Blood Pressure Estimation Based on Photoplethysmography: Finger versus Wrist

Birutė Paliakaitė[1], Peter H. Charlton[2], Andrius Rapalis[1,3], Vilma Pluščiauskaitė[1], Povilas Piartli[1,3], Eugenijus Kaniusas[4], Vaidotas Marozas[1,3]

[1] Biomedical Engineering Institute, Kaunas University of Technology, Kaunas, Lithuania
[2] Department of Public Health and Primary Care, University of Cambridge, Cambridge, UK
[3] Department of Electronics Engineering, Kaunas University of Technology, Kaunas, Lithuania
[4] Institute of Electrodynamics, Microwave and Circuit Engineering, TU Wien, Vienna, Austria

Abstract

The photoplethysmogram (PPG) signal is an attractive candidate for unobtrusive blood pressure (BP) monitoring, as it is widely measured by wrist-worn devices. However, most studies of PPG-based BP estimation techniques have used finger PPG signals. This study compares PPG-based BP estimation when using finger and wrist optical sensors. Subject-specific linear regression models employing pulse transit time, PPG intensity ratio and heart rate as features for BP estimation were trained and tested using PPGs and reference continuous BP values obtained from 22 healthy participants performing 2 cold pressor tests. Mean ± standard deviation of differences, and the mean absolute difference between reference and estimated systolic BP values were: 0.47 ± 10.44 mmHg and 7.78 mmHg for finger PPG signals; and 1.05 ± 12.86 mmHg and 9.69 mmHg for wrist PPG signals. Increases and decreases in systolic BP of at least 10 mmHg were detected with F_1 scores of: 0.81 and 0.76 for finger PPG; and 0.75 and 0.61 for wrist PPG. Models performed better with finger PPG signals. Different signal processing approaches were required for finger and wrist signals, indicating that finger-based BP estimation models should not be generalized directly to wrist PPGs. With improved sensitivity, PPG-based detection of considerable BP changes may be useful in tracking BP trends and abrupt alterations.

1. Introduction

High systolic blood pressure (SBP) is the modifiable risk factor to which the largest proportion of cardiovascular disease and chronic kidney disease burdens can be attributed [1]. High SBP accounts for almost a fifth of all attributable deaths and cardiovascular diseases remain the main cause of global mortality [1, 2]. Currently, conventional office blood pressure (BP) measurements are used to diagnose and treat high BP [3]. However, parameters derived from ambulatory BP monitoring, such as 24-hour mean, day-time and night-time BP, variability, morning surge, and nocturnal dipping are better risk predictors of death, cardiovascular outcomes, and target organ damage [3].

However, it is difficult to adopt ambulatory BP monitoring into clinical practice because conventional ambulatory monitors using inflatable cuffs are expensive and highly obtrusive, especially during sleep. As a result, photoplethysmogram (PPG)-based techniques have gained research attention as a convenient means for BP monitoring. Most PPG-based methods assess pulse transit time (PTT) between two sensors, which is still cumbersome for ambulatory applications [4]. Therefore, BP estimation techniques relying on a single PPG sensor are appealing.

Most previous studies investigating BP estimation from a single PPG were carried out using finger sensors [5]. The wrist site would be much more attractive for use in wearable smartwatch technology. Hence, the aim of this study was to compare the performance of BP estimation models using a single PPG obtained from the finger or the wrist.

2. Materials

2.1. Data acquisition

A wrist PPG signal from a green LED was acquired through reflectance mode using a wrist-worn device at a sampling rate of 100 Hz. Finger PPG signals from red and infrared LEDs were collected through transmittance mode using the Nautilus 2.0 device at a sampling rate of 1000 Hz. Both devices were developed at the Biomedical Engineering Institute (Kaunas, Lithuania). Reference non-invasive beat-by-beat SBP, diastolic (DBP) and mean BP (MBP) values were recorded synchronously from the finger using the CNAP Monitor (CNSystems, Graz, Austria).

The cold pressor test was used to induce BP changes. The study was performed in a quiet, temperature-controlled (24 $\pm$ 1 °C) room with participants seated. All signals were acquired synchronously from the right arm following the protocol in Fig. 1, in which participants immersed half their left forearm in water or rested it on their thigh. 1-min data segments before and during the first cold water (7 °C) immersion were used for model training. 1-min data segments from before, during and after the second cold water (10 °C) immersion were used for testing.

