ANGELS - Smart Steering Wheel for Driver Safety

Published Version:
ANGELS - Smart Steering Wheel for Driver Safety / Amidei, Andrea; Rapa, Pierangelo Maria; Tagliavini, Giuseppe; Rabbeni, Roberto; Pavan, Paolo; Benatti, Simone. - ELETTRONICO. - (2023), pp. 15-20. (Intervento presentato al convegno International Workshop on Advances in Sensors and Interfaces (IWASI) tenutosi a Monopoli (Bari), Italy nel 8-9 June 2023) [10.1109/IWASI58316.2023.10164505].

Availability:
This version is available at: https://hdl.handle.net/11585/933777 since: 2023-07-06

Published:
DOI: http://doi.org/10.1109/IWASI58316.2023.10164505

ANGELS - Smart Steering Wheel for Driver Safety

Andrea Amidei[1], Pierangelo Maria Rapa[2], Giuseppe Tagliavini[2], Roberto Rabbeni [3], Paolo Pavan[1] and Simone Benatti[1]
[1] University of Modena and Reggio Emilia, Modena, Italy — {andrea.amidei, paolo.pavan, simone.benatti}@unimore.it
[2] University of Bologna, Bologna, Italy — {pierangelomaria.rapa, giuseppe.tagliavini}@unibo.it
[3] Maserati, Modena, Italy — roberto.rabbeni@maserati.com

***Abstract*—The automotive industry increasingly recognizes the importance of human-machine interaction in enhancing the driving experience and improving driver safety. Human factors, such as drowsiness and attention deficits, play a primary role in safe driving. There are several research and commercial solutions to address these issues. However, they analyze vehicle behavior and are unable to assess the driver's state in a timely manner. A novel approach to this problem is to monitor the driver's physiological signals. In this context, Photoplethysmography (PPG) is a non-invasive technique that monitors cardiac activity and can provide information regarding the driver's state. This work introduces ANGELS, an embedded system that exploits PPG signals to monitor drivers in a non-invasive way. ANGELS is a low-cost and low-power system that can be integrated into the steering wheel of a car. It acquires and processes the driver's PPG signals in real-time and enables heart rate monitoring without requiring accelerometer data to remove motion artifacts. We perform an experimental assessment using the Maserati driving simulator. ANGELS features a mean absolute error on heart rate detection of 1.19 BPM with a latency of 10 s and power consumption of only 130 mW. These results demonstrate that it is a reliable and promising solution for improving driver safety.**

***Index Terms*—Driver monitoring, Photoplethysmography, driver's physiological signals, embedded system, peaks detection**

I. Introduction

Recently, Human-Machine Interaction (HMI) is becoming very pervasive in the automotive field due to its ability to improve the driving experience and increase driver safety. In particular, numerous research and commercial solutions are available for high-end cars to tackle attention deficits and drowsiness, which are among the leading causes of car accidents.

Currently, several driving and driver monitoring devices are often present, such as lane assistants, braking aids, radar for collision avoidance, and periodic stop warnings. These solutions provide a safety paradigm that analyzes vehicle behavior when it becomes unsafe, but they are unable to extract and monitor the major cause, i.e., the driver's physiological state. Monitoring some physiological parameters, on the other hand, can provide valuable info on a driver's fatigue and stress condition [1], allowing the use of predictive methods that can act proactively in avoiding dangerous situations instead of reacting only to the end effect, namely vehicle behavior [2, 3].

979-8-3503-3694-8/23/$31.00 ©2023 IEEE

Recent studies show how monitoring physiological signals, with sensors worn or included in the cockpit, can aid the detection of states of fatigue or drowsiness, allowing the vehicle to inform the driver or take contingency actions. The most investigated solutions for this purpose are biosignal analysis (i.e., ECG, PPG, and EEG) [4], as well as eye movements and blink rate analysis made through camera-based systems [5]. These techniques are already used on some high-end cars [6]. Camera-based systems are unobtrusive, even though variability of light conditions and line-of-sight (e.g., glasses or sunglasses) severely affect their performance [7]. Moreover, these systems are complex and expensive, thus available only to a limited population.

