

# A Novel Real-Time Redundant System For Aiding Drivers To Increase Their Attention Level

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**Abstract**—Road accidents are a major concern worldwide. Research of technological solutions to improve road safety is an open topic, considering this issue from various perspectives. As widely reported in the literature, driver distraction is one of the most common causes of collisions. Even if vehicles are becoming safer and safer over the years, pedestrians and cyclists are still exposed to severe accidents. Major concerns about driver distraction is mobile phone use and drowsy driving. This paper proposes a *virtual buddy* designed to help drivers, thanks to warning sound messages, improve their attention level. The main idea is to recognize, thanks to different sources (video camera, physiological data, and interior environmental conditions) interpreted by a data-fusion algorithm, whenever there is a distracted or drowsy behavior, recalling the driver to the road. The effectiveness of the data-fusion algorithm in detecting dangerous conditions has been verified thanks to a driving simulator experimentally, obtaining no false negatives from distraction from drowsiness, a sensitivity of about 85% for the distraction caused by mobile phone usage or other activities different from focusing on driving.

**Index Terms**—Physiological data, Sleep, Safety, Vehicle Driving, Camera-based systems, Image processing, Neural Networks

## I. INTRODUCTION

According to the World Health Organization [1], road accidents cause worldwide about 1.3 million fatalities every year, being the first cause of deaths in the age range 15-29. Moreover, nearly half of the victims are pedestrians, cyclists, or motorbike drivers colliding with bigger vehicles. As the leading causes of these accidents, they report speeding, driving under the influence of alcohol and other psychoactive substances, nonuse of helmets, seatbelts, child restraints, distracted driving, unsafe road infrastructure and vehicles, and inadequate traffic law enforcement.

For the sake of this work, we would like to focus on how technology can aid drivers in reducing distracted driving. In particular, the distraction caused by mobile phones is considered a growing concern for road safety. In the same source, it is reported that driving using mobile

phones increases about 4 times the probability of being involved in a crash. Moreover, hands-free phones are not much safer than hand-held phone sets. Furthermore, texting increases the risk of a collision considerably.

In this paper, we would like to propose a novel redundant system based on visible light wave cameras, environmental, and physiological signals to provide a *virtual buddy* aiding drivers to focus on the road by emitting a sound alarm (warning) whenever it is detected a distracted behavior.

## II. STATE OF THE ART

In response to the significance of the issue at hand, various driver monitoring systems have been developed over the years, employing diverse approaches that can be broadly categorized as follows:

- *Driver-behavior analysis*. This approach focuses on examining the actions performed by drivers, primarily seeking specific patterns in the steering angle [25], [26].
- *Camera-based analysis*. This method involves utilizing cameras to assess the level of driver attention by measuring head/eye gazing, as well as evaluating driver sleepiness based on eye blinking rate [4], [5], [6].
- *Physiological-based analysis*. This approach aims to evaluate the driver's biological state and identify their level of sleepiness by analyzing physiological factors. [7] [8]

Researchers and companies have made strides in developing driver monitoring systems by adopting these distinct approaches.

In the literature, some systems to monitor the driver's attention in a real-time fashion have been proposed over a long period, like [12], published in 2005, based on the computation of eyelid movement parameters and head (face) orientation estimation. In the following years, we can find [13], published in 2014, where a system based on robust iconic classifiers and a dictionary of poses have been proposed, and [14], published in 2019, where it has been proposed an approach based on deep learning. From this

This work has been carried out in cooperation with Sleep Advice Technologies S.r.l. (<https://www.satechnologies.eu/>)

perspective, the idea we are proposing has been introduced previously. From this regard, the novelty w.r.t. state of the art is the use of consolidated technologies to focus on a ready-to-use solution suitable for common embedded devices. For this reason, we chose to use a commercial-grade open-source neural network to identify the facial feature positions. We used these positions for implementing an algorithm to perform the binary classification required to determine if the driver is paying attention to the road or something else. As described in the following, our algorithm is based on the face orientation as the older (2005) one. This old fashion technique is now enabled thanks to novel neural networks capable of positioning the points into the 3D environment and not on the plane as in the past. We decided not to consider the eyelid and eyes blinking due to the resolution allowed by cheap cameras, since we experimentally found that they do not provide sufficient pixels to determine the PERCLOS [15].

