

Improved Pulse Pressure Estimation Based on Imaging Photoplethysmographic Signals

Matthieu Scherpf, Hagen Malberg, Martin Schmidt

Institute of Biomedical Engineering, TU Dresden, Dresden, Germany

Abstract

Imaging photoplethysmography (iPPG) enables the extraction of physiological signals from standard RGB video recordings. For the assessment of the human health condition, pulse pressure is of utmost importance and is usually determined from conventional blood pressure signals. Within this work we present the fully automated estimation of pulse pressure using iPPG. We computed the pulse strength from the iPPG signals and performed a linear correlation analysis with the corresponding pulse pressure. We compared different algorithmic iPPG approaches amongst one is an artificial neural network. We measured a maximum pearson correlation of 0.65 for the artificial neural network and 0.63 for the best conventional approach. Our results show 0.1 increase in correlation coefficient compared to previous work based on manual processing, demonstrating the feasibility of automated contactless pulse pressure estimation from RGB videos.

1. Motivation

Pulse pressure, i.e. the difference between systolic and diastolic blood pressure, is of utmost importance for the assessment of the human health condition. In practical, it is derived from conventional, i.e. contact based, blood pressure measurement which is why a fast and easy to use method for pulse pressure estimation would be beneficial in numerous medical settings. Within this work, a comparison of contactless and fully automated methods for pulse pressure estimation from RGB video recordings using imaging photoplethysmography (iPPG) is presented. We analysed two different skin segmentation approaches, namely *Levelset* [1] and *Deeplab* [2], and four elaborated color channel combinations, namely *POS* [3], *CHROM* [4], *O3C* [5] and *GREEN*. In addition, we adapted *Deep-perfusion*, an artificial neural network for iPPG signal extraction [6], for pulse pressure estimation. Our aim was to evaluate the feasibility of automated pulse pressure estimation from RGB videos using state of the art methods for iPPG.

Table 1: Patient characteristics and technical settings of the underlying dataset.

Attribute	Value (std. dev.)	Unit
Number of patients	70	-
Sex (female)	20	-
Age	70.3 (11.4)	years
Systolic blood pressure	111 (16)	mmHg
Diastolic blood pressure	62 (8)	mmHg
Pulse pressure	47 (13)	mmHg
Recording resolution	420x320	pixels
Recording duration	≈1800	sec
Framerate	100	1/sec

2. Methodology

2.1. Dataset

We acquired the dataset within a clinical study which was approved by the Institutional Review Board of the TU Dresden, Germany. The dataset comprises 70 patients recorded while recovering from cardiac surgery. Continuous invasive arterial blood pressure and RGB video were recorded synchronously. Due to the particular setting, the recordings mostly exhibit little motion but varying lighting quality as the experimental setup was handled by a clinician rather than a technical expert and within clinical daily routine. In contrast to other works in this domain, the underlying population mostly consists of older patients. Each video recording has a duration of approximately 30 minutes and was recorded using industrial grade cameras (Manufacturer: *IDS Imaging Development Systems GmbH*, Model: *UI-3060CP*). Patient characteristics and technical settings are summarized in Tab. 1.

2.2. Extraction of iPPG Signals

Our fully automated processing pipeline consists of several steps, shown in Fig. 1. First, we performed framewise skin segmentation using two different approaches: *Levelset* [1] and *Deeplab* [2]. Then, the identified skin pix-

