Blood Pressure Estimation Using a Single PPG Signal

Nima TaheriNejad(✉) and Yasaman Rahmati

Institute of Computer Technology, TU Wien, Vienna, Austria
nima.taherinejad@tuwien.ac.at

Abstract. Early Warning Score (EWS) is a measure commonly used in hospitals since 90's to quantitatively assess the health of patients and predict its deterioration. Currently, nurses perform this assessment periodically by measuring respiration rate, oxygen saturation, systolic blood pressure, heart rate, core body temperature, and level of consciousness. Automation of this process using wearable devices allows for continuous monitoring inside and outside hospitals while reducing nurses' workload and monitoring costs. Current systems designed for this purpose use a separate device for measuring each of those bio-metric signals. This presents a challenge for the comfort and practicality of use in a real-life setup and increases its associated costs. In this work, we present a new method for estimation of systolic blood pressure, which allows reduction of the number of sensors. In our proposed method we use a smartwatch Photoplethysmogram (PPG) signal, which is mainly used for heart rate estimation, to estimate the (systolic) blood pressure too. An important feature of this system, in contrast to State-of-the-Art (SoA), is continuous, easy, and comfortable monitoring of blood pressure.

Keywords: Blood pressure · Smartwatch · Single PPG sensor · EWS

1 Introduction

Wearable devices have claimed many areas of our life; sports [12,22], physical [3,6] and mental [12,13,19,20] health being only a few of them. Despite several challenges such as constrained resources [7,17], changes in the environmental conditions [4,5,17], and excessive noise and artefact introduced by users' activities [14–16], they have been thriving and proved themselves helpful. A key factor in their current and future growth is their design and ease of use [17,18]. In this work, we follow this direction by proposing a method that allows a further extended health monitoring using smart watches.

A patient's health status can be assessed based on their vital signs. Research on cardiac arrests shows that certain symptoms can be observed long before the situation turns into a case of emergency; symptoms may appear even 24 h before

P. Perego et al. (Eds.): ICWH 2020, LNICST 376, pp. 3–11, 2021.
https://doi.org/10.1007/978-3-030-76066-3_1

actual health deterioration [10]. Early Warning Score (EWS) is a standard manual tool for assessing patients' health status and predicting health deterioration. Healthcare professionals periodically monitor patients' vital signs (heart rate, respiratory rate, body temperature, blood pressure, and blood's oxygen saturation) and assess their health status by a criticality level defined as EWS [11]. Each vital value is assessed and assigned a score based on Table 1. A score of 0 indicates an ideal health condition of a vital sign, while score 3 corresponds to the worst. The EWS is the aggregate value of all the individual vital sign scores. The higher the score, the higher the criticality.

Table 1. A conventional Early Warning Score (EWS) chart [21].

Vital sign score	3	2	1	0	1	2	3
Heart rate (beats per minute)	0–39	40–50	51–59	60–100	101–110	111–129	≥130
Systolic blood pressure (mmHg)	0–69	70–80	81–100	101–149	150–169	170–179	≥180
Respiratory rate (breaths per minute)		0–8		9–14	15–20	21–29	≥30
Body temperature (°C)		≤35		35.1–38		38.1–39.5	≥39.6
Blood oxygen saturation (%)	0–84	85–89	90–94	95–100			

This manual procedure has been applied to hospitalized patients, which takes a considerable amount of time from the nurses. A portable device that automates the procedure would save time for the nurses and allow patients to pursue their daily lives with a much higher chance of survival. However, currently, each of these measurements require a separate sensor and separate wearable device which makes the system bulky and impractical. This is the issue that we try to address by extracting Blood Pressure (BP) from the Photoplethysmogram (PPG) signal of a smartwatch, which is easy to wear and measures heart rate as well. In other works [16] authors have proposed a novel method, which can extract Respiratory Rate (RR) from the same PPG signal, accurate enough for EWS and in a fashion much more reliable than other existing works [14]. The reliability of measuring EWS using portable devices (even with dedicated sensors) is an important issue, which has been discussed in many previous works and many methods were proposed for improvement of different issues [3–6].

