Contact-Free Physiological Monitoring of Cardiorespiratory States Using Radar and Optical Sensors

Gašper Slapničar Department of Intelligent Systems, Jožef Stefan Insitute, Ljubljana, Slovenia E-mail: gasper.slapnicar@ijs.si

Thesis Summary

Keywords: contact-free, physiological monitoring, radar, camera, photoplethysmogram, blood pressure, hemodynamics

Received: September 25, 2024

The paper summarizes a Doctoral Thesis that focuses on two new approaches for unobtrusive contact-free monitoring of cardiorespiratory and hemodynamic states. First approach is based on radar signals and proposes a novel branched neural network architecture for classification of hemodynamic scenarios. The second is based on RGB camera signals and proposes multi-wavelength depth-dependant photoplethysmogram reconstruction, allowing for single-site pulse transit time measurement and blood pressure estimation using a consumer camera.

Povzetek: Članek povzema doktorsko dizertacijo, ki se osredotoča na brezstično zaznavanje fizioloških signalov z uporabo radarja in RGB kamere.

1 Introduction

Omnipresence of sensor-equipped devices spurred rapid development of e-health and m-health applications in the past decades. Despite their wide-spread adoption in the form of wearables [\[1](#page-2-0)], such devices are ultimately not a universal or ideal solution for regular health monitoring due to their reliance on battery, requiring skin contact and general obtrusive nature. Ideally, the need for direct userdevice interaction should be completely removed in the paradigm of ubiquitous and pervasive computing, which can be achieved using contact-free sensors such as radars and cameras that monitor different parts of electromagnetic (EM) spectrum [\[2](#page-2-1)]. These devices can be used to monitor different physiological parameters unobtrusively, making them feasible for subjects who cannot use wearables (e.g., neonates, burn victims, elderly with dementia) [\[3](#page-2-2)].

2 Radar-based classification of hemodynamic scenarios

We initially explored the potential of radio-frequency part of the EM spectrum, measured by radars, for detection of complex hemodynamic states. These are expressed via several physiological parameters, including respiration. Radars allow for measurement of periodic thoracic expansion and contraction even in challenging conditions, such as night time and occlusion, making them ideal for sleep monitoring. We proposed a novel branched neural network architecture that can take a different number and type of input signals[[4\]](#page-2-3). Two types of layers were primarily investigated, namely 1D convolutional networks (1D CNN) and fully connected networks (Dense ANN). Several input options were checked in terms of window length, modality (contact, radar, or fusion) and data type (temporal, frequency representation via FFT, or fusion).

We showed that we can detect five different hemodynamic states available in a public dataset [\[5](#page-2-4)] (Apnea, Valsalva, Tilting table ascent, Tilting table descent, Resting) with up to 0.83 accuracy and F1 score when using only contact-free radar signals as input. These results were only 4-5% behind traditional contact sensors, as shown in Table [1](#page-1-0), confirming feasibility of radar-based physiological monitoring.

3 Camera-based MW PTT measurement and BP estimation

In the second part, we investigated the feasibility of using the visible part of the EM spectrum, specifically the feasibility of a modified consumer RGB camera for multiwavelength (MW) pulse transit time (PTT) measurement between different skin layers [\[6](#page-2-5)]. Different wavelengths penetrate to different depths and allow for depth-specific photoplethysmogram (PPG) reconstruction, as shown in Figure [1.](#page-1-1)

These PPGs can be used for MW PTT computation and subsequent blood pressure (BP) estimation. We found that algorithmic channel separation of mentioned PPGs is mandatory due to the imperfect nature of image sensor design, which causes spectral overlap between PPGs from different depths. We thus developed several algorithms that