From the clinical perspective, the only direct measurement of sleep and wake states is carried out through EEG since it can directly detect autonomic nervous system (ANS) activity. Unfortunately, this signal is not suitable for unobtrusive use in the automotive domain, as it requires electrode placement in direct contact with the skin and on the scalp.

Therefore, it is necessary to use indirect measurements, which give information on the onset of drowsy states through the changes in physiological parameters. Electrocardiography (ECG) and Photoplethysmography (PPG) provide an indirect measure of the effects of ANS on drowsiness conditions by monitoring the heart rate (HR) [8]. In particular, ECG is widely used in research to monitor driver status; however, it requires simultaneous contact of 2 active electrodes and a reference electrode. In addition, because it is a signal that measures an electrical potential, a Right Leg Drive (RLD) circuit [9] is often required to avoid saturation.

In contrast, PPG is an optical-type signal, based on an LED-diode pair, that measures the change in blood volume in the microvascular bed that occurs during a heartbeat and correlates directly with HR [10]. The variability of PPG sensor skin-to-electrode contact is a primary cause of signal artifacts, limiting the reliability of the HR measures. The most used approach to tackle such limitations is to couple PPG sensors with accelerometer data and correlate the HR noise with rapid movements. This approach is very effective [11] and is a well-established solution in wearable devices (e.g., wristbands or smartwatches). Unfortunately, combining inertial data with PPG is impossible if the sensors are directly embedded into a car cockpit. Therefore, the integration of one or more PPG sensors in the car (e.g., on the steering wheel) requires a multimodal approach with a dedicated HW and an algorithm capable of recognizing and removing noisy data and calculating HR in real-time without the use of inertial sensors.

In this work, we present ANGELS (smArt steeriNG wheEL for driver Safety), a low-cost embedded system that can be integrated into the steering wheel of a car to acquire and process PPG signals, monitoring HR without the need of accelerometer data for signal processing. The system is composed of a sensor consisting of a highly sensitive LED-photodiode pair [12] developed by ST Microelectronics, which can be integrated into the steering wheel, and a miniaturized embedded platform capable of processing the PPG signal in real-time, through a modified version of the Pan-Tompkins algorithm. As well as being completely unobtrusive, the presented system features a small power envelope with a cost in the order of hundreds of euros. As a result, it could be easily integrated into all cars, significantly improving driving safety.

On a testing dataset collected in the Maserati driving simulator, our algorithm achieves a 99.8% Accuracy score, 97.1% Sensibility, and 99.06% Positive Predictive Value (PPV) in the peak detection task. In terms of HR detection, the Mean Absolute Error (MAE) is 1.19 BPM. The system operates with a latency of 10 s featuring 130 mW of power consumption. Overall, preliminary results suggest that ANGELS is suitable for real-time applications.

The main contributions of the work are:

- An embedded low-power system that can be integrated into a steering wheel;
- A novel algorithm for PPG signal analysis based on a modified version of Pan Tompkins algorithm with an adaptive threshold for the distance of the peaks;

II. Materials and Methods

A. System Descprition

ANGELS is composed of three main blocks: (i) a sensorized steering wheel with PPG sensor probes, (ii) front-end electronics, and (iii) a microcontroller (see Fig 1). PPG probes are directly placed on the steering wheel. In particular, they are inserted in a commercial leather steering wheel cover. The steering wheel image in Fig. 1 refers to the first, less integrated prototype since the final version is covered by a non-disclosure agreement (NDA). The PPG sensor probes are miniaturized optical systems for PPG acquisition. They are composed of a Silicon Photomultipliers (SiPMs) photodetector coupled with infrared and red LEDs used as optical light sources. The SiPM detector is fabricated by STMicroelectronics and features a total area of $4 \times 4mm^2$ and 4871 square microcells with 60 µm of pitch [12]. Probes are encapsulated into a 3D printed support, and an optical long-pass filter covers the SiPM to avoid external light interference. The driving comfort is preserved thanks to the small size of the probes and the tight integration into the steering wheel. As a result, signal acquisition and driver monitoring are entirely unobtrusive. The front-end electronics include a stage for SiPMs (30 V) polarization and LED supply (5 V), a stage for LED drivers, and a stage for analog-to-digital conversion. The microcontroller is an STM32F401RE operating at 3.3 V and 84 MHz.

