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Assessing Fitness to Drive: an IoT-Based System Integrating Driver Emotions and Visual Distraction Metrics

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***Abstract*—In this paper, we propose an integrated IoT-based framework for continuously assessing driver fitness by combining physiological, emotional, and visual distraction data. Our system utilizes wearable devices to capture heart rate data and in-vehicle cameras to monitor driver behavior. By combining these diverse data streams, we compute a Fitness to Drive (FtD) index that provides real-time feedback on driver performance. Experimental evaluations using a driving simulator demonstrate that the proposed system reliably detects critical levels of distraction and arousal, which are known to significantly impair driving performance. The integration of established techniques for emotion assessment and distraction detection further enhances the system's robustness. Overall, our results highlight the potential for advanced driver monitoring technologies to improve road safety and contribute to more sustainable mobility practices.**

***Index Terms*—Fitness to Drive, Visual Distraction, Safe Driving**

I. Introduction

Road safety remains a critical issue worldwide, with driver inattention and distraction being major contributors to traffic accidents [1]. Recent advances in sensor technology and the Internet of Things (IoT) platforms have enabled the development of integrated systems that continuously assess driver fitness in real time. In particular, emerging methods combine physiological signals (such as heart rate data) with computer vision techniques to monitor visual distraction and emotional states, providing a comprehensive measure of driver performance.

The ITF Transport Outlook 2023 by the OECD highlights that private motor vehicle trips dominate road transport in Europe, underscoring the need for enhanced monitoring of driver behavior in increasingly congested urban environments [2]. Moreover, studies have shown that moderate arousal can improve performance [3] while excessive emotional or visual distraction significantly degrades it [4].

Recent advances in digital twin technology are beginning to influence the field of driver monitoring. In particular, the concept of the *Driver Digital Twin* has emerged as a specialized subset of the broader Human Digital Twin [5]. The successful implementation of the Driver Digital Twin requires a comprehensive understanding of the driver's psychophysical state, including real-time monitoring of physiological and psychological parameters. This approach ensures that the system can dynamically assess and adapt to the driver's cognitive and emotional conditions, ultimately enhancing safety and performance.

In this work, we propose an IoT-based system for assessing the FtD index by integrating data from wearable devices and in-vehicle sensors. Our approach leverages a modular architecture that collects and processes real-time data from a smartwatch for heart rate monitoring and a camera for visual distraction analysis. The system calculates the FtD index by fusing these data streams, providing a dynamic and objective evaluation of driver readiness and safety.

The remainder of the paper is structured as follows. Section II reviews related research on driver monitoring and distraction detection. Section III details the system architecture and data fusion methodology. Section IV presents experimental evaluations using a driving simulator, and Section V concludes the paper with discussions on future work.

II. Background

The ITF Transport Outlook 2023 by the OECD [2] highlights the strong dependence on car transport despite efforts to encourage more sustainable mobility modes. While 16 EU27 countries saw a decrease in road mortality, 11 experienced increases. The 2030 European targets aim to halve fatalities and serious injuries compared to 2019 by monitoring Key Performance Indicators — such as speed, protective system usage, and distracted driving. Notably, distracted driving accounts for 22.0% of extra-urban and 12.5% of urban accidents.

A. Psychology and Driving

Psychology, defined by the APA as the study of mind and behavior, plays a key role in road safety [6]. Driver performance is influenced by factors such as emotional state and aggressiveness, which can lead to phenomena like road rage [7].

B. Emotions

Emotions (EA) are "organized and complex patterns" of physiological and cognitive responses. They can be described along two dimensions:

- **Arousal:** "the intensity of an emotion" [8]. According to the Yerkes-Dodson law, moderate arousal can enhance performance [9].
- **Valence:** a measure of an emotion's positive or negative quality, with positive emotions (e.g., joy) favoring safer driving compared to negative ones (e.g., anger) [10].

Methods to measure these include heart rate variation [11], EEG/EMG [12], the Self-Assessment Manikin [13], [14], pupil analysis [15], skin conductance [16], and thermal imaging [17].