Window	Network	Modality	Temp. Data	Freq. Data	Temp. + Freq.
5s	Dense ANN	Contact	0.69/0.68	0.68/0.66	0.69/0.66
		Radar	0.64/0.61	0.72/0.71	0.72/0.72
		Fusion	0.68/0.68	0.66 / 0.65	0.70/0.70
	<i>ID CNN</i>	Contact	0.65/0.65	0.67/0.65	0.70/0.69
		Radar	0.62 / 0.60	0.61 / 0.60	0.62 / 0.62
		Fusion	0.63/0.63	0.63/0.62	0.64/0.63
10 s	Dense ANN	Contact	0.78/0.77	0.80 / 0.80	0.80/0.79
		Radar	0.75/0.75	0.76/0.76	0.75/0.74
		Fusion	0.79/0.79	0.80/0.78	0.79/0.78
	<i>ID CNN</i>	Contact	0.76/0.76	0.73/0.71	0.75/0.74
		Radar	0.74/0.74	0.72/0.71	0.74/0.73
		Fusion	0.79/0.78	0.75/0.75	0.78/0.78
20s	Dense ANN	Contact	0.84/0.84	0.88 / 0.87	0.87/0.86
		Radar	0.81/0.81	0.83 / 0.83	0.82 / 0.81
		Fusion	0.86 / 0.84	0.87 / 0.87	0.88 / 0.87
	<i>ID CNN</i>	Contact	0.85/0.85	0.82 / 0.80	0.84/0.83
		Radar	0.82 / 0.82	0.80 / 0.78	0.81 / 0.80
		Fusion	0.86 / 0.84	0.82 / 0.82	0.85/0.85

Table 1: Accuracy and F1 score (Acc. / F1) for the investigated Dense and 1D CNN networks at different window lengths, input modalities, and input data types, always using the best-performing set of hyperparameters. Best results for each network architecture are bolded, and the overall best results are highlighted in green.

Figure 1: Layered structure of human skin, showing vascular presence and important structures. Pulse waves propagate through the vessels between different sites (horizontal arrow) and between different layers (vertical arrow).

allow for data-driven camera-independent channel separation, which in turn allows for precise measurement of MW PTTs[[7\]](#page-2-6). Initially we checked the performance of existing blind source separation methods such as PCA and ICA. Our first proposed algorithm was based on camera physics – specifically quantum efficiency of the specific image sensor, using it to separate the bands. Subsequent variants were fully data driven, using the genetic algorithm (GA) paradigm to optimize parameters governing the linear combinations of channel mixtures, with different fitness functions – either phase delay (PD) between waveforms or error of a trained BP regressor [\[8](#page-2-7)]. These lead to good channel separation and MW PTT computation, enabling subsequent training of BP estimation models. Finally we confirmed on an in-house dataset with 13 subjects that such MW PTTs are well-correlated with BP, and trained RandomForest regression models to predict both systolic and diastolic BP in a leave-one-subject-out (LOSO) experiment with and without personalization. The best-performing models achieved errors within clinical standards, as shown in Table 2.

	General regressor [mmHg]			Personalized regressor [mmHg]		
Algorithm	MAE _{SRP}	MAE _{DRP}	MAE_{AVG}	MAE _{SRP}	MAE _{DBP}	MAE _{AVG}
Baseline	11.31 ± 1.50	9.02 ± 1.60	10.17 ± 1.55	8.64 ± 1.62	6.12 ± 1.48	$7.38 + 1.55$
PCA	10.22 ± 1.31	8.91 ± 1.19	9.57 ± 1.25	8.01 ± 1.25	5.99 ± 1.35	7.00 ± 1.30
ICA.	9.81 ± 1.20	6.97 ± 1.10	8.39 ± 1.15	6.83 ± 1.10	5.75 ± 1.30	6.29 ± 1.20
Physics (or.)	7.72 ± 1.00	5.46 ± 0.98	6.59 ± 0.99	4.78 ± 0.96	3.89 ± 0.97	4.34 ± 0.97
Physics (ref.)	6.94 ± 1.02	5.03 ± 0.96	6.06 ± 1.01	4.00 ± 0.94	2.88 ± 0.99	3.39 ± 1.00
$GA-BP$	6.89 ± 0.95	4.91 ± 0.98	5.90 ± 0.97	3.48 ± 1.02	2.61 ± 0.90	3.05 ± 0.96
$GA-PD$	7.02 ± 1.03	4.97 ± 0.97	6.00 ± 1.00	4.01 ± 0.98	3.03 ± 0.96	3.52 ± 0.97

Table 2: Comparison of the MAEs in mmHg for SBP and DBP estimation when using different channel separation algorithms. We compare against the baseline of using no channel separation. We report results for experiments with and without personalization in a leave-one-subject-out (LOSO) experiment.

