# Blood Pressure Estimation with a Wristband Optical Sensor

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## Abstract

UPDATED—August 17, 2018. Blood pressure (BP) is the most commonly performed medical office test. We developed a system that uses exclusively wristband-collected photoplethysmogram (PPG) to estimate BP. A dataset was collected and annotated during daily activities of 22 subjects. Preprocessing was applied to remove the signal noise and artefacts. Signal was segmented into cycles and features were computed. The RReliefF algorithm was used to select a subset of relevant features. The approach was validated with a person-independent leave-one-subject-out (LOSO) experiment. The LOSO experiment was updated with personalization to improve the results. The lowest mean absolute error (MAE) was 6.70 mmHg for systolic and 4.42 for diastolic BP. Ensemble of regression trees achieved the best results, which borderline meet the requirements set by two standards for BP estimation devices.

## Author Keywords

blood pressure; photplethysmogram; signal preprocessing; regression

## ACM Classification Keywords

I.2.1. [Applications and Expert Systems (H.4, J)]: Medicine and science; I.5.4. [Applications]: Signal processing; G.3. [Probability and statistics]: Time series analysis

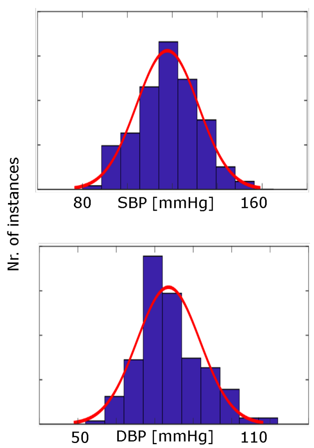


**Figure 1:** Top histogram shows the SBP distribution, while the bottom one shows the DBP distribution. The lines indicate the normal distribution.

## Introduction

Blood pressure (BP) measurement is the most important commonly performed medical office test. It is a direct indicator of hypertension, an important risk factor for a variety of cardiovascular diseases (CVDs), which were the most common cause of death in 2015, responsible for almost 15 million deaths worldwide. Despite its importance, an obvious aversion towards regular BP monitoring is present due to the nature of the measuring devices. Cuff-based devices remain the golden standard in terms of accuracy, however, they also have several downsides, such as a relatively strict measuring protocol, limited physical activity during measuring, and stress during measurement (white coat syndrome).

Due to the aforementioned factors and increasing presence of wearable devices capable of collecting physiological signals, our work focuses on developing a robust unobtrusive BP estimation system, which can offer near real-time periodic BP updates to a user.

There have been several attempts at such a system. Two main approaches were identified in related work. The first one relies on pulse transit time (PTT), which is the time needed for the blood of an individual pulse to travel from the heart to the periphery [4]. This approach is well established, however, its major problem is the requirement of two sensors (commonly ECG and PPG) and their synchronization. The second approach relies on a single PPG sensor and attempts to model the complex relationship between the changes in PPG waveform and BP. A high-quality sensor is typically used in order to capture the subtle waveform changes. This is the subject of intense research for a number of years [5], including our work.

At a glance, there already exist systems for cuff-less BP estimation [1]. However, to the best of our knowledge, the PPG-only approach was never applied or tested on data collected in an uncontrolled non-clinical environment using only a wristband sensor. This is probably due to low sampling frequency and high amount of noise in the waveforms of such wristbands. The main distinction of our work is therefore to use solely a wristband for the PPG-only approach, and to validate the quality of derived models on a challenging dataset collected in an everyday setting.

## Dataset

A dataset was collected from employees at a research institute over a period of several months and was later anonymized. In total, 22 healthy subjects (6 female and 16 male) participated in the experiment. The ages ranged from 22 to 39. The distributions of the collected BP values are shown in Figure 1.

The subjects were given precise instructions regarding the measuring of the ground-truth BP with the Omron M10–IT cuff-based digital monitor, while Empatica E4 wristband was worn in a snug but comfortable way to collect PPG. They were encouraged to measure their ground truth BP at least every 30 minutes if allowed by their obligations. Five subjects also collected data at home, outside of their typical office routine, to increase the variety of the data. Each ground-truth BP value was attributed to the signal 1 minute before and after the measurement was made. We chose a rather short interval, as BP should change very little in such a short time around the measurement.

The final number of instances after cleaning was around 20 000, corresponding to roughly 5.5 hours of signal. Each instance corresponds to a single heart beat.

## Methodology

As the PPG waveform collected with a wristband is often distorted due to movement, lower quality sensor, and poor

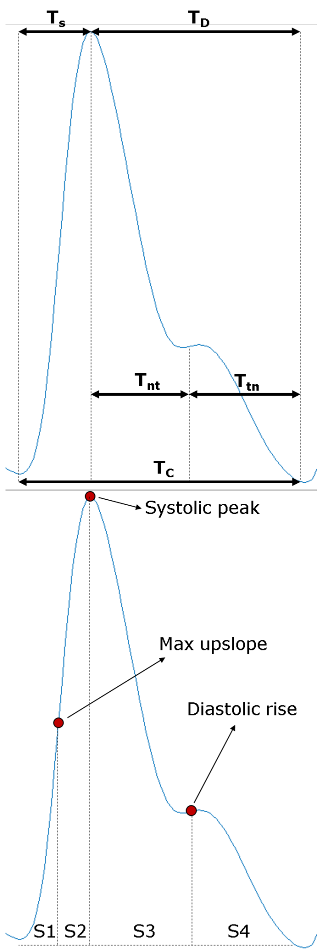


**Figure 2:** Temporal features used in regression. *T* denotes time and *S* denotes areas under or above the curve. Combinations of areas were also used (e.g., $S1 + S2$).

skin-sensor contact, it is vital to extract only high-quality segments. Once such segments are obtained, features are computed and fed into regression models to estimate BP.