From a physiological data analysis perspective, Ramzan et al. extensively reviewed multiple studies that compared various techniques and sensors for detecting drowsy driving. Their findings indicate that physiological-based analysis, which involves measuring parameters such as driver Heart Rate Variability (HRV), Heart Rate (HR), and Respiration Rate (RR) to classify the driver's drowsiness state, consistently yields the most accurate results across different conditions. This approach proves effective because it enables the early detection of fatigue indicators before they manifest as unsafe driving actions [16]. Consequently, there is a growing interest in developing techniques that can reliably predict sleep onset, marking the transition from wakefulness to sleep. In this context, the research paper introduces a sleep prediction algorithm that utilizes a physiological variable as input. Similarly, other studies have presented comparable solutions, such as Francesco Rundo et al.'s EEG-based drowsiness detection system, which boasts a remarkable 100% accuracy in distinguishing between drowsiness and wakefulness [17]. Additionally, Lee Boon Leng et al. proposed a dual sensor system employing Photoplethysmogram (PPG) and Galvanic Skin Response (GSR) sensors, supported by a classification model based on Support Vector Machine (SVM), achieving an impressive accuracy of 98.3% [18].

The primary limitation of physiological-based analysis approaches resides in the sensing technology employed. In the earliest approaches, drivers were required to wear sensors, such as a pulse oximeter, which placed reliance on the driver's diligence to ensure proper usage. However, more recent advancements in this field are investigating alternative sensing solutions to overcome this limitation.

Another important theme is the correlation between environmental conditions and drowsiness and how the first interferes with the second. A study in [19] demonstrates how the thermal environment is crucial to human sleep. By

studying eighteen Chinese students with a Pittsburgh Sleep Quality Index (PSQI)  $> 5$  for cold and warm temperatures, the study demonstrates that the subjects' thermal sensations decreased when they slept under the same thermal condition. They mainly demonstrated that at 23° C, this temperature was uncomfortably cool for sleep; 26 ° C was slightly cool for sleep, from being slightly warm before sleep, while 30° C was assessed to be uncomfortably warm both before and after sleep. Human sleep quality was sensitive to changes in air temperature; for humans, their thermal neutral temperature was higher in sleep than in the waking state. In [20], instead, the authors studied a system for monitoring the CO<sub>2</sub> levels and temperatures inside of a vehicle to avoid side effects like drowsiness, breathing problems, irritation in eyes, nose and throat, reduced activity levels, nausea, dry skin, or itching. They built it using a multipurpose Bluetooth sensor and an Android Smartphone. They focused on how the levels those parameters increase due to leakage given by the car's windows since the environment is full of that gas due to traffic exposure. The last example is a paper written by Landström et al [21], who studied the variation of the temperature inside a vehicle and how this attribute affected the wakefulness of the drivers. Thanks, in fact, to a system that they built with a reduction of 8°C at irregular intervals, they managed to maintain the testers fully awake.

### III. PROPOSED METHODOLOGY

The proposed methodology is based on a data-fusion algorithm that provides a real-time binary classification (attentive/distracted) as done, with the students in [26].

When all the sensors (camera, environmental, and physiological data) are available, it is possible to improve the classification level.

We considered the camera the most available sensor but, in any case, the algorithm can work with all the possible sensors availability combinations.

From the technological perspective, we considered the camera installed inside the car a cheap model equipped with grand angular lenses and capable of 720p (1280x720, 30 fps) video streaming. Moreover, when also the physiological signals are available, it is possible to provide, alongside the binary classification, the rKSS level (defined in the following).

#### A. Camera-based detection

The camera-based system is based on a Python script, based on Google MediaPipe [9], OpenCV [10], and mathpylib [11].

The algorithm is based on these steps:

- 1) Run the MediaPipe neural network on the video streaming, getting a 3D points cloud of the facial features.
- 2) Compute a plane parallel to the face and, from this, a vector orthogonal to the aforementioned plane passing through the nose.
- 3) Compare the vector's vertical component to detect if the driver is facing the road or looking downward, obtaining a vertical angle of the driver's face w.r.t. the horizontal plane.