C. Distraction

Distraction is defined as "a deviation of attention" from safe driving [18] and can impair cognitive functions and working memory [19]. Studies show that performing secondary tasks reduces driving performance and that inattention is present in 57.6% of accidents [20]. Distractions are categorized into:

- **Biomechanical** (manual tasks),
- **Auditory** (sound sources),
- **Cognitive** (internal thoughts),
- **Visual** (diverting gaze).

D. Visual Distraction and Technology

Visual distraction (DV) diverts the driver's gaze from the road, impairing situational awareness and increasing reaction times [21]. Even brief glances away (e.g., exceeding 1.8 seconds on straight roads or 1.2 seconds in curves) can significantly elevate accident risk [22]. The SEEV model (Salience, Effort, Expectancy, Value) further explains how drivers allocate visual attention [23].

Modern vehicles integrate automation and infotainment systems that, while enhancing safety and convenience, can divert attention from driving [24]. In-vehicle displays provide consolidated information, yet studies show they can increase glance frequency. For example, reducing screen information decreased glances from 10.49 to 7.69 per minute [25]. Similarly, an eco-driving system reduced road gaze from 74% to 62%, though no glance exceeded 1.4 seconds [26]. Other studies [27], [28] indicate that drivers adapt by reducing display attention under complex traffic conditions. Moreover, automated driving may lower workload, thereby increasing the frequency and duration of secondary task engagement [29]. However, certain automatic systems, like collision warning sensors, can mitigate distraction effects [30].
This work examines distraction factors including:

- Talking on the phone
- Texting
- Drinking
- Grooming while checking the rearview mirror.

Research shows that conversing with passengers and using hands-free devices have similar distracting effects [31]. Texting, in particular, causes a 0.2-second delay in reaction to braking, leads to unstable car-following behavior, increases unintentional lane departures, and raises accident risk by a factor of six [32]. Although eating or drinking while driving does not significantly alter behavior in non-critical situations, it raises perceived workload and accident risk during emergencies [33]. Similarly, checking the mirror for grooming, while not specifically studied, falls under visual distraction with comparable risks.

E. FtD Index

The FtD index continuously assesses a driver's ability to operate a vehicle safely by combining visual distraction, cognitive distraction, and emotional state [34], [35]. Its calculation is given by the following formula, calculated at each timestep (i), based on the concept introduced in sections II-B,II-D:

$$FtD = \begin{cases} 1 - (DV_i + EA_i) & \text{if } (DV_i + EA_i) < 1, \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

III. The Proposed Model

The FtD index calculation builds on previous work in the FtD domain, which focused on developing modules for detecting *arousal* and *emotion*. These modules transmits the processed data to the client responsible for calculating the FtD index.
The development of the module related to the detection of visual distraction is, instead, the main objective of this paper, as well as its transmission and integration into the calculation of the FtD index.

A. Requirements

To capture the data needed for the calculation of the FtD index, it was necessary to have some technologies capable of collecting various types of data and transmitting them. To calculate the arousal value, it was necessary to evaluate the biometric data of the driver. This was achieved in a discreet and non-invasive way by opting for a smartwatch capable of detecting the person's heart rate.

Regarding the modules for detecting emotions and visual distractions, a system capable of recording the image of the driver and transmitting the captured frame to both modules was needed. A webcam connected to the computer on which the two modules were running was therefore used. In particular, since it was not possible to allow both modules to access the webcam simultaneously, the image is transmitted to the emotions module, which in turn sends it to the visual distraction module.

To acquire data related to visual distraction, a management system similar to that used for the driver's emotional data was implemented, designing it as an autonomous sub-component of the infrastructure.

Having developed an architecture based on the MQTT protocol, it was possible to implement the various elements autonomously and independently. The components can be divided into two main categories: data sources (e.g., the emotions module or the arousal module) and the data consumer (in this specific case, the client for calculating the FtD index). Each data source generates its own data and publishes them on its own MQTT topic, while the client is responsible for processing the received data and using them to calculate the FtD index.

