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Analysis of differences between contact and non-contact estimation of blood pressure

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Abstract: Blood pressure (BP) is a key indicator for cardiac diseases. Although many current works focus on estimating BP using photoplethysmography (PPG), the number of works using imaging PPG, i.e. PPG derived from videos, and works to compare between different PPG settings is limited. This study compares BP estimation methods using regression ensembles across contact and non-contact PPG settings by means of absolute error (MAE), Pearson correlation coefficient and feature importance. Our results show similar BP estimation quality for both contact and non-contact variants. While MAEs are, similar to comparable works, high ($\approx 13\,\mathrm{mmHg}$ and $8\,\mathrm{mmHg}$ for systolic BP (SBP) and diastolic BP (DBP)), particularly for DBP and pulse pressure our analyses yield promising correlation coefficients (> 0.7). We observed notable differences in feature importance underlining the relevance of acquisition setup and processing strategies. This work highlights the potential of iPPG for BP estimation, although further research is needed to fully understand the advantages and limitations of both contact and non-contact methods.

Keywords: Photoplethysmography, Imaging Photoplethysmography, Blood Pressure Estimation

1 Introduction

Cardiovascular diseases are among the leading causes of mortality worldwide. Blood pressure (BP) is a highly relevant physiological parameter for disease prediction and health assessment. Widely used techniques to capture BP involve either an arm cuff-based sphygmomanometer or a catheter. Despite their widespread use, these methods have limitations, including discomfort for the patient and the inability to provide continuous measurements. Photoplethysmography (PPG) has gained a lot of attention as a non-invasive and cost-effective alternative for BP estimation. Among various settings to capture PPG signals, finger photoplethysmography (fPPG) is the most commonly used setting for BP estimation.

However, PPG can also be acquired in different settings, e.g. as it concerns the measurement site such as at the earlobe (ePPG), or with respect to the fixation, where remote measurements via camera, a technique known as imaging PPG (iPPG), has gained much attention recently. Only few works have addressed differences in BP estimation considering the available settings although deeper insights here might be beneficial towards more reliable means to estimate BP from PPG.

In this work, we examine differences in BP estimation using regression ensembles. We compare contact and non-contact PPG modalities and provide a comparative analysis of their efficacy and basic mechanisms of estimation in terms of feature relevance.

2 Material and Methods

2.1 Used Data

We use fPPG, ePPG, iPPG, and BP recordings obtained from an own experimental study. Within our experiments, multiple physiological signals and video recordings of the face were collected during both resting conditions and stimulus exposure. In total, recordings from 43 subjects (29 male, 14 female; aged 20–59 years) were included in this work.

iPPG signals were extracted from videos recorded by the UI-3060CPC-HR Rev 2 RGB camera (IDS Imaging Development Systems GmbH; Obersulm, Germany) at a distance of approximately $40\,\mathrm{cm}$, a resolution of 12 bit and a frame rate of 25 fps. Videos covered the whole face and parts of the shoulders. PPG (ePPG, fPPG) were recorded using biosignal amplifiers Biopac MP36 (Biopac; Goleta, United States of America) and reflective photoplethysmographic signal transducer SS4LA (Biopac; Goleta, United States of America). For continuous reference BP assessment, Finapres Nova (Finapres Medical Systems; Enschede, Netherlands) and thus the volume clamp method (VCM) was used.

The experimental protocol included three types of stimuli: the cold pressor test (CPT), tilting, and paced deep breathing (PDB). Six tilt maneuvers were conducted starting from a supine position (three head-up and four supine recordings). Between tilting, there have always been epochs of $7\,\mathrm{min}$ in the respective position. In such epochs, CPT was performed once or twice (randomly assigned) and PDB was performed when CPT was not carried out. Overall, each recording lasted approximately 49 minutes. More details on the study protocol can be found in [3].

2.2 PPG Extraction

We use contact and non-contact PPG. Contact PPG (fPPG and ePPG) were used as recorded. iPPG signals were extracted by

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segmenting the facial region of each subject using Gaussian Mixture Models and Level Sets following the approach described by Woyczyk et al. [7]. For iPPG extraction, we consider the Green (G) channel and the Plane Orthogonal to Skin (POS) method. Considering a single color channel, the green channel is known to have highest signal quality and has been widely used in prior studies for both PPG measurement and BP estimation [8]. The POS method, which combines raw RGB channels, is also frequently employed in the literature and has been shown to be very powerful [5]. All extracted PPG signals have been resampled to $100\,\mathrm{Hz}$. The subsequent processing of contact and non-contact PPG signals equals all settings.