Our choice to focus on the vertical angle is justified considering how dangerous it can be to move the eyes away from the street: if the driver is looking downward, there is a high probability that he/she is distracted, using the car infotainment system or, even worse, using a mobile phone. The horizon plane is obtained automatically after an automatic calibration phase to avoid a complex camera installation.

### B. Physiological signals-based detection

The current study has utilized physiological signals to predict sleep onset. Several work has been published using difference data sources: the thoracic band [24], the raw PPG [23] and a commercial off-the-shelf smartwatch [25]. In this work the commercial off-the-shelf smartwatch has been utilized.

The utilized architecture (Fig. 1) comprises a Garmin smartwatch and a Raspberry Pi. The Garmin smartwatch works as the sensing device and computation platform for the drowsiness detection task. The Garmin smartwatch senses in real-time the raw PPG signal. It computes, with a sampling frequency of 1 Hz, the physiological variables (HRV, HR, SpO2) and, from them the drowsiness index.

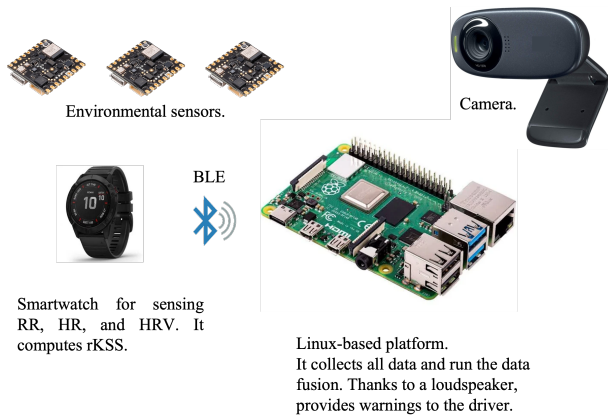


Fig. 1. Built System Representation.

For the drowsiness index calculation a rule-based algorithm has been utilized, as done in [25]. The HR and HRV variables have been chosen due to the correlation between their pattern and the Autonomic Nervous System (ANS) action. The drowsiness level is higher when the sympathovagal activity is low, so when no arousal is found for a certain number of seconds.

The feedback given is in accordance with a reduced Karolinska Sleepiness Scale (KSS):

- 1) rKSS0 represents the calibration stage.
- 2) rKSS1 represents a high-rather good level of alertness state (combining level 1 to up to level 4 of the 9 level KSS).
- 3) rKSS2 represents a grey region where the driver is neither alert nor sleepy and with some signs of sleepiness (combining level 5 and level 6 of the 9 level KSS).

- 4) rKSS3 represents a grey region where the driver is sleepy, varying from non-effort to some effort to keep awake (combining level 7 and level 8 of the 9 level KSS).
- 5) rKSS4 represents a very sleepy with great effort to keep awake state (as the level 9 on the normal KSS).

If the rKSS is not 0 or 1, the Data Fusion Algorithm provides an outcome of Distracted.

### C. Environmental parameters

The environmental parameters are studied using a similar cloud computing system, in which the GARMIN device will represent the Wide Area Network (WAN). As a local center, a Raspberry Pi 4 model B is used and constitutes the Local Area Network (LAN), while, as Personal Area Network (PAN), four Nicla Sense ME are used to measure the different variables.

The Raspberry Pi mounts as an Operative System Raspberry Pi OS 64 bit, with Debian release 11, where the connection with the different peripherals will be implemented using JavaScript and node-ble. The version of the Bluez library is 5.55, and the Node.js library is 16.20.0.

The peripherals used to measure the air quality and the temperatures, the Nicla Sense ME, are devices from Arduino, their most miniature form yet. They contain different Bosch sensors to measure various parameters, communicating through Bluetooth Low Energy (BLE) version 4.2 through an ANNA-B112 module. The sensor used for the measurements is the BME688 for temperatures (in Celsius degrees), pressure (in hpa), humidity (in percentage), and air quality, studying the presence of CO<sub>2</sub> level in the air (ppm) [22].

### D. Data Fusion algorithm

The Data Fusion algorithm (DFa) runs on the Raspberry Pi. It takes as its inputs:

- the vertical angle between the driver's face and the horizontal plane;
- rKSS computed from the physiological data;
- the environmental conditions (temperature, pressure, humidity, CO<sub>2</sub> concentration).