B. Data Acquisition

To evaluate the performance of ANGELS, we conducted a measurement campaign in partnership with Maserati. ANGELS was installed in the static driving simulator located in the Maserati Innovation Lab in Modena. The Driving simulator, also known as DIL (Driver-In-the-Loop) simulator, comprises a simulator room, a server room, and a control room. Fig. 2 shows the simulator room of the Maserati Static DIL Simulator; it includes a vehicle cockpit, a semi-cylindrical screen with a projector, and an audio system. All the engine and transmission components missing in the vehicle cockpit are simulated by means of real-time computers placed in the server room. The virtual scenario is projected onto the white screen and provides an immersive experience (180° of visual experience). The simulated scenario involves a two-lane road with a handful of stimuli. Moreover, the entire setup is contained within a spacious, soundproofed, and dark laboratory to mitigate the impact of external factors. The study protocol was specifically designed to induce drowsiness, as the primary objective of the company was to detect drowsiness in drivers. Fourteen drivers participated in three night-time sessions, as this was deemed the optimal time to elicit drowsiness. The protocol involved a straightforward procedure where each driver was instructed to continue driving until their driving style became dangerous, such as swerving off the road or colliding with other vehicles. This ensured that a dangerous drowsiness condition was effectively achieved.

C. Algorithm description

One of the main components of ANGELS is a novel algorithmic approach to detect peaks in the acquired PPG signal. This robust time-domain algorithm relies on three main blocks: i) a filtering stage, ii) an artifact removal block, and iii) a peak detection block based on a modified version of the PamTompkins algorithm. Fig. 3 shows a block scheme of the developed algorithm and an example of the PPG elaboration pipeline for a signal segment.

1) Filtering stage: A Butterworth high-pass filter and low-pass filter with a cut-off frequency of 0.5 Hz and 10 Hz, respectively, are applied to the raw PPG signal. Both filters are applied twice, once backward and once forward, to obtain a zero-phase filtering. This filtering is performed by the *Filter* block depicted in Fig. 3c).

2) Artifact removal: The position of the PPG sensors on the steering wheel requires a method to cope with the driver's hand movements. In this setup, poor or absent contact between the steering wheel and the palm causes severe signal degradation. We use a rolling standard deviation to define the quality of the signal and to reject windows affected by motion artifacts, represented by the *Artifacts Removal* block in Fig. 3c). The rolling standard deviation works on a 1 s time window and moves one sample at a time; if the standard deviation is greater than an empirically chosen threshold, a window of 5 s (2.5 s backward, 2.5 s forward) is removed. Fig. 3b) shows the result of artifact removal on a signal segment.

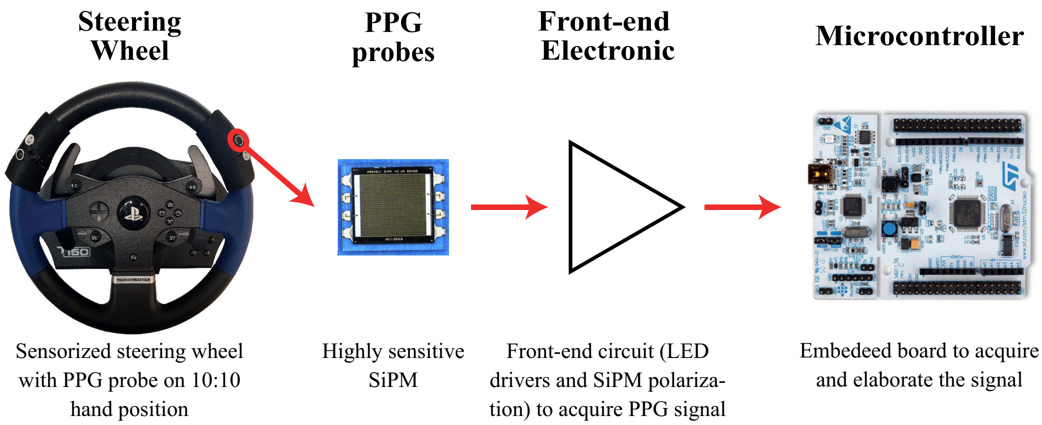

Fig. 1: Block scheme of the proposed system. There are three main blocks, from the left: a sensorized steering wheel with two PPG probes equipped with a highly sensitive SiPM as photodiode; an analog front-end comprising the probe's power rail and the ADC converter; a microcontroller for online data elaboration.