2.3 PPG Processing

Tab. 1: Extracted features for BP estimation. The column *Signal* describes the base for the respective feature's extraction Where *kern* are features extracted from the two kernels, *rec* describes features from the reconstructed pulse wave and *org* are features extracted from the original PPG beat. If *rec* and *org* are given for a single feature, this feature was calculated twice.

Category	Signal	Feature	Description
	kern	T_{sysdia}	time difference between systolic and diastolic components (4 different variants of finding components - 4 different features)
PWD	kern	W2	width of second kernel
	kern	W1	width of first kernel
	kern	P2	amplitude of second kernel
	kern	P1	amplitude of first kernel
	kern	T2	mode of second kernel
	kern	T1	mode of first kernel
	kern	RI_{peaks}	quotient of amplitudes of systolic and diastolic components
	kern	RI_{area}	quotient of area of diastolic wave and area of systolic waves
Frequency	rec, org	freq4	fourth harmonic
	rec, org	freq3	third harmonic
	rec, org	freq2	second harmonic
	rec, org	freq1	fundamental frequency
Statistical	rec, org	SD	standard deviation
	rec, org	skew	skewness
	rec, org	kurt	kurtosis
	rec, org	Height	difference of minimum and maximum amplitude
	rec, org	Width	duration of pulse wave in s
	rec, org	PWHA	pulse width at half amplitude
Derivative	rec, org	p	maximum of first derivative
	rec, org	b/a	quotient of amplitudes of b and a wave of second derivative
Quality	org	corrPPG	mean correlation of PPG beat compared to neighboring beats in $10\,\mathrm{s}$ window

PPG processing covers preprocessing and feature extraction and is based on the work of Fleischhauer et al. [2]. The general pipeline consists of four main steps: data filtering, beat detection, pulse wave decomposition (PWD) and recomposition, and feature extraction. All PPG signals are bandpass filtered between $0.4\,\mathrm{Hz}$ and $12\,\mathrm{Hz}$ to remove artifacts and noise. Beat detection is performed using the AMPD beat detection algorithm proposed by Scholkmann et al. [4], which detects the onset of each beat. For each detected beat, the corresponding signal segment (up to the next beat) is extracted, and subsequently multiple features are derived.

To capture the morphology of pulse wave, we extract 37 features from the original signal, the frequency domain, the decomposed signal (kernel), and reconstructed PPG waveforms. These features are categorized into PWD, frequency, statistical, derivatives, and quality features. PWD uses two kernel functions (a gamma function and a Gaussian function), as they provide stability and minimize noise through reconstruction. The gamma distribution is particularly suited for modeling the rising edge of the PPG waveform and is therefore used as the first kernel [2]. Features considering a whole beat waveform are extracted from both the original and reconstructed signals. An overview of the extracted features is provided in Tab. 1.

2.4 BP Estimation

The reference BP values are obtained from beat-to-beat SBP and DBP measurements using the Finometer. SBP and DBP values are smoothed using a median filter within a $10\,\mathrm{s}$ window and $1\,\mathrm{s}$ sliding step, resulting in one BP value per second. Obvious outliers (SBP < $70\,\mathrm{mmHg}$ and DBP < $40\,\mathrm{mmHg}$) are replaced by the closest value above these thresholds. PP is then calculated from the difference between SBP and DBP.

BP estimation is performed using decision trees as regression ensembles with bagging for each detected beat in the PPG. Each beat and belonging feature set is mapped to the closest corresponding reference BP values, allowing estimations of SBP, DBP, and PP per beat. We implemented a leave-one-subject-out-cross-validation (LOSOCV). Due to the computational complexity of LOSOCV, only every 20th beat and belonging feature set is used for training. The estimated BP values per beat are finally smoothed using a Gaussian moving average filter within a sliding window of $15\,\mathrm{s}$.

2.5 Metrics

The performance of the BP estimation is evaluated using mean absolute error (MAE) and Pearson's correlation coefficient (r) according to

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{1}$$

and

$$r = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2 \sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}} \tag{2}$$

where N is the number of instances, y_i represents the reference BP and $\hat{y}_i$ is the corresponding estimated BP. $\bar{y}$ and $\bar{\hat{y}}$ denote

the mean values of the reference and estimated BP, respectively. MAE and r are computed for each test subject, and the median results over all subject are reported. To allow a quantitative assessment of our performance for MAE, we implemented a mean estimator that consistently predicts the mean SBP, DBP and PP of the training set.