A schematic view of the DFa is shown in Fig. 2.

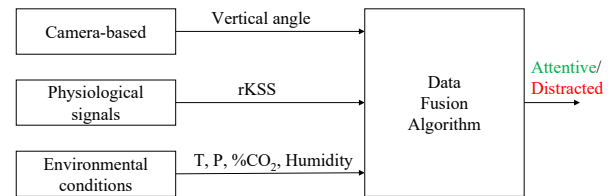


Fig. 2. Data Fusion algorithm schematic representation.

Summarizing, we can state the following assumptions. The camera allows DFa to determine where the driver is looking at.

Physiological and environmental data are useful to obtain the drowsiness level as reported in the literature. The physiological ones have better accuracy compared to the environmental ones but require the driver to wear a smartwatch. This choice can be suitable for professional drivers but cannot be applied to casual drivers or car owners.

In Fig. 3, it is possible to see the truth table adopted for the data fusion algorithm. It reports only the rows where distraction is detected. It is possible to see that the main source of detection is the camera by checking if the driver is looking at the road or not. This is of particular importance considering distraction in those cases when he/she looks inside the vehicle, possibly using a mobile phone or the infotainment system embedded in the car. Another source is the rKSS obtained from the physiological parameters, which is proved to be sufficient by itself to detect a distraction status. The last condition to trigger distraction is the level of CO<sub>2</sub>. All the other conditions are related to combinations of two environmental measurements: the first one considers an increase of temperature at a rate greater than 3°C/h and a current temperature higher than 32°C, while the second a humidity level greater than 45% and a temperature higher than 28°C. Pressure is not a parameter important by itself, but can be useful to determine the altitude at where the moving vehicle is driven.

#### IV. EXPERIMENTAL RESULTS

We conducted the experimental campaign resorting to a truck driving simulator.

Each driving session lasted about 15 minutes. A picture of the setup is shown in figure 4.

The volunteers driving in the simulator are 4, 3 males and 1 female, aged 24 to 32.

We adopted the following setup:

- Truck Simulator
- 50-inch full-HD screen
- IP camera (to get the driver’s face image)
- GARMIN Enduro to measure physiological signals
- temperature sensor connected to

In each driving session, all the data are available. Moreover, to allow offline execution, we not provided the warning signal to the driver during the experimental session. If the warning were issued, we would get the driver’s attention, increasing the attention level for a specific time window.

An experimenter receives the *virtual buddy* warning and decides (scoring), knowing all the raw data from the sensor (including the video streaming from the camera), if the driver is attentive or distracted. Moreover, they monitor the session, annotating when the driver appears distracted (and the DFa has not raised a warning).

These data are used as the ground truth. The confusion matrix for these experiments is shown in Fig. 5.

Since the system, most of the time, provides a true negative, we computed the sensitivity (true positive / (true positive + false negative)) only during the *events* where distraction

TABLE I  
THE EXPERIMENTAL RESULTS. FP = FALSE POSITIVE, FN = FALSE NEGATIVES, H.O. = HUMAN OBSERVER

Experiment	Events	Events (h.o)	FP	FN	Sensitivity
1	6	6	2	2	75,00%
2	17	13	1	0	100,00%
3	18	8	6	2	90,00%
4	7	11	0	4	73,33%

is detected by the experimenter (ground truth) or the DFa (classification). For each experiment is reported the number of events, the number of false positives, and the number of false negatives.

During all the experiments, we classified considering a time window of 10 seconds.

As shown in Fig.6 it is noticeable that the different parameters measured have little fluctuations around their mean values, and the general computations can be considered quite stable. Interesting is how the humidity decreases during the time, while the pressure goes higher. In this case the sensors are still, so the altitude does not change, but the weather was changing, going from a sunny day to a rainy day: the rain will remove water vapor through air condensation and deposit it on the surface, and the pressure goes higher due to the clouds. While the temperature is overall constant, the CO<sub>2</sub> levels change more. These variable swings are not affecting the driver status, since they not reach the critical values. The room was indoor and with no air flow, apart for the main entrance, causing the fluctuations since the air was circulating internally.