B. Integration of Driver Monitoring Modules

Message exchange occurs via MQTT, an OASIS standard messaging protocol for the Internet of Things (IoT). The MQTT protocol is based on a publish/subscribe message transport architecture. It is extremely lightweight, making it ideal for connecting remote devices with a small code footprint and minimal bandwidth. To comply with the MQTT protocol, the topics listed below have been adopted, where the corresponding data are published. For the message body, JSON, a simple data-exchange format, has been used.

- **Emotions:** topic concerning the data related to the driver's emotions.
  The messages from this topic occur at a higher frequency compared to others; therefore, to reconcile the produced data, a sliding window has been implemented whose average is considered.
- **Distractions:** topic concerning the data related to visual distraction.

- **Arousal:** topic concerning the data related to arousal, which are associated with the driver's emotional data.
- **VD:** topic concerning the data related to the simulator, used to receive the vehicle's speed that is employed as a weight for distractions in the calculation of the FtD index.

C. Visual Distraction Detection Module

The objective of the visual distraction detection module is to classify several possible actions performed by the driver while the vehicle is in motion into five categories, using a CNN, similar to the emotion detection module.
The development of this module was carried out in three phases:

- Data Preparation
- CNN Model Creation
- Model Testing

1) Data Preparation: The fundamental part of creating algorithms and predictive models is data preparation. To build and train a convolutional neural network, it is essential to have an adequately large dataset with specific characteristics. The first goal of any programmer is to find or create a dataset that meets the model's requirements: some models require labeled data, others do not; the dataset must be of a certain size, etc.

The dataset used was provided by the Vicomtech Technology Center [36] through a series of mp4-format videos of various subjects driving a vehicle or a simulator. This dataset was chosen because it was necessary to find one recorded with a front-facing camera capturing the drivers' faces, as the emotion detection module was based on a large dataset of frontal images, and thus the camera used for the project needed to have the same orientation. The mp4 videos were converted into multiple jpg images using the PotPlayer media player, setting the image capture frequency to every 0.5 seconds. The generated images were then manually sorted into five different folders, each named according to the represented class: *safe driving, brushing hair, drinking, talking phone, texting*. A total of 15,678 images were collected. These images were then split into two categories, *train* and *test*, following an 80-20 ratio. The images were processed by resizing them to 48x48 pixels and applying a random vertical flip (with a 50% probability of being flipped).

2) CNN Model Creation: The software was developed using *Python 3* and the *TensorFlow* library for model creation and training.

In defining the model structure, a sequential model was set up with four convolutional layers alternated with three pooling layers.

The *categorical_crossentropy* loss function was chosen, as it is commonly used for classification tasks with multiple classes. This function produces an array containing the most probable match among the various classes.

Among the various optimizers, the *Adam* optimizer was selected because it is an improved version of the classic Stochastic Gradient Descent (SGD) optimizer, speeding up training and improving performance. The learning rate was left at the model's default value of 0.001.

The model registered class names by acquiring the names of the folders in which the dataset was divided. Subsequently, the model was trained for 20 epochs using batches of 32 elements. For each training epoch, the model was tested on the dataset's test images, progressively evaluating the results obtained. Finally, the training results were saved in an .h5 file so that they could be recalled when needed without re-running the training process. The results of the training are shown in Fig.1 and Fig.2.