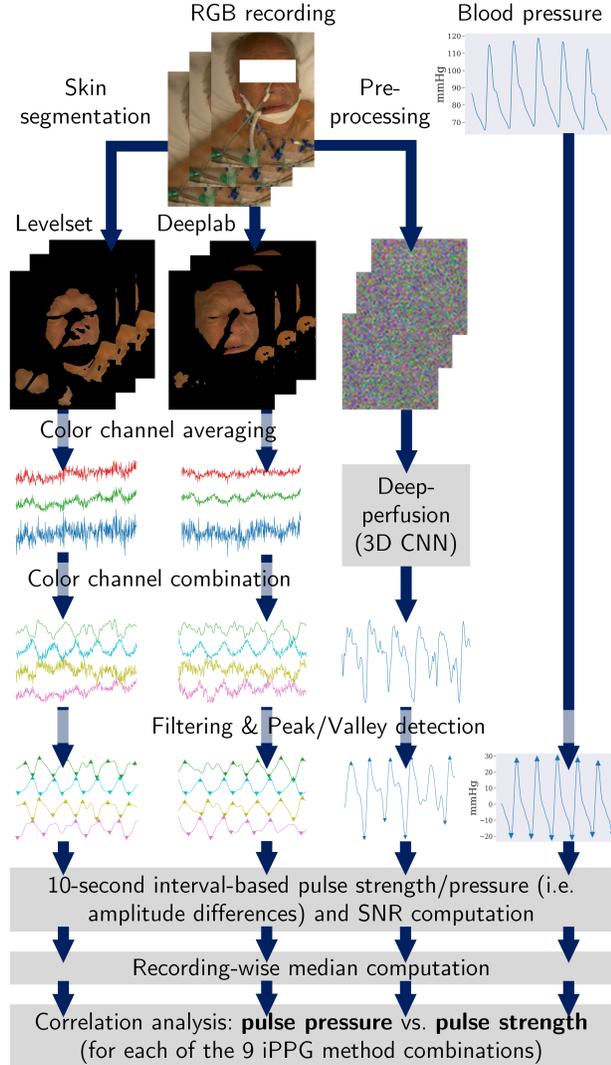


Figure 1: Processing pipeline: Two different skin segmentation approaches alongside four different color combination methods are compared in addition to an end-to-end deep learning based approach.

els were averaged over each of the three color channels and for each frame. Subsequently, the three color channels were combined using elaborated methods, namely *POS* [3], *CHROM* [4] and *O3C* [5]. We additionally evaluated the *GREEN* color channel for comparison reasons. For *Deepperfusion*, we applied the processing steps described in [6]. Overall, nine different iPPG signals were extracted.

2.2.1. Signal Postprocessing and Correlation Analysis

Subsequently, all iPPG signals as well as the reference blood pressure signal were resampled to 100 Hz and fil-

tered using a zero-phase 5th order butterworth filter with a pass band ranging from 0.5 Hz (30 bpm) to 3.33 Hz (200 bpm) (chosen according to *IEC 60601-2-27*). Next, the peaks and valleys were detected to compute the differences in between, i.e. the pulse strength for iPPG signals and pulse pressure for the reference blood pressure signal. Subsequently, non-overlapping 10-second intervals were built and the signal-to-noise ratio (SNR) was calculated as described in [2] for each window. Because the SNR quantifies the signal quality, it can be used as a filter to sort out intervals exhibiting low SNR (probably due to artifacts like movement or low lighting quality). After applying the SNR threshold on the intervals of each record the median pulse strength and median pulse pressure were computed resulting in one pair of values for each patient. We then performed an inter-patient linear correlation analysis between pulse strength and pulse pressure using pearson correlation coefficient (r) as the parameter that quantifies the linear correlation strength.

By nature, *Deepperfusion* can process any input regardless of the recording quality. However, this is not the case for skin segmentation based approaches which may fail due to non detected skin pixels. In such cases the signal extraction is impossible. Therefore, the number of available intervals varies, i.e. the sample size is greater or smaller what inturn effects the linear correlation analysis. To mitigate this effect, we only computed the weighted pearson correlation coefficient where the weight (w_i) for each patient (i) was computed by

$$w_i = \frac{n_i}{N_i} \quad (1)$$

to respect the ratio of available intervals (n_i) after applying a SNR threshold filter over the maximum number of intervals (N_i). The maximum number of intervals is received if no threshold is applied. This effect is depicted in Fig. 2 and further discussed in Section 4.

3. Results

The results for the linear correlation analysis are depicted in Tab. 2. *Deepperfusion* demonstrated highest linear correlation if no SNR threshold filtering was performed, with $r = 0.65$. If a threshold of $SNR \geq 0$ dB was applied, i.e. at least equal signal and noise power, the combination of *Deeplab* with *POS* color combination demonstrated highest linear correlation with $r = 0.63$. Independent from the skin segmentation approach and any applied SNR threshold, the *GREEN* color channel exhibited the lowest performance in comparison to the different color channel combination methods. Our best methods show an increase of r of about 0.1 compared to previous work which based on the combination of manual skin segmentation and the *GREEN* color channel [7].