From the physiological data, there are no false positives. At the same time, there are no false negatives since the distractions are from cell phones or other situations (like speaking with other people) unrelated to the sleep onset. Considering this perspective, we traded off the physiological data’s greater accuracy with the camera’s higher sensitivity to cell phone usage. This is due to a high level of attention not focused on the driving activity itself but on other occupations.

#### V. CONCLUSIONS

The wearable device would be substituted or complemented by a contactless sensing device, like a Doppler-effect RADAR or a camera capable of extrapolating PhotoPlethysmography Imaging (PPGI).

In this work, we observed a good recognition of distraction patterns thanks to the camera. In particular, all the usage of mobile phones has been recognized. This result makes us strongly optimistic about the effectiveness of the proposed approach. Considering the data fusion perspective, while the camera triggered alarms, the physiological and environmental data remained inside *safe* ranges in all the experiments. For this reason, and in particular to achieve how these data can improve the detection rate, we are planning sessions on real

Camera	Environment					Physiological		Remarks
Vertical Angle* [deg]	CO <sub>2</sub> [ppm]	ΔT (1 h)	T [°C]	P	Humidity [%]	rKSS	Distracted?	
< 10							✓	Possible cell-phone usage.
						≥2	✓	High drowsiness level.
	> 1000					≥1 or unavailable	✓	Drowsiness due to high carbon bi-oxide level.
		> 3	> 32			≥1 or unavailable	✓	Drowsiness due to excessive temperature.
			> 28		> 45 %	≥1 or unavailable	✓	Drowsiness due to excessive humidity.

\* with respect to the "look forward" automatically calibrated angle

Fig. 3. Data Fusion Truth Table



Fig. 4. Experimental setup picture.

<b>DFa classification</b>	Distracted	True positive	False positive
	Attentive	False negative	True negative
		Distracted	Attentive

**Ground truth**

Fig. 5. Confusion matrix adopted for these experiments. The ground truth comes from the experimenter's scoring during the driving session, compared with the DFa output.

cars and on simulator with longer (more than 1 hour) driving sessions.

Other ideas for incrementing the effectiveness of this experimental setup is to introduce external ambient factors to modify the characteristics of the experiment, like an air conditioning system or some smoke inside the room, to modify the parameters and see the effects on the drowsiness levels. Another method could be leaving the driver alone, not providing company and so a source of distraction or entertainment, causing maybe a more probability of falling

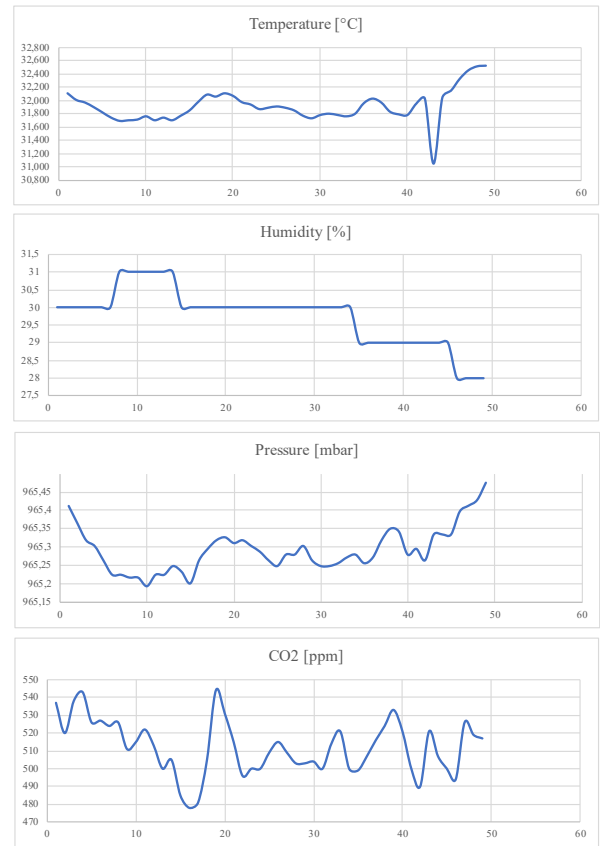


Fig. 6. Environmental data.

asleep during the driving simulation. About the privacy, the computations are all done locally on the Raspberry Pi, without sharing them with an external cloud to protect the data.

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