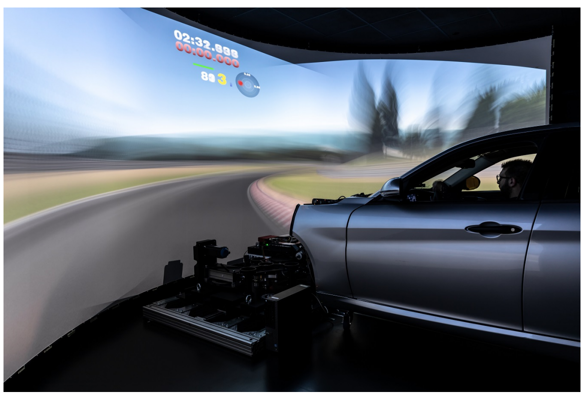

Fig. 2: Static driving simulator of Maserati company [13].

3) Peak detection: The peak detection combines a modified version of the Pam-Tompkins (PT) algorithm [14] with an adaptive refractory period. We modified the original PT algorithm to adapt it to the inherent features of the PPG signal and to the signal acquisition setup. PT has been initially introduced for detecting QRS complexes in electrocardiogram (ECG) signals and consists of several phases. As a first step of the original algorithm, the signal is preprocessed through a bandpass filter to remove noise; our design does not require this stage since the filtering stage already accomplishes this task. Then, PT computes the first derivative of the preprocessed signal to highlight the QRS complex, and this value is also squared to suppress other signal components. The final preprocessing stage of PT is a moving window integration performed on the squared signal to smooth out the waveform. We found experimental evidence that this stage is not strictly required for the PPG signal, and we replaced derivative+squaring+integration with a simpler algorithmic step saturating to zero all the negative values. Since the signal is at zero-mean after the initial filtering, the calculation of the adaptive thresholds works appropriately.

After the signal preprocessing stages, PT finds the temporal location of the signal peaks by operating a dual threshold approach. This operation is performed by the *Moving Window Detection* block shown in Fig. 3c). Each sample is compared with a threshold value th_1 that estimates signal and noise peaks: samples greater than the current threshold value are peak candidates. This first threshold is computed as:

$$th_1 = npk + 0.25 * (spk - npk)$$

where spk and npk are running estimations of signal and noise peaks, respectively; both values are updated by the *Adaptive Thresholds Detection* block in Fig. 3c) whenever a new peak is detected:

$$spk = 0.125 * peak + 0.875 * spk$$

$$npk = 0.125 * peak + 0.875 * npk$$

In addition, the algorithm considers two additional parameters called min_rr_width and max_rr_width, which model the minimum and maximum distance between adjacent peaks. min_rr_width is a physiological constraint due to the refractory period during which ventricular depolarization cannot occur even in the presence of a stimulus. max_rr_width is initially set to zero, and then it is updated based on the mean peak-to-peak distance considering the mean of the last 8 signal peaks as $1.6 * mean\_8\_peaks$. If no peak candidate is detected after max_rr_width samples from the previous one, the algorithm performs a search-back stage using a lower threshold th_2:

$$thr_2 = 0.5 * thr_1$$

Fig. 3d) shows the evolution of the thresholds over the signal samples.

In our design, max_rr_width is set to the window size (i.e., max number of preprocessed samples available for a single computation), and the refractory period min_rr_width changes adaptively. The algorithm starts with an initial guess of 50 samples (corresponding to 120 BPM), then this value