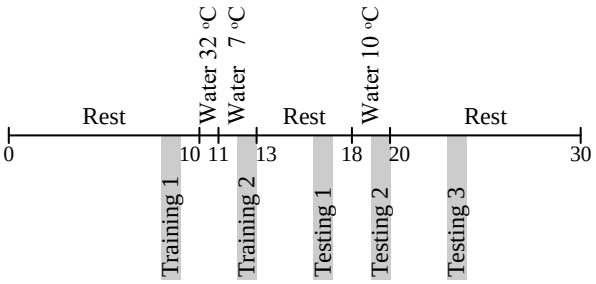

Figure 1. Study protocol with shaded 1-min segments for model training and testing. Timeline given in minutes.

2.2. Dataset

Data were used from a study of healthy volunteers at the Biomedical Engineering Institute (Kaunas, Lithuania), with approval by the Kaunas Region Biomedical Research Ethics Committee (No. BE-2-24). The required finger and wrist PPG signals were acquired from a total of 36 participants. Of these, 14 participants were eliminated from the analysis due to PPG quality issues (12), frequent premature beats (1) and missing BP values (1). The remaining dataset consists of signals from 22 participants (11 females), with age 36.4 $\pm$ 8.6 years and body-mass index 24.4 $\pm$ 3.8 kg/m^2.

3. Methods

3.1. Choice of PPG pulse wave features

Three PPG pulse wave features selected for BP estimation were PTT, PPG intensity ratio (PIR), and heart rate (HR).

The majority of PPG-based models relate BP to PTT through the Moens–Korteweg equation. Its squared inverse, $1/\text{PTT}^2$, is proportional to pulse pressure [6]. Conventional PTT measurement requires at least two sensors. In contrast, in this study we define a surrogate PTT as the time difference between systolic and diastolic peaks of a single PPG pulse wave obtained using a single sensor. It is assumed that the diastolic peak following the dicrotic notch represents the reflected wave.

PIR is the ratio of PPG peak intensity to valley intensity [6] and reflects the change in arterial diameter from diastole to systole. Based on a two-element Windkessel model, it is assumed that $1/\text{PIR}$ is proportional to DBP.

HR was included as an additional feature based on the observation that HR information can improve the performance of PTT-based BP estimation models [7].

3.2. PPG signal processing

Baseline wander was removed from the PPG segments using a high-pass finite impulse response (FIR) filter with a cut-off frequency of 0.5 Hz. Finger and wrist PPG segments were filtered with low-pass FIR filters with cut-off frequencies of 13 and 5 Hz, respectively. The onset of the k^{th} PPG pulse wave o_k was defined as a minimum before the rising slope of the pulse. Instantaneous HR was defined as

$$\text{HR}_k = 60/\big(t(o_{k+1}) - t(o_k)\big), \tag{1}$$

where t is time in seconds.

Pulses were eliminated if their instantaneous HRs deviated from a smoothed HR by $>$20%. The quality of the remaining pulses was assessed through correlation with a pulse template, obtained as an average over a 1-min segment. Pulses with a correlation coefficient $>$0.95 were considered high quality and retained for analysis.

By analyzing PPG signals, it has been noticed that systolic peak, sys, is not necessarily the maximum of the pulse. Therefore, the fiducial point representing sys was defined as the zero-crossing of the tangent to the maximum negative gradient of the 1$^{\text{st}}$ derivative, represented by b on the 2$^{\text{nd}}$ derivative (see Fig. 2a). If b could not be found, sys was defined as the maximum of the pulse.

The diasolic peak, dia, was detected using different methods for finger and wrist PPG pulse waves. In finger PPG pulses, dia was defined as the first local maximum of the pulse after e and before 80% of the pulse duration [8] (see Fig. 2a). If no such maximum could be found, dia was defined as the corresponding maximum on the 1$^{\text{st}}$ derivative. In wrist PPG pulses, the diastolic peak was often difficult to identify. Therefore, pulse decomposition was performed by subtracting a symmetrical forward wave from the pulse [9]. dia was defined as the maximum of the residual signal, representing the reflected wave (see Fig. 2b).

