segmented into wakefulness and sleep using the GGIR open-access software on E4 accelerometer data [10], [11].

A previously developed PPG signal quality algorithm [12] was employed to extract good-quality PPG pulses by using both PPG and accelerometer data. The algorithm assigns each PPG pulse wave one of two quality levels: basic quality, suggesting that the pulse wave can be used only to extract features that do not rely on the presence of the dicrotic notch and the diastolic peak, or high quality, indicating that the dicrotic notch and diastolic peak can be clearly detected in the pulse wave.

To mitigate the influence of changes in HR on feature extraction, we normalized the duration of each good-quality pulse signal by resampling it into 100 samples using cubic spline interpolation [13].

Twenty-three morphological features were then extracted from each good-quality PPG pulse during the in-lab, real-world wakefulness, and real-world sleep conditions using an adapted version of the pyPPG python library [14]. For real-world recordings, we averaged the features obtained in each consecutive non-overlapping 2.5-minute window to be consistent with the procedures employed in the in-lab recordings. The morphological features and their abbreviations are reported in Table 1, along with the pulse wave quality level deemed necessary to extract each feature.

2.3. Statistical analysis

The Kolmogorov-Smirnov test was applied to evaluate the distribution normality of the PPG pulse features. Since none of the features followed a normal distribution, non-parametric tests were employed to assess statistical differences. Specifically, a Friedman test was used to evaluate differences across the three conditions (in-lab, real-world wakefulness, and real-world sleep), followed by a Wilcoxon signed-rank test as a post-hoc analysis to compare paired differences.

We then divided the participants into high-BP and low-BP groups using a threshold of 120 mmHg [15] for the systolic BP recorded during the in-lab session. A Mann-Whitney U test was conducted to determine whether each PPG pulse feature differed between the low-BP and high-BP groups within each of the three conditions.

Finally, we evaluated potential statistical differences in the PPG pulse features over 24 hours by comparing the values for low-BP and high-BP groups at each hour of the day. In particular, we calculated the mean values for each feature for each participant obtained from the 2.5-minute time windows over each hour.

3. Results

We extracted PPG morphological features from the recordings of 39 healthy participants (19M, 20F, age 45.7 ± 10.7 years, height 170 ± 10 cm, weight 67.9 ± 12.0 kg, mean ± SD). We identified 13 participants having high BP (3M, 10F, age 50.1 ± 10.1 years, height 168.4 ± 9.9 cm, weight 69.4 ± 11.4 kg, systolic BP 127.7 ± 9.6 mmHg, diastolic BP 84.8 ± 12.8 mmHg), while the remaining 26 had low BP (16M, 10F, age 42.7 ± 10.6 years, height 171.1 ± 10.8 cm, weight 67.1 ± 12.4 kg, systolic BP 107.4 ± 8.0 mmHg, diastolic BP 70.8 ± 9.2 mmHg).

Table 1 Morphological features extracted from good quality PPG pulses

Acronym	Definition	Quality pulse
	Time interval features	
Tsys	Time between pulse onset and dicrotic notch	High
Tdia	Time between dicrotic notch and pulse offset	High
Tsp	Time between pulse onset and systolic peak	Basic
Tdp	Time between pulse onset and diastolic peak	High
dT	Time between systolic peak and diastolic peak	High
	Amplitude features	
Asp	Amplitude between onset and systolic peak	Basic
Adn	Difference in amplitude between onset and dicrotic notch	High
Adp	Difference in amplitude between onset and diastolic peak	High
	Area features	
AUCpi	Area under the whole pulse wave	Basic
AUCsys	Area under the pulse wave between onset and dicrotic notch	High
AUCdia	Area under the pulse wave between dicrotic notch and offset	High
	Ratio features	
Tsys/Tdia	Ratio between Tsys and Tdia	High
Adp/Asp	Ratio between Adp and Asp (reflection index)	High
IPA	Ratio between AUCdia and AUCsys	High
Tsp/Asp	Ratio between Tsp and Asp	Basic
Asp/dT	Ratio between Asp and dT	High
Asp/(Tpi-Tsp)	Ratio between Asp and (Tpi - Tsp)	
Rslope	Ratio between Asp and Tsys	High
h/dT	Ratio between subject height and dT (stiffness index)	High
	Derivative features	
Tu	Time between pulse onset and u point	Basic
Tv	Time between pulse onset and v point	High
Ta	Time between pulse onset and a point	High
Tb	Time between pulse onset and b point	High

All 23 PPG morphological features significantly differed between in-lab, real-world wakefulness, and real-world sleep conditions (Supplementary materials, Table S1).