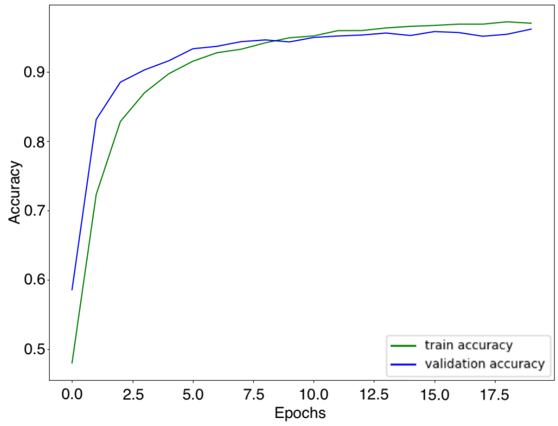

Fig. 1. Graph showing the model's accuracy over training epochs

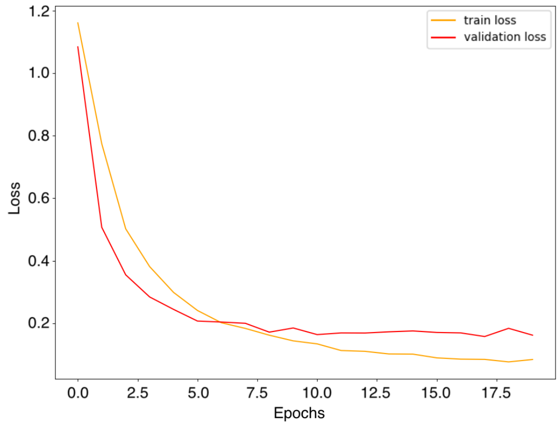

Fig. 2. Graph showing the model's loss function over training epochs

IV. Experimental Evaluation

The final objective of this work was to collect the data necessary to analyze the effect of visual distraction on the FtD index and to evaluate the assignment of weights to the various modules used in the calculation of the index. An in-laboratory simulation environment was set up in which various subjects performed a driving test while data regarding the driver and the driving conditions were recorded. For the implementation of the various modules, different technologies were used. Each of these is described in the following subsections.

A. Simulation Environment and System Modules

To enable communication between modules, a broker was required, and *Eclipse Mosquitto* was chosen.

1) Arousal Calculation Module: To compute arousal, the Fitbit Sense smartwatch (chosen for its non-invasive ECG capability) collects heart rate data.

a) Components:

- **Smartwatch App:** Runs on the Fitbit, reading heart rate values and sending them via the Messaging API 2.9.
- **Companion App:** Runs on the paired smartphone, receives the data, and forwards it over a WebSocket. It allows users to control data transmission and server settings.

- **MQTT Arousal Forwarder:** A script listens to the WebSocket, converts heart rate data into arousal values, and publishes them on an MQTT topic.

A provisioning app, developed previously [], calculates the baseline (resting) heart rate by averaging values over one minute; this baseline is then used to compute the arousal value.

b) Using Containers: To run the script related to arousal detection, containers were created using *Docker Compose* in order to be compliant with Digital Twin deployment platform such as the one presented in [5]. A container was used to abstract the entire management of heart rate detection, conversion of the value into arousal, and its transmission via the MQTT protocol from the execution environment. The container creation script was designed so that the baseline heart rate value of the subject (B_{hr}) and the normalization value (D_{hr}) used in the previously described formula can be modified before the containers are executed, thereby personalizing the simulation environment setup for each participant.

2) Driving Simulator and Data Flow: To perform laboratory tests for calculating the FtD index, the driving simulator *Carla* [37] was utilized. In the laboratory where this project's studies were conducted, the simulator was available as an open-source tool designed for developing, training, and validating autonomous driving systems in urban environments. Carla offers open-source code, protocols, and digital assets—such as vehicles, buildings, and more—that can be used and customized. Additionally, its APIs allow control over various aspects of the simulation, including traffic density, environmental conditions, and sensor configurations.

Since Carla was also used in the previous project [35], it was chosen again for this study, allowing reuse of the previously developed code for periodic transmission of vehicle speed on a specific MQTT topic, as well as data related to driving errors like collisions or lane departures. The simulation environment setup is shown in Fig.3.

Fig. 3. Simulation environment setup for laboratory tests

In order to implement the proposed scheme, it was also necessary that all processes running on the PC side reside on a single computer. Therefore, it was decided to use the same computer on which the simulator was run to also execute the clients for detecting arousal, emotions, and visual distraction, in addition to the client for calculating the FtD index, which listens to all messages from the MQTT Broker. On the same computer, the script for receiving data from the WebSocket and publishing it on the MQTT topic was executed. The device used to detect heart rate is the *Fitbit Sense*, paired with a smartphone connected to the same Wi-Fi network as the computer, allowing it to interact with the system.

B. Test Campaign and Protocol

1) Test Campaign: The testing process took place for two days in a laboratory, where the simulation environment was set up. For the driving simulation, the *Town10*[1] map was used, and a traffic scenario was set up including 5 vehicles and 10 moving pedestrians. The selected car was a BMW.