To analyse the function of the different variants, we analysed the feature relevance for each BP estimator by calculating predictor importance using a built-in Matlab function. For each feature and decision tree split the method sums up the changes in the node risks (mean squared error of node weighted by node probability) and divides it by the number of branches. A feature with no contribution to the estimation process has a predictor importance value of zero.

To avoid inadequate parameter settings to negatively affect BP estimation, we performed a constrained grid search, varying the number of variable splits, the minimum leaf size, and the number of base classifiers. The optimal parameter configuration was selected based on the highest mean of median correlation coefficients and the greatest percentage reduction in MAE relative to the mean estimator for SBP, DBP, and PP.

3 Results

Our quantitative results are presented in Tab. 2. The MAE is slightly improved compared to the mean estimator (except for SBP in iPPG POS and fPPG), where improvements in SBP are minor than in DBP and PP. While the correlation coefficient for SBP is low (fPPG shows highest correlation with 0.42), DBP and PP show high correlations up to 0.72 and 0.78 for DBP and PP. Such results indicate the difficulty of absolute BP estimation without calibration. Found correlation coefficients in turn, at least for DBP and PP, are promising.

Notably, best results were obtained according to the quantity and quality measure using different settings, ePPG for MAE and fPPG or iPPG POS for correlation.

Tab. 2: Results for BP estimation across all PPG variants. The *Mean Estimator* represents the error between the test data and the mean of the training data (using fPPG in this case). Since the mean estimator predicts a single continuous value, r is not given.

Type	MAE in mmHg			r without unit		
	SBP	DBP	PP	SBP	DBP	PP
fPPG	14.16	9.05	7.38	0.42	0.72	0.72
ePPG	11.51	7.72	7.07	0.20	0.68	0.68
iPPG POS	13.53	8.96	7.27	0.22	0.70	0.78
iPPG G	13.20	8.81	7.26	0.21	0.66	0.75
Mean Estimator	13.28	11.01	9.03	n.a.	n.a.	n.a.

Considering feature importance, we calculated the predictor importance for each model in LOSOCV, for each PPG setting and for SBP, DBP and PP. As a representative example, fig.1 shows the importance of features for DBP estimation. Notably, T_{sysdia} (and its variants) distinctly contribute to BP estimation across all four models. Additionally, in iPPG POS, features related to the absolute amplitudes of the PPG signals (including the original, reconstructed, and kernel signals) and their first derivatives are particularly influential. In contrast, for iPPG G, the feature b/a has a substantial impact on the results. For ePPG, b/a is also among the best five features, with the top four features being variants of T_{sysdia}. T2 also contributes to the BP estimation by fPPG.

4 Discussion

Overall Results: Although our results, particularly the MAE and SBP estimates, do not indicate satisfactory BP estimation, they are consistent with findings in the literature where subject-wise test-train splits are applied and no calibration was performed. Studies reporting better performance often employ less stringent data splitting or some form of calibration. [8] However, r yields for DBP and PP across all PPG variants promising results, even under strict data splitting.

Feature Importance: As already stated, T_{sysdia} (and its variants) consistently appear as the most important features for DBP estimation across all models. T_{sysdia} describes the time between the systolic and diastolic peak of a pulse wave, which correlates with the time it takes for the pressure to propagate from the heart to the periphery and back [1]. When vessels are stiffer, the SBP and pulse transit time increases, and thus T_{sysdia} also increases [6]. Moreover, Webb [6] has stated that arterial stiffness is a strong indicator for DBP, even more than for SBP. Notably, the relationship between DBP and arterial stiffness is inverse e.g. an increasing arterial stiffness, represented by (T_{sysdia}), corresponds to a lower DBP. For fPPG T2 also contributes to the BP estimation with high importance. T2 and T_{sysdia} are highly correlated and of similar importance. The effect of stimuli are most prominent in fPPG signals due to vasconstriction and centralization [3]. Therefore changes in T2 might be more prominent in fPPG. Moreover, fPPG is known to have the best signal quality which leads to a more stable T2.

