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Sensor Fusion for Robust Heartbeat Detection during Driving*

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Abstract— **Private spaces like apartments and vehicles are not yet fully exploited for health monitoring, which includes continuous measurement of biosignals. This work proposes sensor fusion for robust heartbeat detection in the noisy and dynamic driving environment. We use four sensors: electrocardiography (ECG), ballistocardiography (BCG), photoplethysmography (PPG), and image-based PPG (iPPG). As ground truth, we record a 3-lead ECG with wet electrodes attached to the chest. Twelve healthy volunteers are monitored in rest and during driving, each for 11 min. We propose sensor fusion using convolutional neural networks to detect the sensor combination delivering the most accurate heart rate measurement. For rest, we achieve scores of 95.16% (BCG + iPPG), 96.08% (ECG + iPPG), 96.35% (ECG + BCG), 96.53% (ECG + PPG), 96.58% (PPG + iPPG), and 97.15% (BCG + PPG). In motion, the highest scores are 92.46% (BCG + iPPG, PPG + iPPG, ECG + iPPG), 92.83% (ECG + PPG), 93.03% (BCG + PPG), and 93.08% (ECG + BCG). Fusing all four signals with the best fusion approach results in scores of 97.24% (rest) and 94.38% (motion). We conclude that sensor fusion allows robust heartbeat measurement of car drivers to support continuous and unobtrusive health monitoring for early disease detection.**

I. Introduction

According to the World Health Organization (WHO), cardiovascular diseases cause 17,9 million deaths per year [1]. Early detection of symptoms improves therapeutic outcomes and reduces mortality [2], but requires continuous health monitoring or regular medical check-ups [3]. In western countries, people spend 35 minutes per day in a car [4], where the positions of the seat, belt, and steering wheel are static meaning that medical sensing can be integrated unobtrusively.

Leonhard et al. [5] review sensors that are already used for heartbeat detection: electrocardiography (ECG) [6], capacitive ECG (cECG) [7], radar [8], ballistocardiography (BCG) [7], photoplethysmography (PPG) [9], and image-based PPG (iPPG) [10]. The majority of works use a single sensor and only a small number of publications use two or more sensors [5]. For instance, Walter et al. used cECG, BCG, and magnetic impedance sensors to prove the feasibility of these sensors during driving [7]. Heuer et al. evaluate the feasibility of ECG, cECG, infrared thermometer, and a pulse oximeter to advance driver assistance and active safety [11]. However, the challenge of changing signal quality remains.

Due to the motion of the driver and the vehicle, the number and length of dropout periods, as well as the signal quality, are inappropriate for a medical check-up with a single sensor [6],[12]. Therefore, redundant systems fusing multiple signals are needed to be able to choose at least one signal with a high signal-to-noise ratio (SNR) at each instance of time.

The sensor fusion approaches proposed by Münzner et al. [13] focus on human activity recognition, which can be applied to heartbeat detection. They compare three fusion approaches using convolutional neural networks (CNN): I) early fusion merges the signal after the first layer, II) sensor-based late fusion merges the signal in the dense layer with two convolutional layers per signal, which increases the number of extracted features, and III) signal-based late fusion has one convolutional layer per signal.

A review from Tejedor et al. [14] covers sensor fusion for heartbeat detection and recommends the algorithm from Chandra et al. [15]. This algorithm estimates the heartbeat location with CNN-based information fusion and is generalizable regarding the input modalities [15]. We assume that the combination of the approaches from Münzner et al. and Chandra et al. with a majority "voting" mechanism could enable higher reliability. In this work, we present a robust sensor fusion approach for vehicles and determine the performance gain on heartbeat detection. In particular, we answer the question: 'Does the fusion of multiple sensors increase the reliability of heartbeat detection?'.