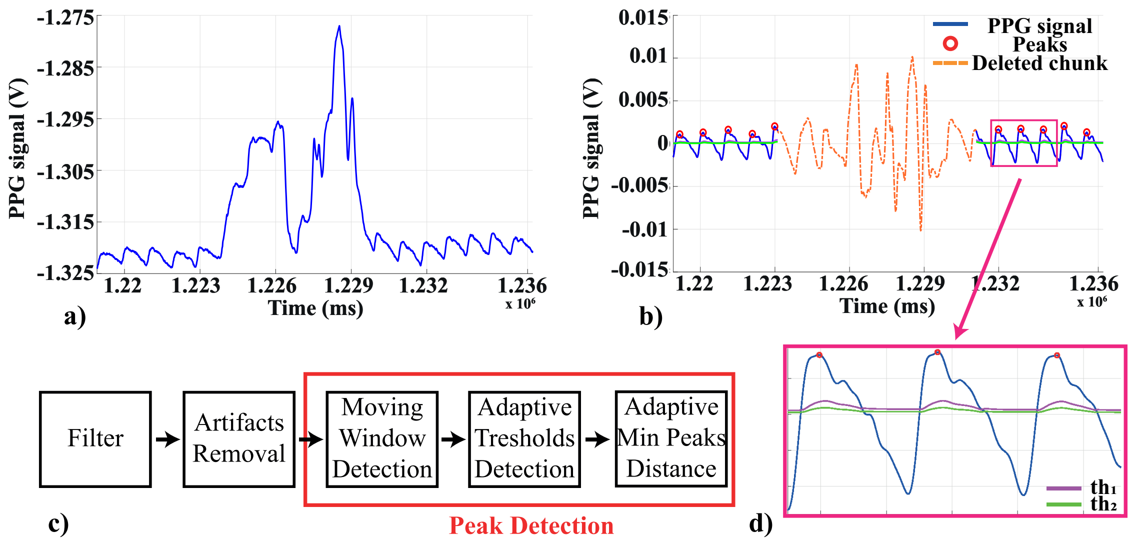

Fig. 3: Block diagram of the developed algorithm and an example of the ANGELS elaboration pipeline for a signal window. In a) there is a window of raw PPG signal. In b) there is the same window after the algorithm processing: the blue line represents the PPG signal, the orange dotted line represents the removed corrupted portion of the signal, and the red circles represent the detected peaks. In c) there is a block diagram of the algorithm with the main steps. In d) there is a detailed part of the processed segment where the purple line is th_1 and the green one is th_2.

TABLE I: PPV, Sensitivity and Accuracy for each driver analyzed.

Driver	PPV (%)	Sensitivity (%)	Accuracy (%)
1	99.10	93.45	99.93
2	98.90	98.72	99.98
5	99.42	98.31	99.98
7	99.56	97.12	99.97
9	99.94	98.92	99.99
11	98.10	95.19	99.94

is updated by looking at the mean of the last eight peak-to-peak distances. To further regularize this estimation, the algorithm applies an adjustment factor $0.01 * fs$ up/down in case of ascending/descending trend in the peak-to-peak distance. Overall, the algorithm sets the first threshold at a conservative value of $0.5 * fs$ to detect whether the peak-to-peak distance is growing or diminishing and then decrements/increments the refractory period only if its trend is constant. This last part of the algorithm is handled by the *Adapted Min Peaks Distance* block in Fig. 3c).

The original PT algorithm performs peak detection in two stages To improve robustness, after the bandpass filter and after the integrating window. This option is not available in our design since we modified the preprocessing stages, but experimental results show this does not affect accuracy.

III. Experimental Results

In this section, we evaluate the performance of ANGELS in terms of accuracy, latency, and power consumption. We test the performance of the peak detection algorithm using the private dataset described in Sec. II-B. The dataset does not have a ground truth ECG. Thus, six randomly picked sessions of the dataset have been manually annotated by an expert to obtain the correct location of the on-set peaks. To evaluate the algorithm performance in peak detection, we adopted three different metrics, namely, Positive Predictive Value (PPV), Sensitivity, and Accuracy. The following equations specify how to calculate these metrics.

$$PPV = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n}(TP_i + FP_i)}$$

$$Sensitivity = \frac{\sum_{i=1}^{n} TP_i}{\sum_{i=1}^{n}(TP_i + FN_i)}$$

$$Accuracy = \frac{\sum_{i=1}^{n}(TP_i + TN_i)}{\sum_{i=1}^{n}(TP_i + FP_i + TN_i + FN_i)}$$

TP, TN, FP, FN, and n are True Positive, True Negative, False Positive, False Negative, and total samples, respectively. We set a tolerance window (maximum offset from the annotation for a detected on-seat peak to be considered valid) of 100 ms.