An interesting finding is the high feature importance for features considering absolute amplitudes in iPPG POS. It is reasonable that absolute PPG amplitude relate to BP. However, when pressure is applied to the measurement site and without proper normalization (DC levels are assumed to affect amplitudes), absolute amplitude are hardly comparable across subjects and situations. POS bypasses both making absolute amplitudes a highly relevant feature.

Moreover, the feature b/a is highly prominent in iPPG G and also has some influence in ePPG but not in iPPG POS and fPPG. Since b/a is extracted from the second derivative, it is very sensitive to morphological changes in PPG beats. As POS is a combination of all RGB channels with a focus on

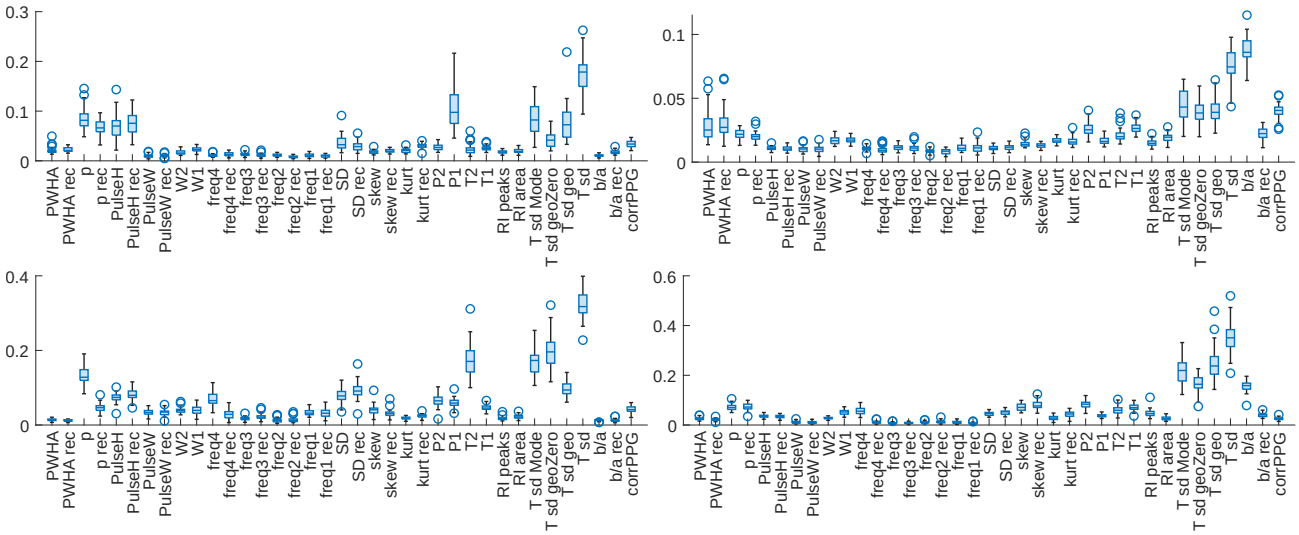

Fig. 1: Feature importances for DBP estimation by iPPG POS (top left), iPPG G (top right), fPPG (bottom left), ePPG (bottom right). Each Boxplot contains feature importances for all subjects.

keeping the pulsation, not on morphology, it is possible that the morphological characteristics of the beats in this variant might be lost. For ePPG, the impact of b/a is lower compared to T_{sysdia} while in iPPG G these features are of comparable importance. This might be due to the contact pressure of ePPG, which can affect the PPG waveform morphology (that also holds for fPPG).

Limitations: There are limitations to our work, which should be kept in mind. Amongst others, iPPG was measured under laboratory conditions and thus signal quality is high compared to real world settings. Moreover, our blood pressure reference can be impaired, e.g. due to centralization. According to visual inspection, especially our reference SBP might be influenced in some cases obviously impacting the quantitative results. As we detect the beats automatically, the chosen detection algorithms might impact the results of beat-to-beat BP estimation as well.

5 Conclusion

In summary, iPPG shows few deviation in absolute BP estimation and correlation compared to contact PPG. The absolute results are consistent with comparable works from the literature and need further improvements but results of DBP and PP (MAE and r) are promising. The importance of iPPG features for BP estimation highly depend on the iPPG extraction algorithm. Further research is needed to develop extraction methods that ensure high signal quality, preserve morphological beat information, and enable consistent interpretability. Additionally, comparisons between contact and non-contact PPG will be extended to analysis of functionality across specific experimental conditions (tilting, PDB, and CPT).

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