II. Methods

A. Sensor System

We choose four types of sensors. The 1-lead ECG with dry electrodes (BiosignalPlux Explorer, Plux Wireless Biosignals, Lisboa, Portugal) is attached to the steering by copper plates. The PPG (BiosignalPlux Explorer, Plux Wireless Biosignals, Lisboa, Portugal) is placed on the steering wheel with two LEDs for the red and infrared spectrum. The BCG (SCA11H, Murata, Nagaokakyō, Japan) is placed on the backrest and measures ballistic forces generated by the heart. For iPPG, an off-the-shelf red, green, blue (RGB) camera (Real Sense D435i, Intel, California, United States) is directed towards the driver from behind the steering wheel. The green channel of the video is cropped to a region of interest (ROI) that covers the driver's face and is averaged [16].

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The ground truth is recorded using a 3-lead ECG (BiosignalPlux Explorer, Plux Wireless Biosignals, Lisboa, Portugal) with wet electrodes attached to the driver's thorax.

B. Experimental Design

We mounted four devices in a driving simulator (RaceRoom simulator RR3055, KW automotive, Fichtenberg, Germany) in appropriate positions (Fig. 1). $N = 12$ healthy volunteers performed two recordings, each lasting 11 min: I) sitting without intentional movement (rest), and II) simulated driving (motion). We performed the study under the declaration of Helsinki [17].

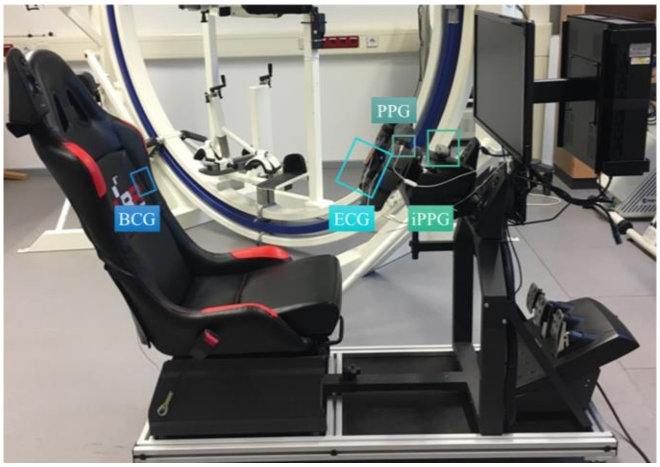

Figure 1. Driving simulator with placed sensor devices.

C. Data Processing

Signal processing is based on Chandra et al. [15] and is performed in four steps: i) downsampling to 250 Hz using *resample_sig()* from the wfdb python library, ii) median filtering with lengths of 150 samples for noise removal, iii) amplitude normalization to the interval [-1,1], and iv) synchronization based on landmarks and leftwards shift. This data is then divided into snippets of 251 samples, which results in 12·11·60 = 7,920 snippets for each activity. Following Chandra et al. [15], we choose an overlap of 250 for generating test snippets. For training snippets, the overlap is 240. These snippets are divided into training and test data using leave-one-out cross-validation (LOOCV), therefore one volunteer is used as a validation set and the remaining as a test set, which is repeated 11 times. We chose LOOCV due to the rather small amount of data.

D. Hybrid Algorithm

The hybrid algorithm is based on the CNN layer design from [15] and is implemented using Python as glue code and the libraries Keras and TensorFlow (Fig. 2). Training and testing are performed on the "Phoenix" cluster of the TU Braunschweig [18]. The input vector contains the ECG, BCG, PPG, or iPPG signal. The convolutional layer extracts the features of the signals and generates a feature map. Similar to Chandra et al. [15], we use 4 filters of length 20 in the convolutional layer for each of the sensor signals. The dropout layer with a dropout rate of 0.2 prevents overfitting. The pooling layer reduces unnecessary information. The dense layer classifies the provided segment in binary classes: no heartbeat and heartbeat, coded 0 and 1, respectively.