Regarding the extraction of BP from PPG, however, we are not the first ones. Johnson et al. [9] proposed using Pulse transit time (PTT) and linear regression. In this method, two PPG sensors are required, and the time that a peak requires to travel between the two points is used to estimate the BP. They achieve a high accuracy but their approach has shown to be sensitive to hand movements. A more similar study has been performed in [8]. They use the change of blood volume (BV) and blood vessel resistance (VR), considering of the influence of two external factors, namely the pressure between index finger and sensor and the temperature of the interest region. Even though this approach has a good accuracy, it is more complex and it needs to be worn on the finger, which is less convenient than a smartwatch, which is the approach we propose here.

The rest of this work is organized as follow; In Sect. 2, we propose our novel method for extracting the BP information from PPG signals. Next, we present the setup and result of our experiments in Sect. 3, and finally draw the conclusions in Sect. 4.

2 Proposed Method

Since the amount of light that returns to the photo-detector of the smartwatch PPG sensor is proportional to the volume of blood in the tissue, the PPG signal represents an average of all blood volume in the arteries and any other tissue, through which the light has passed. Therefore, changes in the Blood Volume Pulse (BVP) signal can indicate increase or decrease in blood perfusion as well as changes in the elasticity of the vascular walls, reflecting changes in BP. We plan to use this phenomenon to extract systolic and diastolic BP from the BVP signal captured by PPG optical sensor. Figure 1 shows a typical PPG signal and various Points of Interest (PINs) on that signal, particularly systolic and diastolic points.

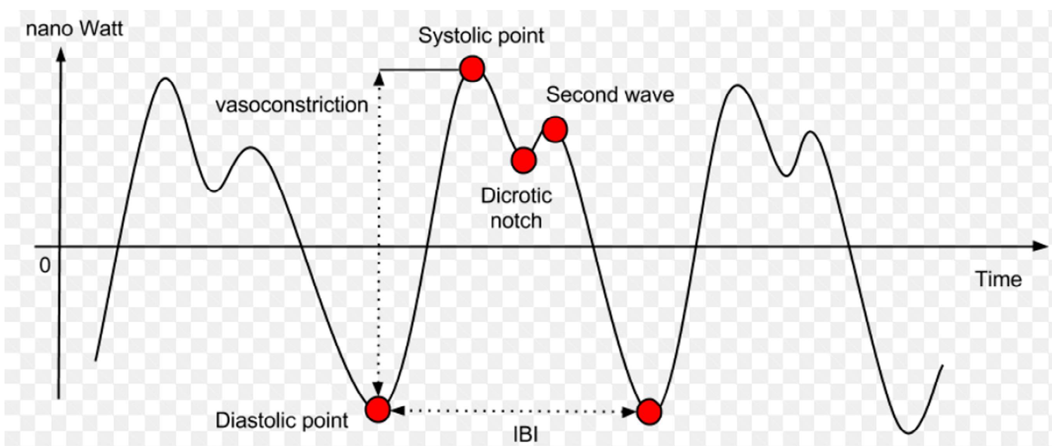

Fig. 1. PINs related to BP on a BVP signal.

2.1 Pre-processing

The pre-processing step includes Inter beat interval (IBI) extraction and band-pass filtering. In the IBI extraction, "good" heart beats (cycles) are separated from "bad" heart beat cycles. That is, the extremely noisy portion of the signal, which do not assimilate normal heart beats in a typical BVP, are tagged for removal. This process is symbolically shown in Fig. 2.