Finally, PTT and PIR for the k^{th} pulse were defined as

$$\text{PTT}_k = t(dia_k) - t(sys_k), \tag{2}$$

$$\text{PIR}_k = 2 \cdot x(sys_k)/\big(x(o_k) + x(o_{k+1})\big), \tag{3}$$

where x is the low-pass filtered PPG pulse but with baseline retained.

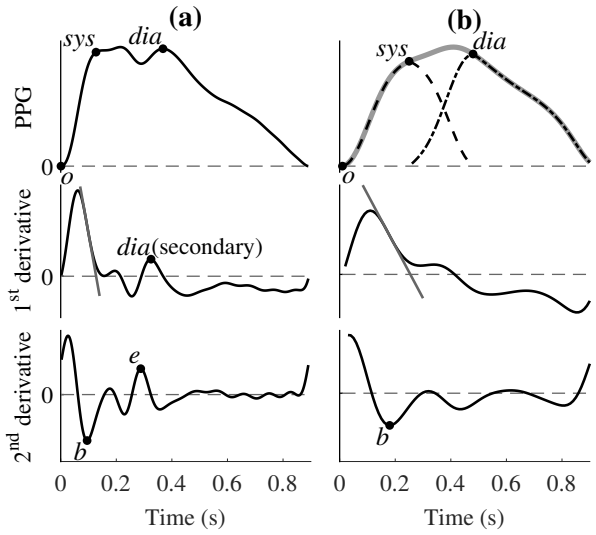

Figure 2. Detection of fiducial points on (**a**) finger and (**b**) wrist PPG pulses. Dashed and dash-dotted black lines represent forward and reflected waves, respectively.

3.3. Model training and testing

Feature outliers in each segment were eliminated from the analysis, defined as values more than 1.5 times the interquartile range above (and below) the upper (and lower) quartiles. Subject-specific linear regression models were used to estimate SBP, DBP, and MBP:

$$\text{BP}_i = (a_i/\text{PTT}^2) + (b_i/\text{PIR}) + c_i \cdot \text{HR} + d_i, \quad (4)$$

where i indicates SBP, DBP or MBP, and a, b, c, d are the coefficients estimated on the training segments.

Model performance was assessed on the testing segments. The mean and standard deviation of differences, as well as mean absolute difference between reference CNAP and estimated BP values were calculated. Average SBP values over each 1-min segments were used to evaluate the ability of the models to classify SBP changes into three categories: (1) ≥ 10 mmHg, (2) non-significant change of $(-10; 10)$ mmHg, and (3) ≤ -10 mmHg. Classification performance was expressed as sensitivity, specificity, positive predictive value and F_1 score.

4. Results

Table 1 presents the agreement between reference and estimated BP values. PPG-based estimates had a small bias, although differences varied substantially with mean absolute differences as large as 10 mmHg. Finger-based estimation was slightly superior to wrist-based estimation.

Table 2 presents the performance of models for classification of SBP changes. Finger-based models were more sensitive to substantial increases and decreases in SBP, whereas wrist-based models were more specific. In general, the accuracy, measured as the F_1 score, was higher for finger-based models than wrist-based models.

Table 1. Agreement between reference and estimated BP values using finger and wrist PPGs.

		SBP	DBP	MBP
Mean of	Finger	0.47	0.41	0.56
differences (mmHg)	Wrist	1.05	0.54	0.64
p value		0.01	0.26	0.26
Standard deviation of	Finger	10.44	8.60	9.08
differences (mmHg)	Wrist	12.86	9.00	10.20
p value		<0.01	<0.01	<0.01
Mean absolute	Finger	7.78	6.36	6.77
difference (mmHg)	Wrist	9.69	6.86	7.76

Table 2. Performance of PPG-based classification of changes in SBP. PPV stands for positive predictive value.

	Sens.	Spec.	PPV	F_1 score
Finger				
≥ 10 mmHg	0.79	0.93	0.85	0.81
$(-10; 10)$ mmHg	0.63	0.79	0.63	0.63
≤ -10 mmHg	0.79	0.87	0.73	0.76
Wrist				
≥ 10 mmHg	0.64	0.97	0.90	0.75
$(-10; 10)$ mmHg	0.81	0.57	0.52	0.63
≤ -10 mmHg	0.50	0.93	0.78	0.61

Table 3 presents individual SBP changes during cold water immersion (*i.e.* between testing segments 1 and 2), and recovery afterwards (*i.e.* between testing segments 2 and 3). Detection of SBP changes was problematic in several individuals, such as No. 1, 2 and 8.