We selected a sigmoid function such that the output layer generates an output vector $\hat{Y}$ containing multiple labels that are either 0 or 1. Thereby, j represents the number of a snippet, and s stands for the signal. The output vector is:

$$\hat{Y} = \{\hat{y}_{1j} + \hat{y}_{2j} + .. + \hat{y}_{nj}\} \ \forall j = [1, s] \quad (1)$$

The three sensor fusion approaches: I) early fusion, II) sensor-based late fusion, and III) signal-based late fusion proposed by Münzner et al. [13] is integrated into the CNN layer design. These approaches have the same CNN layer design (Fig. 2).

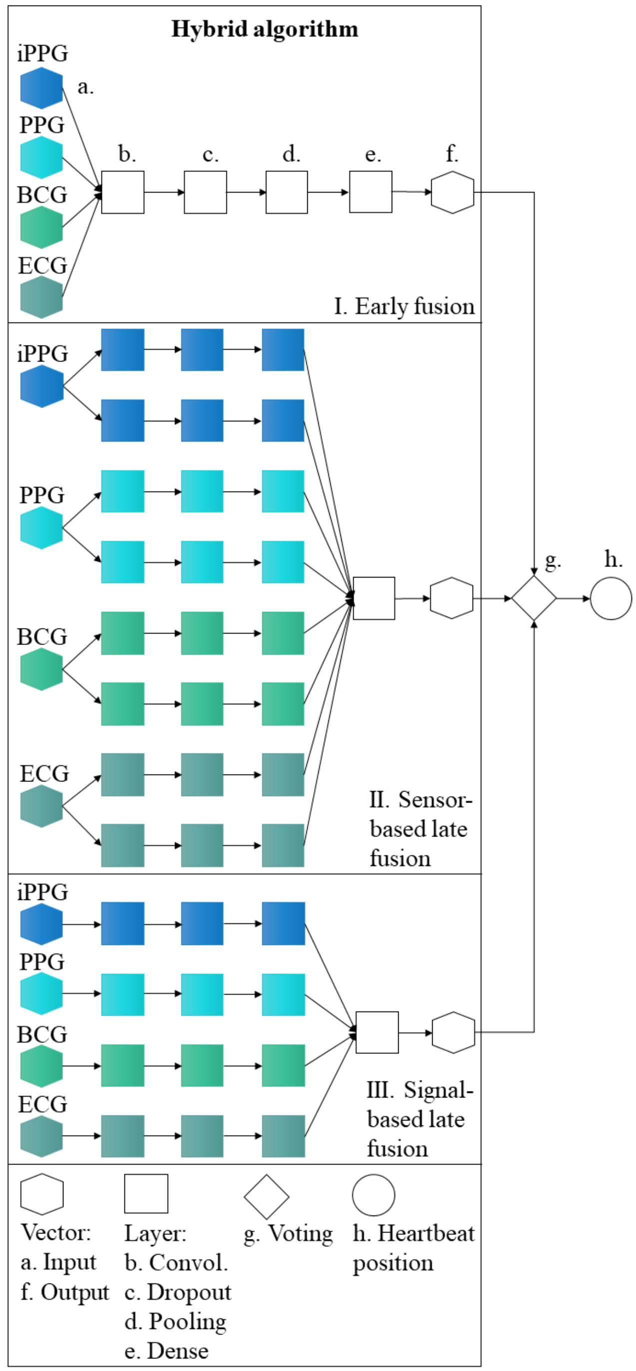

Figure 2. Basic structure of the hybrid algorithm for four signals.

The early fusion approach consists of a single integrated CNN and signals are fused in the convolutional layer. This decreases the number of learned features. The sensor-based late fusion approach has two CNN per signal and therefore the sum of integrated CNNs is eight. It then follows that more features are extracted per signal. The signal-based late fusion uses one CNNs per signal and the number of integrated CNNs is four. The fusion of these two approaches is conducted in the dense layer.