*Peak and cycle detection*
In order to do per-cycle cleaning and subsequent feature extraction, cycles (corresponding to heart beats) must first be detected. First, a 4th order Butterworth band-pass (0.5 – 4Hz) filter is used on the raw signal. Then a linear-phase differentiator (LPD) filtering transformation is used, which enhances the systolic upslopes of the PPG pulses, allowing for subsequent systolic peak detection. Such an upslope and peak can be seen in Figure 2. The LPD transformation is based on the first derivative of the filtered PPG signal (see Lázaro et al. [3] for details). Once the peaks are detected, dominant valleys between two subsequent peaks are marked as the cycle start-end locations.

*Cleaning with templates*
A custom cleaning procedure based on some ideas proposed by Li et al. [2] was developed. The procedure traverses the PPG signal with a 15-second sliding window and creates a cycle template $T$ of length $L$ as the average of all the detected cycles in the current window. Then, individual cycles are compared to the template and kept when the matching is high, and discarded otherwise. Cycle-template matching is assessed using three signal quality indices (SQIs): 1.) SQI1 – direct linear correlation using the Pearson's correlation coefficient, 2.) SQI2 – direct linear correlation, only now each cycle is linearly resampled to length $L$, using piecewise linear interpolation or extrapolation, 3.) SQI3 – correlation between the time-warped cycle and the template, as given by Dynamic Time Warping.

*Machine learning*
In order to predict BP, a number of features describing the morphology of the PPG waveform were computed. Temporal features based on related work are shown in Figure 2. The base set of temporal features was expanded with some from the frequency domain, namely the amplitudes and the phases of the frequency domain representation of the 15-second PPG segment containing the current cycle. Finally, the set of features was completed with complexity and mobility (Hjorth parameters), which were also computed for a given 15-second segment.

The set of computed features was fed into a feature selection algorithm, which aims to select a smaller subset of features that minimize redundancy and maximize relevance to the target variable. The RReliefF algorithm was used. The algorithm was ran 10 times, each time applied to 10% of data instances chosen randomly. The features with overall positive non-zero importance were chosen to be used in regression.

## Experimental evaluation
Leave-one-subject-out (LOSO) experiment was conducted, as it is the most robust in terms of generalization, being completely subject-independent. To evaluate the performance, mean absolute error (MAE) was chosen as the metric as it is widely used and intuitive. Initial errors were around 10 mmHg for SBP and 6 mmHg for DBP. Results were further improved using personalization. This means that a small number of instances of the left-out subject was used for training and removed from the test data. This additionally lowered the MAE as shown in Figure 3.

Using this experiment, several algorithms were compared. The results were always superior to a baseline dummy regressor, which always predicted the mean of the train data. A bagged ensemble of regression trees using only the selected relevant features has been consistently the best.

**Discussion points**

- Dummy errors seem relatively low. Its performance can be explained by the fact that almost all the BP data is in a rather limited range, since all the subjects have similar BP.
- Personalization in practice means the user should do a few ground-truth BP measurements with a validated commercial device. The model can then personalize to the user, improving its accuracy.
- A complex model shows much better performance compared to a linear model, hinting at a complex relationship between PPG and BP.
- There is a default error in ground-truth BP coming from the device itself. For precise evaluation, arterial BP should be used as ground truth.
- System could be used informatively, but probably not yet in medicine.

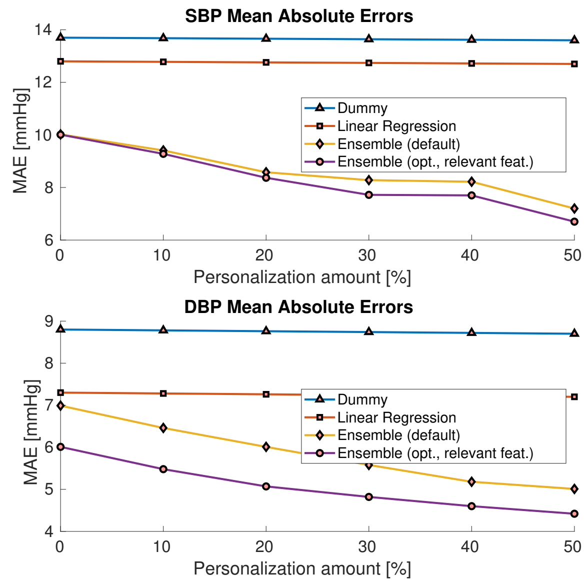


**Figure 3:** LOSO experiment results with personalization.

## Conclusion

The major contribution of our work is the creation and validation of an unobtrusive system capable of continuous BP estimation using only a wristband. The system removes the need for a professional PPG sensor in a fingertip device or additional sensors required by the PTT approach. The main novelty lies in the robust preprocessing module capable of obtaining high-quality cycles from a noisy wristband signal. Another contribution is the collection and use of a unique wristband-collected PPG dataset. It was shown through evaluation that the system is capable of building regression models with good predictive performance, as the errors borderline meet the requirements set by the British Hypertension Society (BHS) and the Association for the Advancement of Medical Instrumentation (AAMI) standard.

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