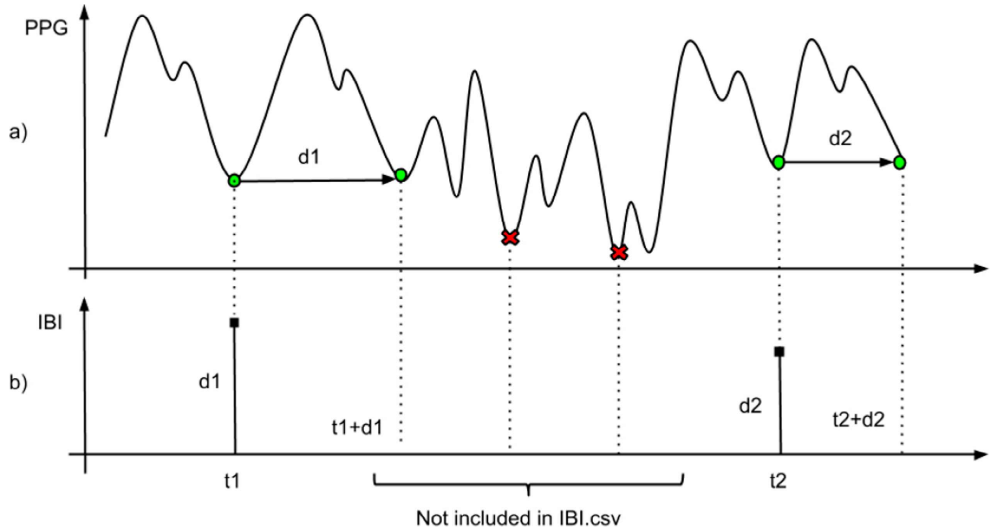

Fig. 2. Corrupted portions of the signals removed by IBI pre-processing.

2.2 Band-Pass Filtering

The BVP signal captured by PPG sensor of a smartwatch is often contaminated with noise, and especially with movement artifacts. Therefore, we apply a 4^{th} order Butterworth band-pass filter in the range of $[\frac{0.8}{f_s}0.8/f_s,\ 4.4/f_s]$ with $f_s = 64$ Hz. This proved to be very helpful in improving the quality of the signal, hence, the PINs, and consequently overall performance of the system.

2.3 Extracting PINs

In the next step, five critical points or PINs were extracted from each cycle of the PPG signal. These five PINs, shown Fig. 1, are: systolic point, diastolic point, dicrotic notch, second wave peak, and the fifth point. The fifth point is defined as $\frac{1}{2}$(systolic point + diastolic point).

It is important to bear in mind that the shape of the PPG signal changes depending on age of the subject. As shown in Fig. 3, for older people, second wave peak points are somehow smoothed out and dicrotic notches are placed at higher positions in comparison with people at younger ages.

2.4 Linear Estimation

We studied the correlation between the systolic and diastolic BPs and sundry of variables such as the mean, median and Standard Deviation (STD) of the PINs, as well as the ratio of the medians of four PINs over the median of the diastolic points. In addition, we studied their correlation with the difference and sum of the systolic and diastolic points. We found out that there are moderate to strong correlations between some of these parameters. This means that we