The hybrid algorithm contains all three fusion algorithms and the voting function to determine the heartbeat position. This voting function is independent of the CNN and processes the output vector $\hat{Y}$ for making the final decision if a segment contains no heartbeat (class 0) or one heartbeat (class 1) based on a majority vote. Thereby, if more than two sensor fusion approaches have a label $\hat{y} = 1$ then the voting concludes the segment contains a heartbeat.

E. Evaluation

The ground truth heartbeat positions are generated by a simultaneous truth and performance level estimation (STAPLE) method, which is based on a majority vote of nine state-of-the-art R-wave detection algorithms [19]. We calculate an overall performance score for each approach, which consists of the metrics' positive predictive value (PPV), and sensitivity. These metrics are based on the calculation of true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN). The PPV calculates the ratio of TP to TP and FP classified segments:

$$PPV = \frac{TP}{TP+FP} \tag{3}$$

The sensitivity calculates the ratio of TP to TP and FN classified segments:

$$Sensitivity = \frac{TP}{TP+FN} \tag{4}$$

The overall performance score is a combination of the average PPV and sensitivity overall performance score:

$$Score = \frac{PPV+Sensitivity}{2} \tag{5}$$

III. Results

A. Performance of Two Sensors for Resting Subjects

As a first step, we calculate the overall performance score of two sensors for each approach for resting subjects. This enables a comparison between the different signals.

TABLE I. Score for Two Sensors for Resting subjects

Approach	Score (in %)					
	BCG + iPPG	***ECG + iPPG***	***ECG + BCG***	***ECG + PPG***	***PPG + iPPG***	***BCG + PPG***
Early fusion	44.64	90.85	94.62	95.21	84.02	86.67
Sensor-based late fusion	**95.16**	95.91	96.22	96.49	**96.58**	96.22
Signal-based late fusion	94.97	95.83	96.05	96.41	96.18	96.88
Hybrid algorithm	95.09	**96.08**	**96.35**	**96.53**	95.63	**97.15**

The BCG and iPPG signals have the lowest score with 44.64% with early fusion. The highest score has the BCG and PPG sensors with the hybrid algorithm (97.15%).

B. Performance of Two Sensors for Subjects in Motion

As a second step, we calculate the overall performance score of two sensors for each approach for subjects in motion. The combination with BCG and iPPG shows the lowest performance (44.58%) with the early fusion approach. The highest score has the ECG and BCG sensors with 93.08%. For motion, the sensor-based late fusion has four times the highest score for a specific sensor pair.

TABLE II. Score for Two Sensors for subjects in motion

Approach	Score (in %)					
	BCG + iPPG	***PPG + iPPG***	***ECG + iPPG***	***ECG + PPG***	***BCG + PPG***	***ECG + BCG***
Early fusion	44.58	72.93	91.20	89.94	67.35	92.59
Sensor-based late fusion	**92.46**	**92.46**	**92.46**	92.88	**93.03**	93.03
Signal-based late fusion	92.73	91.56	91.56	92.02	92.72	92.72
Hybrid algorithm	92.45	92.54	92.22	**92.83**	93.01	**93.08**

C. Performance of Four Sensors for Rest and Motion

The score for the four sensors ECG, BCG, PPG, and iPPG, and the hybrid algorithm for rest is 97.01%, and motion (94.38%). The sensor-based late fusion algorithm achieves the highest score for resting subjects with 97.24%.

TABLE III. Score for Four Sensors for Rest and Motion

Approach	Score (in %)	
	Rest	***Motion***
Early fusion	94.85	90.71
Sensor-based late fusion	**97.24**	93.95
Signal-based late fusion	95.13	93.58
Hybrid algorithm	97.01	**94.38**

IV. Discussion

For unobtrusive monitoring in private spaces, e.g. the vehicle, the changing data quality of the measured bio-signals is a major challenge [7],[16]. Combining all four sensors achieves the highest scores with 97.24% for resting subjects and 94.38% for subjects in motion. This indicates that the fusion of multiple sensors increases reliability. The sensor pairs BCG and PPG (rest), as well as ECG and BCG (motion), have the highest scores with 97.15% and 93.08%. However, PPG and ECG require continuous physical contact with the hands at a specific position of the steering wheel. Under real driving conditions, the driver does not always hold the hands in a specific position. In these situations, BCG and iPPG are presumably still required.