Starting from the detected peaks, we compute the heart rate on windows of 8 s with an overlap of 6 s. We repeat the same process using the annotated peaks. Then, we use the mean absolute error (MAE) to measure the accuracy of the heart rate estimation. The MAE is defined as follows:

$$MAE = \frac{\sum_{i=1}^{n}(BPM_i^{pred} - BPM_i^{true})}{n}$$

Where BPM^{pred} indicates the predicted HR (BPM) value, BPM^{true} indicates the true HR (BPM) value, and n is the number of windows. We chose this window duration to compare our solution with other state-of-the-art algorithms used for PPG-based HR estimation.

In Table I, we report the performance of our algorithm using

TABLE II: State-of-the-art comparison table.

Work	Dataset	Activities	Sign.	Pre-Processing	Algorithm	Post-Proc.	MAE
TROIKA, 2014 [15]	SPC2015*	Rest, Running	PPG, Acc.	0.5-4 Hz filtering, Downsampling	Signal decomp., reconstruct., spectral peak track	th., hist. track.	2.34 BPM
JOSS, 2015 [16]	SPC2015*	Rest, Running	PPG, Acc.	0.5-4 Hz filtering, Downsampling	MMV, spectral subtract	th., hist. track.	1.28 BPM
SpaMa, 2016 [17]	SPC2015* SPC2015[1] Chon Lab[2] PPG-Dalia[3]	Rest, Running, Rehab. ex., Rest, Running 8 daily activities	PPG, Acc.	0.5-3 Hz filtering, Downsampling	spectral filtering based on PSD	hist. track., spline interp.	0.89 BPM 3.36 BPM 1.38 BPM 11.06 BPM
Schack2017 [18]	SPC2015* PPG-Dalia[3]	Rest, Running, 8 daily activities	PPG, Acc.	0.5-6 Hz filtering, Downsampling	Corr.-based Freq. indicating func., FFT	th.	1.32 BPM 20.5 BPM
FSM, 2018 [19]	SPC2015[1]	Rest, Running, Rehab. ex.	PPG, Acc.	0.5-4 Hz filtering, z-score scaling, Downsampling	Winer filtering	FSM	0.99 BPM
TAPIR, 2020 [20]	SPC2015* SPC2015[1] PPG-Dalia[3]	Rest, Running, Rehab. ex., 8 daily activities	PPG, Acc.	0.5-4 Hz filtering	Adaptive filter Peak detection Linear Transform.	Notch filter	2.5 BPM 5.9 BPM 4.6 BPM
Arunkmar, 2020 [21]	SPC2015* SPC2015[1]	Rest, Running, Rehab. ex.	PPG, Acc.	0.4-3.5 Hz filtering	RLS, NLMS MA reduction FFT based HR track.	Phase Voc.	1.03 BPM 1.89 BPM
CurToSS, 2020 [22]	SPC2015* SPC2015[1] PPG-Dalia[3]	Rest, Running, Rehab. ex., 8 daily activities	PPG, Acc.	0.5-4 Hz filtering	SSR Curve tracking	N/A	2.2 BPM 4.5 BPM 5.0 BPM
Our Work	Maserati Dataset [4]	Driving	PPG	0.5-10 Hz filtering	Adaptive artifacts removal Modified PamTompkins	N/A	1.19 BPM †

* 12 subjects [1] 23 subjects [2] 10 subjects [3] 15 subjects [4] 14 subjects

† The result is validated on 6 subjects randomly picked

TABLE III: Cycles, Latency, and Energy consumption for each block of the proposed algorithm. All the results are computed on a 10s window.

	Cycles (#)	**Latency (ms)**	**Energy (mJ)**
Filtering stage	250.868k	2.99	0.20
Artifacts removal	191k	2.27	0.15
Peak detection	5120k	60.95	4.02