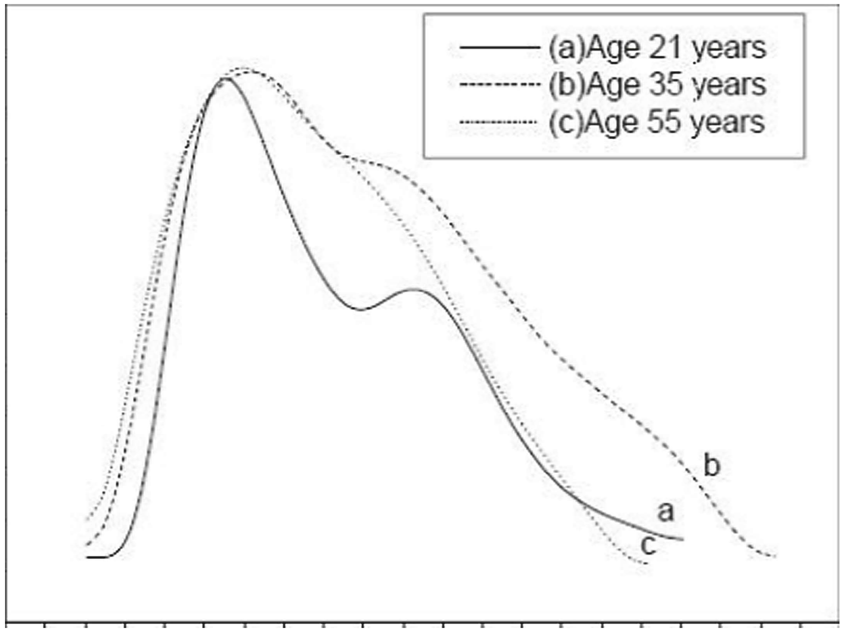

Fig. 3. Shape of PPG signal, particularly regarding second wave peak and dicrotic notch, changes based on the age.

can calculate such parameters, specifically BPs, one from another using a simple linear regression, i.e.;

$$y = \beta_1 x + \beta_0, \tag{1}$$

where y is the desired parameter, x the measured value, and β_i respective coefficients. In Sect. 3.2, we present the β_i values obtained through our experiments.

3 Experiments

3.1 Setup

We conducted our experiments on 36 subjects aged 6–80 years old, the distribution of which is shown in Table 2. Three subjects were removed from the data since due to excessive noise contamination (no clean part was detected in the pre-processing step.). In addition, due to reasons which we will describe in the next subsection, we collected another data set consisting of 11 subjects 20–40 years old. The subjects were asked not to drink alcohol or coffee and not to smoke for at least 2 h before the experiment.

During the experiments, the subjects were asked to sit relaxed and wear Empatica smartwatch [1], which measures the BVP using a PPG sensors, on their right wrist. The watch was connected via Bluetooth to an iPhone to record and monitor the output signals from all sensors in real time. One minute after starting to record a session, blood pressure was measured via the Smart Blood Pressure Wrist Monitor (BP7S) [2], which was worn on the subjects' left wrist. The BP7S took approximately 40 s to measure systolic and diastolic BP. Since it is very important that the cuff is positioned at our heart level during BP measurements, BP7S is equipped to detect wrist position and the measurement will start only when the correct position is detected. This helps us to obtain accurate results from BP7S, which we use as ground truth. BP7S is also able to sync its readings to iPhone via Bluetooth using iHealth MyVitals App and save data to the secure iHealth cloud.

Table 2. The division of collected data into age ranges, the number of subjects in each group, and estimation coefficients for systolic and diastolic BPs.

Age range	# of subjects	Estimation	β_0	β_1
All ages	32	Systolic	115.61	−0.41
		Diastolic	74.66	0.75
Under 20	6	Systolic	119.86	−0.41
		Diastolic	87.83	0.29
20–40	12	Systolic	105.79	0.80
		Diastolic	76.60	0.17
40–60	10	Systolic	78.87	0.77
		Diastolic	53.99	0.41
Over 60	4	Systolic	123.12	4.96
		Diastolic	73.63	0.01

3.2 Results

We first studied the correlations between different parameters across the entire age range. The strongest correlation —with a large margin— was 0.483, between diastolic BP and the median of the sum of the systolic and diastolic points. However, this correlation is not very strong. Therefore, we divided the collected data to the age ranges shown in Table 2 and extracted the estimation coefficients, β_i, of Eq. (1) for each group. This grouping based on age increased the highest correlation to 0.77. However, once we used our linear estimation model, Eq. (1), the uniform model (extracted for all ages) provided better results in most cases and on average too. These results are inserted in Table 3, where we observe that except for the age range of 20–40, the uniform model has a smaller error.

To further verify this observation, we collected an extra set consisting of 11 subjects aged between 20–40 years old, which was not included in our previous analysis and extraction of the coefficients. We then ran both unified and the model adjust to 20–40 years data on this new test data set and obtained the following results, shown in Table 4. This is consistent with the previous results, reported in Table 3.

Table 3. Error percentage in systolic and diastolic BPs estimation using different methods.