2) Participants: Fifteen participants, all licensed drivers, were involved in the tests, with ages ranging from 20 to 27 years and an average age of 23.3 years.

3) The Test Procedure: The driving simulation lasted approximately 25 minutes per participant and was conducted uniformly for everyone:

- The subject's heart rate was measured for 60 seconds using the application developed for the Fitbit, and the average was calculated to be used as the baseline value in the arousal calculation.
- This value was then recorded in the container creation script to obtain the subject-specific arousal calculation.
- The participant was given the opportunity to use the simulator to become familiar with the driving system. Once the participants declared themselves ready, the test began.
- The test was conducted by assigning the participant several tasks to be performed while driving, to simulate the various types of visual distraction analyzed in the project:
  - Identify a moving vehicle to follow for the entire duration of the test.
  - Safely follow the selected vehicle for a specific period.
  - Simulate a phone call while driving by using the right arm to bring the phone to the ear for a specific period.
  - Simulate a phone call while driving by using the left arm to bring the phone to the ear for a specific period.
  - Send text messages on the phone with the right hand for a specific period.
  - Send text messages on the phone with the left hand for a specific period.
  - Drink from a water bottle using the right arm to bring it to the mouth for a specific period.
  - Drink from a water bottle using the left arm to bring it to the mouth for a specific period.
  - Adjust one's hair by simulating a glance in the rearview mirror of the driven vehicle for a specific period.

The objective of performing these tasks while following another vehicle was to simulate a situation as close as possible to a real traffic scenario, forcing the participants to become visually distracted while remaining aware of the collision risk with the vehicle ahead.

It was observed that the participants were able to immerse themselves in the testing situation, attempting to simulate their normal behavior in a real-world scenario. It was noted that the tasks assigned during the test caused agitation in many participants, who later reported that they were not

[1] https://carla.readthedocs.io/en/latest/map_town10/

accustomed to performing certain actions while driving, especially texting. Some participants reported experiencing high levels of stress and anxiety in certain situations during the test, which was also reflected in an increased heart rate at certain moments. In general, an increase in driving errors, such as collisions and lane departures, was observed in situations of greater visual distraction, such as in the cases of texting and adjusting one's hair in the rearview mirror. These observations are consistent with the analysis of visual distraction presented in the previous sections.

C. Analysis of the Collected Data

1) Dataset Creation: Thanks to the recordings made during the tests, it was possible to gather a dataset of 15 videos at 1920x1080 resolution of people driving while performing various actions that cause visual distraction. The recordings were made from the front, with the camera positioned in front of the steering wheel; thus, the dataset includes various situations in which the steering wheel interferes with a clear capture of the driver. This result has allowed for the creation of a dataset that includes situations normally not considered, which, however, are real and present due to the driver's height and seating position. Therefore, having such a dataset could facilitate the detection of various distraction situations by a model trained on it.

Additionally, for the training of the model used in this project, a dataset of 15,678 images of drivers was created, divided into 5 folders corresponding to different situations, named *safe driving, brushing hair, drinking, talking phone, texting*. This dataset could prove very useful for future research, making it a highly valuable data collection.

During the tests, various data were collected regarding both the driver and the simulator.

2) FtD Index Evaluation: The FtD value ranged from a minimum of 0.69 up to the maximum (i.e., 1, the optimal condition). A histogram showing the variation of this value during the tests is visible in Fig.4.

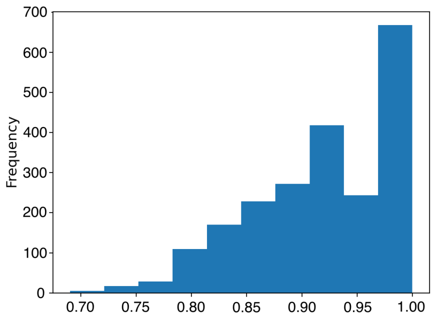

Fig. 4. Histogram of FtD values recorded during the tests

In general, the FtD index remained fairly high, which was expected because part of the tests involved maintaining safe and attentive driving. Furthermore, the effects of emotions were not analyzed in depth, as this was not the main topic of this work; thus, the participants experienced predominantly neutral or happy emotions.