A limitation of our work is the synchronization of the signals. ECG and PPG signals are time-synchronized as they were obtained using the same hardware. BCG and iPPG signals were collected through separate devices.

The signals were synchronized by a manually generated short-time artifact with an up and down movement. This time synchronization could result in inaccuracies, which could be an explanation for the lower scores using the iPPG signal.

In future work, we will adjust the sensor system to improve the time synchronization. For the ECG sensor, an additional layer as corrosion protection for the copper plates will be used to increase its reliability. Furthermore, pressure sensors could be used to detect the electrodes with the best contact. For the BCG signal, noise-cancellation with an additional sensor will be implemented. Additionally, for the iPPG, an adaptable ROI for the face could improve the SNR. Moreover, tests in real driving situations are necessary.

We observed a high degree of variability regarding SNR between volunteers in our conducted experiments. We explain this effect by different body sizes, skin types, and gender. Therefore, more testers are needed. Besides, the skin type and melanin level have an impact on the SNR and the iPPG analysis [20].

In this paper, we analyzed the entire length of the signal without a method for signal quality assessment. However, movement artifacts presumably lead to segments with such a high SNR that they are unusable for detecting heartbeats. Therefore, a method for selecting only signal segments with a low SNR could improve the results.

In the future, we aim for extending the developed algorithms from mere heartbeat detection to diagnostics, e.g. atrial fibrillation detection. After proof of technical feasibility, it is important to answer comparative research questions by including patients with cardiovascular diseases. This could be realized by a large-scale and long-time study comparing clinical endpoints of patients that use a car with the proposed sensor system to patients that do not.

In that case, data storage within the vehicle and transmission are important technical aspects. The increased data rates and reduced latency of fifth-generation (5G) cellular networks could enable real-time data transmission. Eventually, if the proposed system shows it can detect cardiac emergencies, it could be used for sending fully automatic emergency alerts [21].

V. Conclusion

In this work, we aimed to increase the reliability of heartbeat measurement by fusing multiple sensors within a car. The results show that the proposed hybrid algorithm and a higher number of sensors improve reliability. Furthermore, the proposed setup is extendable to record further vital signs, e.g., respiratory rate, blood pressure, and temperature. Moreover, it holds the potential for monitoring the emotional state based on face landmarks or via electrodermal activity measuring skin resistance. Eventually, this could enable not only physiological monitoring but also unobtrusive psychological monitoring within the vehicular environment.

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References

[1] World Health Organization, Cardiovascular diseases [Internet]. [cited 2021 January 1]; [about 1 screen]. Available from: https://www.euro.who.int/en/health-topics/noncommunicable-diseases/cardiovascular-diseases/cardiovascular-diseases2.

[2] Gheorghiade M, Pang PS. Acute heart failure syndromes. J Am Coll Cardiol. 2009 Feb;53(7):557–73.

[3] Steinhubl SR, Waalen J, Edwards AM, Ariniello LM, Mehta RR, Ebner GS. Effect of a home-based wearable continuous ECG monitoring patch on detection of undiagnosed atrial fibrillation: the mSToPs randomized clinical trial. JAMA. 2018 Jul;320(2):146–55.

[4] Department of Transportation, National travel survey: England 2018 [Internet]. [cited 2020 October 1]; [about 14 page]. Available from: https://www.gov.uk/government/statistics/national-travel-survey-2018.

[5] Leonhardt S, Leicht L, Teichmann D. Unobtrusive vital sign monitoring in automotive environments: a review. Sensors (Basel). 2018 Sep;18(9):3080.