Age range	Uniform model			Age-based		
	Systolic	Diastolic	Average	Systolic	Diastolic	Average
Under 20	14.10	12.64	13.37	15.20	27.94	21.57
20–40	15.08	11.51	13.30	7.85	10.31	9.08
40–60	9.70	7.50	8.60	41.12	21.17	31.15
Over 60	7.70	6.12	6.91	23.42	4.60	14.00
Average	12.29	09.80	11.04	21.57	16.30	18.93

Even though the average of these two estimations is not considerably different, given that in EWS, systolic BP is the main used metric and the difference of estimation for this metric is higher between the two methods, we propose a combination of two as the final solution. In other words, to use the coefficients fitted to the 20–40 years old data for subjects in that age range, and the unified model for everyone else. That is;

$$SysBP = \begin{cases} 0.8x + 105.79 \; 20 \leq \text{age} \leq 40 \\ -0.41x + 115.61 \text{ otherwise} \end{cases} \tag{2}$$

where

$$x = Med(\text{SP} + \text{DP}), \tag{3}$$

that is, the median of the Systolic Point (SP) and the Diastolic Point (DP), extracted from the PPG signal, as explained in Sect. 2.

Table 4. Error percentage in systolic and diastolic BPs estimation using different methods.

Age range	Uniform model			Age-based		
	Systolic	Diastolic	Average	Systolic	Diastolic	Average
20–40	14.43	11.61	13.02	9.36	10.80	10.08

This gives us an average error of 9.52% for the systolic BP estimation over all 43 data sets. Even though, this error is not ideal, it is acceptable for the purpose of EWS, since in most cases it not very likely lead to any error. Particularly for the normal range (healthy subject or score 0), which has a 43% width with respect to its middle point. In other blood pressure ranges this width is lower, however, 9.52% error in such cases, the worst case scenario, will lead to maximum 1 score error.

4 Conclusions

In this paper, we presented a new method for estimating BP based on the SP and the DP of the PPG signal. This method requires only a single PPG signal, which is available -virtually- in all smartwatches. Therefore, it is cheap (no additional costs if integrated in a smartwatch) and comfortable to use. The average accuracy of this method is 90.48%, which is acceptable for many applications such as EWS[1]. Moreover, by reusing PPG signal that is used for heart rate estimation, it reduces the number of sensors required for monitoring patients. Thus taking one step towards a practical, comfortable, and continous monitoring of EWS.

References

1. Empatica smart watch. https://support.empatica.com/hc/en-us/categories/200023126-E4-wristband. Accessed 15 May 2019
2. ihealth wireless wrist blood pressure monitor. https://ihealthlabs.com/blood-pressure-monitors/wireless-blood-pressure-wrist-monitor-view-bp7s/. Accessed 15 Feb 2020
3. Anzanpour, A., et al.: Self-awareness in remote health monitoring systems using wearable electronics. In: Proceedings of Design and Test Europe Conference (DATE). Lausanne, Switzerland, March 2017
4. Götzinger, M., et al.: Confidence-enhanced early warning score based on fuzzy logic. ACM/Springer Mob. Netw. Appl. 1–18 (2019). https://doi.org/10.1007/s11036-019-01324-5
5. Götzinger, M., Anzanpour, A., Azimi, I., TaheriNejad, N., Rahmani, A.M.: Enhancing the self-aware early warning score system through fuzzified data reliability assessment. In: Perego, P., Rahmani, A.M., TaheriNejad, N. (eds.) MobiHealth 2017. LNICST, vol. 247, pp. 3–11. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-98551-0_1
6. Götzinger, M., Taherinejad, N., Rahmani, A.M., Liljeberg, P., Jantsch, A., Tenhunen, H.: Enhancing the early warning score system using data confidence. In: Perego, P., Andreoni, G., Rizzo, G. (eds.) MobiHealth 2016. LNICST, vol. 192, pp. 91–99. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-58877-3_12
7. Hadizadeh, E., Elmi, M., TaheriNejad, N., Fotowat, A., Mirabbasi, S.: A low-power signal-dependent sampling technique: analysis, implementation, and application. IEEE Trans. Circ. Syst. I: Regular Papers, 1–14 (2020)
8. Jeong, I.C., Ko, J.I., Hwang, S.O., Yoon, H.R.: A new method to estimate arterial blood pressure using photoplethysmographic signal. In: 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 4667–4670, August 2006. https://doi.org/10.1109/IEMBS.2006.260663