4 Conclusion

Overall we showed that contact-free sensors leveraging the information from the EM spectrum are an affordable unobtrusive alternative to wearables, and can achieve similar performance in monitoring of important physiological parameters and states. While some limitations and challenges remain, such as difficult uncontrolled conditions and privacy concerns, there is potential for implementing the proposed methods in a single device, which could immensely improve the speed, cost and comfort of physiological monitoring both at home and in hospitals.

Acknowledgements

I would like to acknowledge the support of my supervisor prof. dr. Mitja Luštrek, my co-supervisor prof. dr. Wenjin Wang, Department of Intelligent Systems (E9), the Slovenian Research and Innovation Agency (ARIS), and Jožef Stefan International Postgraduate School.

References

- [1] Matthew Smuck, Charles A Odonkor, Jonathan K Wilt, Nicolas Schmidt, and Michael A Swiernik. The emerging clinical role of wearables: factors for successful implementation in healthcare. *NPJ digital medicine*, 4(1):1–8, 2021. URL [https://doi.org/10.1038/](https://doi.org/10.1038/s41746-021-00418-3) [s41746-021-00418-3](https://doi.org/10.1038/s41746-021-00418-3).
- [2] He Liu, Yadong Wang, and Lei Wang. A review of non-contact, low-cost physiological information measurement based on photoplethysmographic imaging. In *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pages 2088–2091. IEEE, 2012. URL [https://doi.org/](https://doi.org/10.1109/EMBC.2012.6346371) [10.1109/EMBC.2012.6346371](https://doi.org/10.1109/EMBC.2012.6346371).
- [3] Yongshen Zeng, Dongfang Yu, Xiaoyan Song, Qiqiong Wang, Liping Pan, Hongzhou Lu, and Wenjin Wang. Camera-based cardiorespiratory monitoring of preterm infants in nicu. *IEEE Transactions on Instrumentation*

and Measurement, 2024. URL [https://doi.org/](https://doi.org/10.1109/TIM.2024.3395314) [10.1109/TIM.2024.3395314](https://doi.org/10.1109/TIM.2024.3395314).

- [4] Gašper Slapničar, Wenjin Wang, and Mitja Luštrek. Classification of hemodynamics scenarios from a public radar dataset using a deep learning approach. *Sensors*, 21(5):1836, 2021. URL [https://doi.org/10.](https://doi.org/10.3390/s21051836) [3390/s21051836](https://doi.org/10.3390/s21051836).
- [5] Sven Schellenberger, Kilin Shi, Tobias Steigleder, Anke Malessa, Fabian Michler, Laura Hameyer, Nina Neumann, Fabian Lurz, Robert Weigel, Christoph Ostgathe, et al. A dataset of clinically recorded radar vital signs with synchronised reference sensor signals. *Scientific data*, 7(1):291, 2020. URL [https://doi.org/](https://doi.org/10.1038/s41597-020-00629-5) [10.1038/s41597-020-00629-5](https://doi.org/10.1038/s41597-020-00629-5).
- [6] Gašper Slapničar, Wenjin Wang, and Mitja Luštrek. Feasibility of remote pulse transit time estimation using narrow-band multi-wavelength camera photoplethysmography. In *Adjunct Proceedings of the 2022 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2022 ACM International Symposium on Wearable Computers*, pages 115–117, 2022. URL [https://doi.org/10.1145/3544793.](https://doi.org/10.1145/3544793.3560339) [3560339](https://doi.org/10.1145/3544793.3560339).
- [7] Gašper Slapničar, Wenjin Wang, and Mitja Luštrek. Feasibility of remote blood pressure estimation via narrow-band multi-wavelength pulse transit time. *ACM Transactions on Sensor Networks*, 20(4):1–21, 2024. URL <https://doi.org/10.1145/3597302>.
- [8] Gašper Slapničar, Wenjin Wang, and Mitja Luštrek. Generalized channel separation algorithms for accurate camera-based multi-wavelength ptt and bp estimation. *Biomedical Optics Express*, 15(5):3128–3146, 2024. URL <https://doi.org/10.1364/BOE.518562>.