[6] Gomez-Clapers J, Casanella R. A fast and easy-to-use ECG acquisition and heart rate monitoring system using a wireless steering wheel. IEEE J Sensors. 2012 Mar;12(3):610–6.

[7] Walter M, Eilebrecht B, Wartzek T, Leonhardt S. The smart car seat: personalized monitoring of vital signs in automotive applications. J Pers Ubiquit Comput. 2011 Jan;15(7):707–15.

[8] Shyu KK, Chiu LJ, Lee PL, Lee LH. UWB simultaneous breathing and heart rate detections in driving scenario using multi-feature alignment two-layer EEMD method. IEEE J Sensors. 2020 May;20(17):10251–266.

[9] Munir MA, Misal, Hassan A, Tariq H, Khalid Z. IoT based automotive driver drowsiness prediction system using heart rate variability and galvanic skin response. Annu Int Conf IEEE Eng Emerg Tech. 2020 Feb;2020:1-6.

[10] Huang PW, Wu BJ, Wu BF. A heart rate monitoring framework for real-world drivers using remote photoplethysmography. IEEE J Biomed Health Inform. 2020 Sep;25(5):1397-408.

[11] Heuer S, Chamadiya B, Gharbi A, Kunze C, Wagner M. Unobtrusive in-vehicle biosignal instrumentation for advanced driver assistance and active safety. Annu Int Conf IEEE Eng Med Biol Soc. 2010 Dec;2011:252–6.

[12] Warnecke JM, Wang J, Deserno TM. Noise reduction for efficient In-vehicle respiration monitoring with accelerometers. Annu Int Conf IEEE Eng Med Biol Soc. 2019 Jul;2019:3257-61.

[13] Münzner S, Schmidt P, Reiss A, Hanselmann M, Stiefelhagen R, Dürichen R. CNN-based sensor fusion techniques for multimodal human activity recognition. Annu Int Conf ACM Int Symp Wear Comp. 2017 Sep;2017:158-65.

[14] Tejedor J, García CA, Márquez DG, Raya R, Otero A. Multiple physiological signals fusion techniques for improving heartbeat detection: a review. Sensors (Basel). 2019 Oct;19(21):4708.

[15] Chandra BS, Sastry CS, Jana S. Robust heartbeat detection from multimodal data via CNN-based generalizable information fusion. IEEE Trans Biomed Eng. 2019 Mar;66(3):710–7.

[16] Wang J, Warnecke JM, Haghi M, Deserno TM. Unobtrusive health monitoring in private spaces: the smart vehicle. Sensors (Basel). 2020 Apr;20(9):2442.

[17] World Medical Association. WMA declaration of Helsinki [Internet]. [cited 2021 Jul 20]. Available from:https://www.wma.net/policies-post/wma-declaration-of-helsinki-ethicalprinciples-for-medical-research-involving-human-subjects/.

[18] TU Braunschweig, Hardware [Internet]. [cited 2021 January 1]; [about 1 screen]. Available from: https://www.tu-braunschweig.de/en/it/dienste/21/phoenix/hardware.

[19] Kashif M, Jonas SM, Deserno TM. Deterioration of R-wave detection in pathology and noise. IEEE Trans Biomed Eng. 2017 Sep;64(9):2163–75.

[20] Nowara EM, McDuff D, Veeraraghavan A. A meta-analysis of the impact of skin type and gender on non-contact photoplethysmography measurements. Annu Int Conf IEEE Comp Vis Pat Recog. 2020 Jun;2020:1148–55.

[21] Spicher N, Barakat R, Wang J, Haghi M, Jagieniak J, Öktem GS, Hackel S, Deserno TM. Proposing an International Standard Accident Number (ISAN) for interconnecting ICT systems of the rescue chain. Methods Inf Med. 2021 Jan;60(S 01):e20-e31.