the adopted metrics for each analyzed driver. We reach an accuracy higher than 99.9% for all the drivers, with an overall sensitivity of $\sim$ 97%. In Table II, we show an accuracy comparison between our approach and some popular SoA algorithms used for PPG-based HR estimation. The comparison is not directly done on the same dataset because most SoA algorithms require a combination of PPG and 3D accelerometer signals. On the contrary, our solution operates on a PPG signal acquired from a steering wheel and not from a wristband device. In this situation, the inertial signal cannot be used to mitigate the effect of the motion artifacts. Nevertheless, the result obtained in terms of MAE of 1.19 BPM is in line with the state-of-the-art, demonstrating that our solution is able to cope with the complex site of acquisition and the resulting motion artifacts even if the inertial signals are not used to clean the PPG. Furthermore, the filtering stage coupled with the artifact removal block ensures the removal of the non-usable portion of the signal when there is no contact between the steering wheel and the driver's hand. The scatter plot in Fig. 4 shows the correlation between the ground-truth HR values (on the horizontal axis) and the estimated HR values (on the vertical axis) for each window and all the drivers. It can be seen that the vast majority of the data lies on the identity line meaning that our algorithm correctly estimates the HR values.

We also tested the proposed solution in terms of latency. As detailed in Sec. II-C, the algorithm includes different blocks, so we performed a break-down analysis. Considering that the filtering is applied backward and forward, it is necessary to

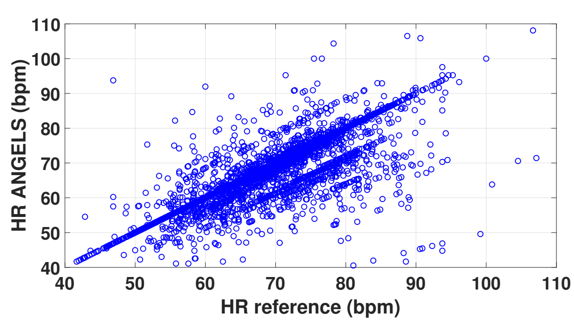

Fig. 4: Comparison between the HR values, expressed in BPM, from the reference signals (horizontal axis) and the HRs estimated by ANGELS (vertical axis).

buffer data before this stage. We use a buffer of 10 s for PPG data; consequently, the reported latencies are specific for a window of this duration. As shown in Table III, all the blocks have a combined latency of $66.21\ ms$: this value is less than the window duration; consequently, the latter represents the maximum latency of the system. Given the specific application of ANGELS, this latency is manageable because the biological parameter we want to monitor (i.e., drowsiness and stress) have a slow change rate with respect to HR. Furthermore, we measured the power consumption of ANGELS, comprising the analog front-end, the LED, and the μC, resulting in a total average power of 130 mW. This result is totally compatible with an automotive application.

IV. Conclusion

The use of biosignal-based HMIs is also becoming widely used in the automotive domain to improve driving safety and driver comfort. In this paper, we presented a system that can acquire PPG signal and process it in real-time to detect heart rate. The system is integrated into a steering wheel so that it is completely transparent to the user. It is also able to clean up the signal by eliminating motion artifacts, which are typical of the PPG signal, even without the use of accelerometers, which are used in wearable systems instead. ANGELS achieves 1.19 BPM accuracy in beat detection with a power envelope of 130 mW. The work will be extended with the analysis of other sensors that will be integrated into the steering wheel so as to provide a very robust, low-cost system that can also be used for cars in the lower-middle market sector.

Acknowledgment

This research was partially funded from the National Funded Programme 2014-2020 under grant agreement n. 1733, (ADAS+ Project). This research was partially funded from the National Funded Programme 2. A special thanks to Eng. Gianfranco Bordonaro for leading the DIL simulator setup and the night-time driving sessions together with: Eng. Beniamino Canu, Eng. Pasquale Sessa, Eng. Gabriele Maria D'Auria, Eng. Matteo Angelini, Dr. Mario D'Agostino, Eng. Enrico Maria Talarico, Eng. Dario Rezaei Riabi.

References

[1] Muhammad Qasim Khan et al. "A Comprehensive Survey of Driving Monitoring and Assistance Systems". In: *Sensors* 19.11 (2019).

[2] Messaoud Doudou et al. "Driver drowsiness measurement technologies: Current research, market solutions, and challenges". In: *International Journal of Intelligent Transportation Systems Research* (2019), pp. 1–23.

[3] Muhammad Qasim Khan et al. "A Comprehensive Survey of Driving Monitoring and Assistance Systems". en. In: *Sensors* 19.11 (Jan. 2019). Number: 11 Publisher: Multidisciplinary Digital Publishing Institute, p. 2574.