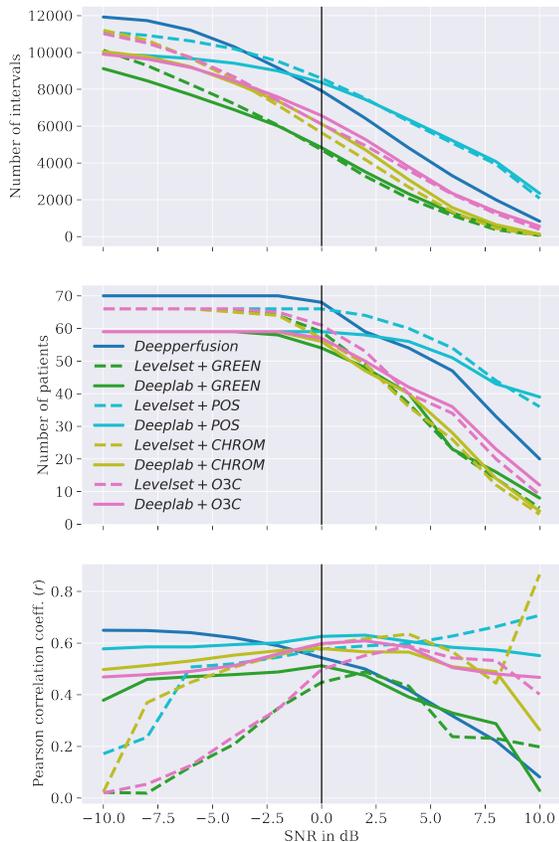


Figure 2: The effect of the signal-to-noise ratio (SNR) on the number of available patients, the number of available 10-second intervals and the pearson correlation coefficient (r). The black line indicates the 0 dB SNR threshold.

The linear correlation analysis is depicted in Fig. 3 for *Deepperfusion* and the combination of *Deeplab* with *POS*. For *Deepperfusion*, the pulse pressure (PP) could be estimated from pulse strength (PS) using

$$PP = 17 \text{ mmHg} \cdot PS + 12.8 \text{ mmHg} \quad (2)$$

without the necessity of SNR threshold filtering. For the combination of *Deeplab* with *POS*, it could be estimated with

$$PP = 13.6 \text{ mmHg} \cdot PS + 35.1 \text{ mmHg} \quad (3)$$

after filtering all intervals with $SNR \geq 0$ dB.

4. Discussion

From our results, we draw three major conclusions. **First**, the combination of color channels is beneficial in the context of pulse pressure estimation from iPPG. **Second**, *Deeplab* is superior to *Levelset* and therefore more

Table 2: Weighted pearson correlation (r) with and without SNR threshold filtering. *Manual + GREEN* represents the result of previous work where the skin segmentation was performed manually [7]. Bold text indicates the best performing method regarding the SNR threshold filter.

Method	r	
	No threshold	$SNR \geq 0$ dB
<i>Deepperfusion</i>	0.65	0.54
<i>Manual + GREEN</i>	0.54	-
<i>Deeplab + POS</i>	0.58	0.63
<i>Deeplab + CHROM</i>	0.50	0.58
<i>Deeplab + O3C</i>	0.47	0.60
<i>Deeplab + GREEN</i>	0.38	0.51
<i>Levelset + POS</i>	0.17	0.58
<i>Levelset + CHROM</i>	0.02	0.59
<i>Levelset + O3C</i>	0.02	0.50
<i>Levelset + GREEN</i>	0.02	0.45

suitable for automated skin segmentation especially in the clinical context where objects like tubes and wires often occlude parts of the skin (see Fig. 1). **Third**, *Deepperfusion* is superior to all methods, although comparability is challenging due to the effect of sample size on linear correlation analysis with respect to SNR-based filtering of intervals. However, this effect applies to every comparison and is depicted in Fig. 2 where the available number of intervals and patients is shown in respect to the applied SNR threshold. For all methods we observe a decrease in the number of available intervals as the SNR threshold is increased. Beginning with -2.5 dB a decrease in the number of available patients can also be observed as for some patients there is no interval left exhibiting higher SNR. While this effect is approximately linear for the number of intervals, it is non-linear and different for each method regarding the change of the pearson correlation coefficient. Considering that SNR can only be computed in the presence of the ground truth heart rate which is unfavorable in a practical application, *Deepperfusion* is the most promising approach from our perspective. The correlation analysis, depicted in Fig. 3, shows that data points are more equally distributed along the regression line for *Deepperfusion*. This might indicate that the derived Eq. 2 is more reliable when applied to a new dataset. Nevertheless, this must be further investigated in future work.

5. Conclusion

Our results demonstrate the feasibility of fully automated remote acquisition of pulse pressure using iPPG. Our goal for future work is to incorporate additional features from the iPPG signal exploiting the time and fre-