[1] We note that as shown in Table 1, the values of various vital signal used in EWS assessment are abstracted to a score and in this abstraction often a range of numbers lead to the same score. At the border of various scores smaller errors may lead to a change of score, however, a single point error in the overall score is often negligible. For a patient to be considered in a critical condition, the aggregate score of many vital signs is important.

9. Johnson, A.M., Jegan, R., Mary, X.A.: Performance measures on blood pressure and heart rate measurement from PPG signal for biomedical applications. In: 2017 International Conference on Innovations in Electrical, Electronics, Instrumentation and Media Technology (ICEEIMT), pp. 311–315, February 2017. https://doi.org/10.1109/ICIEEIMT.2017.8116856
10. McGaughey, J., et al.: Outreach and early warning systems (EWS) for the prevention of intensive care admission and death of critically ill adult patients on general hospital wards. The Cochrane Library (2007)
11. Morgan, R.J.M., et al.: An early warning scoring system for detecting developing critical illness. Clin. Intensive Care **8**(2), 100 (1997)
12. Perego, P., Rahmani, A., Taherinejad, N. (eds.): Proceedings of the 7th International Conference on Wireless Mobile Communication and Healthcare, MobiHealth 2017, Vienna, Austria, 14–15 November 2017 (2017). https://doi.org/10.1007/978-3-319-98551-0
13. Pollreisz, D., TaheriNejad, N.: A simple algorithm for emotion recognition, using physiological signals of a smart watch. In: 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2353–2356, July 2017. https://doi.org/10.1109/EMBC.2017.8037328
14. Pollreisz, D., TaheriNejad, N.: Detection and removal of motion artifacts in PPG signals. ACM/Springer Mob. Netw. Appl. 1–10 (2019)
15. Pollreisz, D., TaheriNejad, N.: Efficient respiratory rate extraction on smartwatch. In: 42nd Annual International Conferences of the IEEE Engineering in Medicine and Biology Society in conjunction with the 43rd Annual Conference of the Canadian Medical and Biological Engineering Society EMBC. Montreal, Canada, pp. 1–4, July 2020
16. Pollreisz, D., TaheriNejad, N.: Reliable respiratory rate extraction using PPG. In: 11th IEEE Latin American Symposium on Circuits and Systems - LASCAS, San José, Costa Rica, pp. 1–4, February 2020
17. TaheriNejad, N.: Wearable medical devices: challenges and self-aware solutions. IEEE Life Sci. Newslett. **2**, 5–6 (2019)
18. TaheriNejad, N.: Functional or fictional. IEEE Life Sci. Special Issue on: Consumer Technology meets Health Care, 13–15, February 2020
19. TaheriNejad, N., Jantsch, A., Pollreisz, D.: Comprehensive observation and its role in self-awareness: an emotion recognition system example. In: the Federated Conference on Computer Science and Information Systems (FedCSIS), September 2016
20. TaheriNejad, N., Pollreisz, D.: Assessment of physiological signals during happiness, sadness, pain or anger. In: 6th MobiHealth (2016)
21. Urban, R.W., et al.: Modified early warning system as a predictor for hospital admissions and previous visits in emergency departments. Adv. Emerg. Nursing J. **37**(4), 281–289 (2015)
22. Yin, H., Akmandor, A.O., Mosenia, A., Jha, N.K.: Smart healthcare. Found. Trends® Electron. Des. Autom. **2**(14), 401–466 (2018)