3) Visual Distraction Detection and Driving Errors: Heterogeneity was observed in the detection of types of visual distraction, which ranged among 4 out of the 5 considered cases (because, as previously mentioned, the detection of texting while driving proved problematic due to the simulation environment setup). In particular, the model was able to

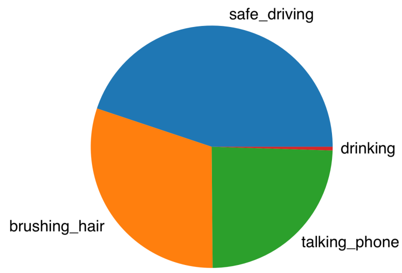

Fig. 5. Visual distraction data collected during the simulation

record the presence of the various types of visual distraction, as shown in Fig.5.

The simulator was also used to record any errors committed during driving, with particular attention to collisions of the driven vehicle. It was thus possible to analyze the correlation between any driving errors and the values of the FtD index as well as the presence of visual distraction. It was found that collisions occurred when the FtD index was lower, as shown in Fig.6.

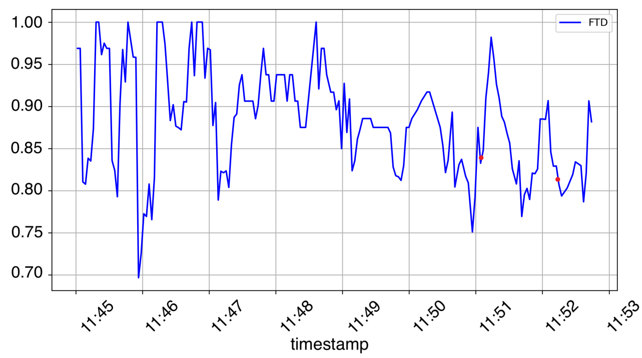

Fig. 6. FtD index values with collision events (highlighted by red points on the graph)

A similar behavior was observed in relation to the presence of visual distraction, recorded as the duration of visual distraction, as shown in Fig.7.

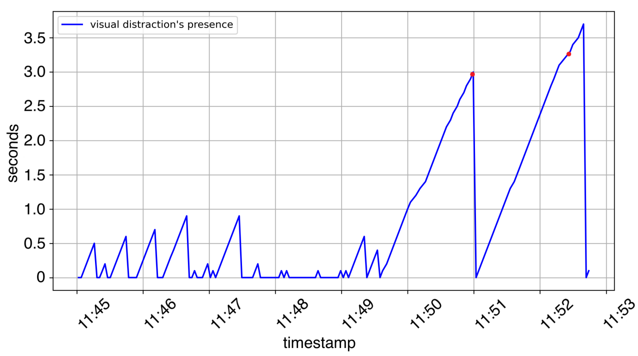

Fig. 7. Visual distraction duration values with collision events (highlighted by red points on the graph)

This result was expected, having also noted that visual distraction becomes increasingly dangerous the longer it lasts.

V. CONCLUSION

In this paper, we presented an integrated IoT-based system for evaluating driver fitness by combining physiological, emotional, and visual distraction data. Our approach leverages data from wearable devices and in-vehicle sensors to compute a FtD index, which has the potential to provide real-time feedback on driver performance. Experimental evaluations using a driving simulator confirmed that our modular system is capable of capturing relevant driver states and can reliably detect critical distractions that may compromise road safety.

The findings underscore the importance of continuous driver monitoring in mitigating risks associated with driver inattention–a key cause of road accidents. With Europe's heavy reliance on private vehicles, such systems are vital for improving road safety and supporting sustainable mobility.

Future work will focus on extending the system to real-world driving conditions, integrating additional sensor modalities, and refining the data fusion algorithms. We also plan to explore advanced machine learning techniques and paradigms [38] to further enhance the accuracy and sustainability of distraction detection and emotion recognition. Moreover, the pervasiveness of IoT opens to the possibility to seamlessly integrate the system in everyday scenarios, providing users with valuable insights, promoting proactive behaviors and fostering user's awareness as exploited in a similar work [39]. By addressing these areas, we aim to contribute to a safer and more sustainable driving environment.

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