[4] Andrea Amidei et al. "Validating Photoplethysmography (PPG) data for driver drowsiness detection". In: *2021 IEEE International Workshop on Metrology for Automotive (MetroAutomotive)*. July 2021, pp. 147–151.

[5] *Various Approaches for Driver and Driving Behavior Monitoring | Proceedings of the 2013 IEEE International Conference on Computer Vision Workshops*.

[6] *Lexus Safety System+*. URL: https://www.lexus.com/models/GX/safety/pre-collision-system (visited on 03/17/2023).

[7] Anirban Dasgupta et al. "A Vision-Based System for Monitoring the Loss of Attention in Automotive Drivers". en. In: *IEEE Transactions on Intelligent Transportation Systems* 14.4 (Dec. 2013), pp. 1825–1838.

[8] Benedetta Mazzoni et al. "An Optimized Heart Rate Detection System Based on Low-Power Microcontroller Platforms for Biosignal Processing". en. In: *Advances in System-Integrated Intelligence*. Lecture Notes in Networks and Systems. Cham: Springer International Publishing, 2023, pp. 160–170.

[9] Ali Hassan Sodhro et al. "An Energy-Efficient Algorithm for Wearable Electrocardiogram Signal Processing in Ubiquitous Healthcare Applications". en. In: *Sensors* 18.3 (Mar. 2018). Number: 3 Publisher: Multidisciplinary Digital Publishing Institute, p. 923.

[10] Koichi Fujiwara et al. "Heart Rate Variability-Based Driver Drowsiness Detection and Its Validation With EEG". In: *IEEE Transactions on Biomedical Engineering* 66.6 (June 2019). Conference Name: IEEE Transactions on Biomedical Engineering, pp. 1769–1778.

[11] Alessio Burrello et al. "Embedding temporal convolutional networks for energy-efficient PPG-based heart rate monitoring". In: *ACM Transactions on Computing for Healthcare (HEALTH)* 3.2 (2022), pp. 1–25.

[12] Massimo Mazzillo et al. "Silicon Photomultiplier Technology at STMicroelectronics". en. In: *IEEE Transactions on Nuclear Science* 56.4 (Aug. 2009), pp. 2434–2442.

[13] *Maserati Media Site*. URL: https://www.media.maserati.com/it-ww/gallery (visited on 03/22/2023).

[14] Jiapu Pan et al. "A real-time QRS detection algorithm". In: *IEEE Transactions on Biomedical Engineering* 3 (1985), pp. 230–236.

[15] Zhilin Zhang et al. "TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise". In: *IEEE Transactions on Biomedical Engineering* 62.2 (2014), pp. 522–531.

[16] Zhilin Zhang. "Photoplethysmography-based heart rate monitoring in physical activities via joint sparse spectrum reconstruction". In: *IEEE Transactions on Biomedical Engineering* 62.8 (2015), pp. 1902–1910.

[17] Seyed Salehizadeh et al. "A novel time-varying spectral filtering algorithm for reconstruction of motion artifact corrupted heart rate signals during intense physical activities using a wearable photoplethysmogram sensor". In: *Sensors* 16.1 (2016), p. 10.

[18] Tim Schäck et al. "Computationally efficient heart rate estimation during physical exercise using photoplethysmographic signals". In: *2017 25th European Signal Processing Conference (EUSIPCO)*. IEEE. 2017, pp. 2478–2481.

[19] Heewon Chung et al. "Finite state machine framework for instantaneous heart rate validation using wearable photoplethysmography during intensive exercise". In: *IEEE Journal of Biomedical and Health Informatics* 23.4 (2018), pp. 1595–1606.

[20] Nicholas Huang et al. "Robust PPG-based Ambulatory Heart Rate Tracking Algorithm". In: *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE. 2020, pp. 5929–5934.

[21] KR Arunkumar et al. "Robust De-Noising Technique for Accurate Heart Rate Estimation Using Wrist-Type PPG Signals". In: *IEEE Sensors Journal* 20.14 (2020), pp. 7980–7987.

[22] Menglian Zhou et al. "Heart Rate Monitoring using Sparse Spectral Curve Tracing". In: *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE. 2020, pp. 5347–5352.