5. Discussion

This study investigated BP estimation based on a single PPG signal acquired using an optical sensor at either the finger or wrist. Personalised models were found to perform better with finger signals than wrist signals. The models accurately identified changes in BP during a cold pressor test. However, their estimates of BP values did not agree strongly with the reference BP values.

The approaches used in this study may have utility for detecting changes in BP, with potential clinical applications. For example, the absence of a nocturnal dip in SBP is predictive of stroke recurrence and left ventricular hypertrophy [10, 11]; an excessive morning surge in SBP is a risk factor for poor kidney function [11]; and a drop in SBP is indicative of clinical deterioration in acutely-ill

Table 3. Changes in SBP during cold water immersion and recovery afterwards. ↗, —, and ↘ represent ≥ 10 mmHg, $(-10; 10)$ mmHg, and ≤ -10 mmHg, respectively.

	Water 10 °C			Recovery		
No.	CNAP (mmHg)	Finger	Wrist	CNAP (mmHg)	Finger	Wrist
1	↗ **(15.73)**	**—**	**—**	**— (−8.01)**	↘	↘
2	↗ **(10.87)**	**—**	**—**	↘ **(−16.40)**	**—**	**—**
3	— (−4.18)	—	—	— (−1.10)	—	—
4	— (1.83)	—	—	— (−1.25)	↘	—
5	↗ (18.63)	↗	—	↘ (−24.27)	↘	—
6	↗ (17.40)	↗	↗	↘ (−12.44)	↘	—
7	↗ (48.25)	↗	↗	↘ (−11.76)	↘	↘
8	↗ **(21.09)**	**—**	**—**	↘ **(−25.38)**	**—**	**—**
9	— (−2.84)	↗	—	— (8.72)	↘	—
10	↗ (10.16)	↗	↗	↘ (−14.76)	↘	↘
11	↗ (13.40)	↗	↗	↘ (−21.70)	↘	↘
12	— (9.29)	—	—	↘ (−18.76)	↘	—
13	— (−5.60)	↗	—	— (−2.11)	—	—
14	↗ (17.51)	↗	↗	↘ (−16.58)	—	—
15	↗ (19.89)	↗	↗	↘ (−28.18)	↘	↘
16	↗ (27.00)	↗	↗	↘ (−30.96)	↘	↘
17	— (−4.19)	—	↘	— (−6.89)	—	↗
18	↗ (31.41)	↗	↗	↘ (−19.49)	↘	↘
19	— (−2.35)	—	—	— (4.76)	↘	—
20	— (7.53)	—	—	— (−1.22)	—	—
21	↗ (23.56)	↗	—	↘ (−19.53)	↘	—
22	↗ (20.99)	↗	↗	↘ (−20.53)	↘	↘

hospital patients, who are usually assessed only every 4–6 hours [12].

Though the use of smartwatches for unobtrusive BP monitoring is attractive, this study shows that different approaches may be needed for wrist-based and finger-based BP estimation. Finger sensors, usually of a form similar to a pulse oximeter, are intended for use in stationary settings at home, clinics or a laboratory; hence, they benefit from a high sampling frequency, transmittance mode and red or infrared wavelengths, which penetrate deeper into the tissues. In contrast, wrist sensors use reflectance mode, a green wavelength, and a lower sampling frequency. These differences may influence PPG morphology and BP-related features.

6. Conclusions

This study found that PPG-based BP estimation models performed better when using finger signals compared to wrist signals. The models were able to accurately identify substantial changes in SBP, demonstrating their potential utility for tracking changes in BP. Different signal processing approaches were required for finger and wrist signals to account for the different pulse wave morphologies, indicating that approaches developed using finger PPG signals may require modification before use in wrist-worn sensors.

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Address for correspondence:

Birutė Paliakaitė

Biomedical Engineering Institute, Kaunas University of Technology, K. Baršausko st. 59, LT-51423 Kaunas, Lithuania

birute.paliakaite@ktu.lt