We found statistically significant differences by comparing low-BP vs high-BP participants (Supplementary materials, Table S2). Specifically, the derivative features (Tu, Ta, and Tb) significantly differed between individuals with high and low BP across all conditions. However, other features showed significant differences between high-BP and low-BP subjects only in specific conditions (Figure 2).

Several PPG morphological features showed different behaviors in low-BP vs high-BP participants during 24-hour recordings (Supplementary materials, Table S3). For instance, Tsp showed a gradual decrease during the night in both groups. However, subjects with low BP experienced a greater drop in Tsp during the nightly hours than those with high BP (Figure 3).

Supplementary materials are available online at 10.5281/zenodo.13867342.

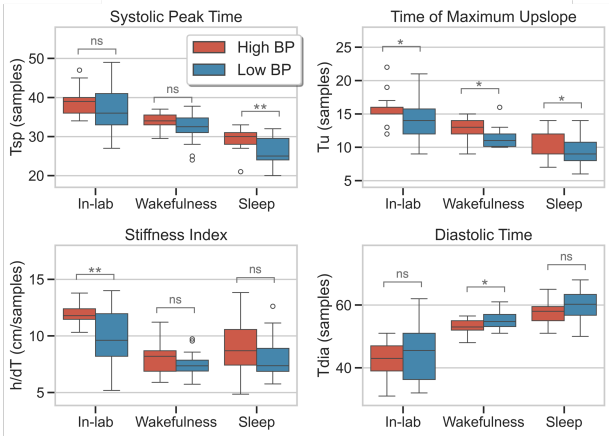

*Figure 2. Distribution of 4 features during in-lab recording, real-world wakefulness and real-world sleep, stratified according to BP levels. Each data point corresponds to one subject. Time-domain features are expressed in samples due to the time-normalization. * = p-value < 0.05, ** = p-value < 0.01, ns = not significant (Mann-Whitney U test).*

4. Discussion

This study evaluated potential differences in PPG morphological features across three settings (i.e., in-lab, real-world wakefulness, and real-world sleep) and compared their behavior in subjects with systolic BP above or below 120 mmHg.

Our findings suggest that PPG features can be valuable for assessing cardiovascular function and distinguishing between different BP categories.

While previous studies have predominantly focused on predicting BP from PPG using machine learning [16], our approach is more explainable, having the advantage of providing direct insights into the differences in PPG morphology between high- and low-BP subjects, which are often hidden within the "black box" nature of machine learning models.

A limitation of our study is represented by the sample size, which was small and not well-balanced when comparing low- vs high-BP participants in terms of sex. Furthermore, we did not apply any multiple comparison

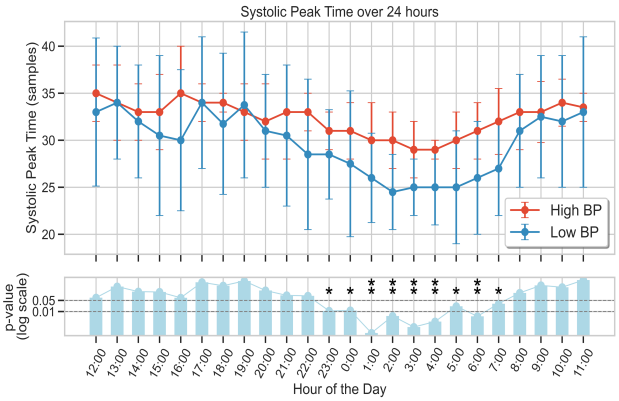

*Figure 3. Systolic peak time (Tsp) per hour of the day during real-world recordings. Values are in samples (due to the time-normalization) and are expressed as median ± interquartile range. The bottom panel shows the p-values for the hour-wise comparison between subjects with high and low BP. * = p-value < 0.05, ** = p-value < 0.01(hour-wise Mann-Whitney U test).*

correction to the p-values obtained from the statistical analysis. Another limitation is the reliance on a single BP measurement to provide the gold standard classification between high- and low-BP participants, which may wrongly classify individuals with borderline BP values or those whose BP fluctuates significantly throughout the day and night.

However, the significant differences observed in several features between high- and low-BP individuals highlight the potential of these metrics as biomarkers of high BP based on non-obtrusive PPG wearable devices.

Our study provides a foundation for further exploration into the use of real-world PPG morphological features as a tool for BP assessment.

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