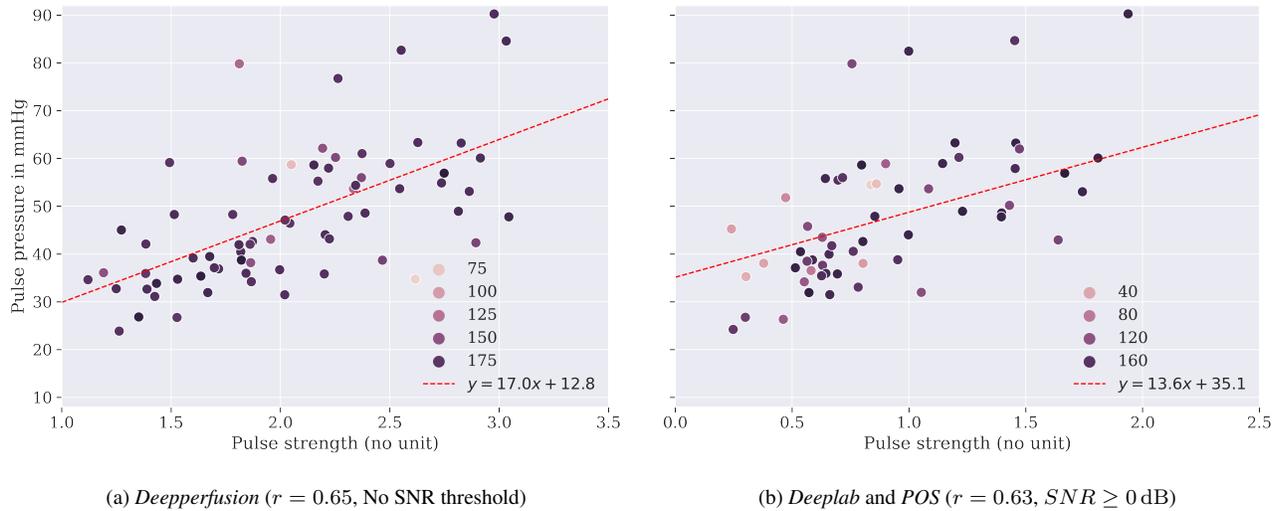


Figure 3: Results of the linear correlation analysis for (a) *Deepperfusion* and (b) the combination of *Deeplab* and *POS* (with SNR threshold filtering). Each dot in the scatter plots represents one patient (i.e. one recording) and its color indicates the number of intervals the median computation was based on. Because of the SNR threshold filtering of intervals the number for each patient differs for the two methods.

quency domain and therefore increase the precision of remote pulse pressure estimation. In addition, we will investigate the remote estimation of absolute blood pressure values in the same way.

Acknowledgments

The authors are grateful to the Centre for Information Services and High Performance Computing at TU Dresden for providing its facilities for high throughput calculations.

Funding

This work was supported by grants of the European Regional Development Fund (ERDF 100278533).

References

- [1] Trumpp A, Rasche S, Wedekind D, Schmidt M, Waldow T, Gaetjen F, Plötze K, Malberg H, Matschke K, Zaunseder S. Skin detection and tracking for camera-based photoplethysmography using a bayesian classifier and level set segmentation. In *Bildverarbeitung für die Medizin*. Heidelberg: Springer Vieweg, Berlin, Heidelberg, 2017; 43–48. URL https://doi.org/10.1007/978-3-662-54345-0_16.
- [2] Scherpf M, Ernst H, Misera L, Malberg H, Schmidt M. Skin segmentation for imaging photoplethysmography using a specialized deep learning approach. In *2021 Computing in Cardiology (CinC)*. IEEE. ISBN 978-1-6654-7916-5, 2021; 1–4. URL <https://doi.org/10.23919/CinC53138.2021.9662682>.
- [3] Wang W, Den Brinker AC, Stuijk S, de Haan G. Algorithmic principles of remote ppg. *IEEE transactions on bio medical engineering* 2017;64(7):1479–1491. URL <https://doi.org/10.1109/TBME.2016.2609282>.
- [4] de Haan G, Jeanne V. Robust pulse rate from chrominance-based rppg. *IEEE transactions on bio medical engineering* 2013;60(10):2878–2886. URL <https://doi.org/10.1109/TBME.2013.2266196>.
- [5] Ernst H, Scherpf M, Malberg H, Schmidt M. Optimal color channel combination across skin tones for remote heart rate measurement in camera-based photoplethysmography. *Biomedical Signal Processing and Control* 2021;68:102644. ISSN 17468094. URL <https://doi.org/10.1016/j.bspc.2021.102644>.
- [6] Scherpf M, Ernst H, Malberg H, Schmidt M. *Deepperfusion*: Camera-based blood volume pulse extraction using a 3d convolutional neural network. In *2020 Computing in Cardiology*. 2020; 1–4. URL <https://doi.org/10.22489/CinC.2020.388>.
- [7] Trumpp A, Rasche S, Wedekind D, Rudolf M, Malberg H, Matschke K, Zaunseder S. Relation between pulse pressure and the pulsation strength in camera-based photoplethysmograms. *Current Directions in Biomedical Engineering* 2017;3(2). URL <https://doi.org/10.1515/cdbme-2017-0184>.

Address for correspondence:

Matthieu Scherpf
 Institute of Biomedical Engineering, TU Dresden
 Fetscherstraße 29, 01307 Dresden
 Matthieu.Scherpf@tu-dresden.de