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Driver State Monitoring through Driving Style Estimation

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***Abstract*—Human factor is a major component in jeopardization of road safety. Driver State Monitoring (DSM) systems are solutions in charge of detecting impaired driving situations in order to let a vehicle raise an alert and take counteractions.**

The current paper presents the steps that we are taking towards the development of an AI-powered indirect DSM system based on Driving Style Estimation (DSE) techniques.

The paper demonstrates the feasibility of detecting the driver state by analyzing his or her driving behavior. We validated the proposed approach on the detection of aggressive driving situations. This DSM system proved to be effective considering input data spanning a time window of just one second.

I. Introduction

Based on the European Union road mortality statistics, approximately 94% of car accidents are caused in part by human error [1]. According to Euro NCAP, impaired driving behaviors can be classified into fatigue, distraction (visual, auditory, manual, or cognitive), Driving Under the Influence (DUI) of alchohol, drugs, etc., sudden sickness, or aggressive driving [2], [3].

Driver State Monitoring (DSM) refers to systems capable of directly or indirectly determine the driver status. The current paper aims to preliminarly show the feasibility of detecting driver conditions solely based on the analysis of his or her driving patterns. To this purposes, Driving Style Estimation (DSE) techniques are exploited, which consist in creating a model of how the driver is behaving, knowing how the vehicle responds to his or her actions.

The proposed indirect monitoring approach avoids the use of biometric data for privacy-concerned matters. Specifically, it relies on telemetry signals, accessible via vehicle CAN bus, coming from sensors already installed in the vehicle (e.g., IMU and ADAS sensors).

II. State of the Art

Recently, with the aim to reduce human-caused car crashes, the EU Commission issued regulations about DSM adoption [4]; these regulations suggest to avoid using biometric data, in order to preserve the citizens privacy. Specifically, they imposes on all passenger vehicles registered by 2022 the presence of Driver Drowsiness and Attention Warning (DDAW) systems for drowsiness detection [5], and for those registered by 2024 the presence of Advanced Driver Distraction Warning (ADDW) systems tackling distracted behaviors [6].

The methodologies presented in literature and the commercial solutions already available in the market mainly rely on biometric sensors installed in the vehicle (e.g., collecting data about seat posture or steering wheel grip, driver face images, etc.) or worn by the driver (e.g., gathering EEG or ECG signals). Some car makers already installed indirect DDAW systems that avoid camera-based metrics to detect drowsiness [7]. For distraction detection (ADDW) there are fewer solutions (mainly at the R&D stage) and most of them exploit biometric data [8], [9]. There is only one patent, apparently, focusing on how to detect driver distraction based on vehicle variables (specifically, lateral jerk, oversteering, and other travel data) [10].

III. Proposed System

The methodology we propose in this paper is summarized in Fig. 1. The DSM system is designed to operate onboard, in order to reduce the response latency for real-time operation. It considers the driver actions (e.g., steering wheel angle, throttle, and brake), the vehicle response (e.g., variables like body dynamic, engine RPM, etc.), and the surrounding environment perceived through the ADAS sensors (e.g., lane lateral distance, obstacles, etc.) acting as a context to interpret the driver behavior. Data are fed to the DSE module, in charge of inferring the current driving style and producing its mathematical representation. The downstream task detects the functional drift between the generated driving style and the nominal model of the driver, and raises an alert in case the expected behavior deviates from the observed one.

Besides the described processing stream, one of the peculiarities of the devised methodology lays in its adaptation

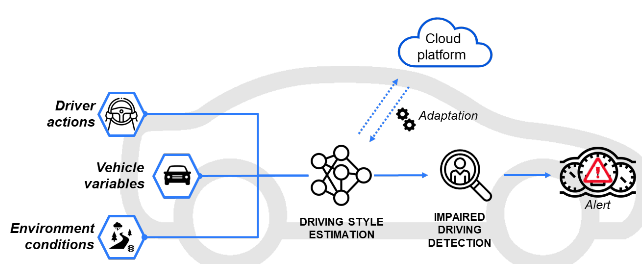


Fig. 1: DSM architecture and workflow

capabilities. Given the complexity of generalizing the subjective behavior of human beings, we took the direction of over-specializing the driver estimator model and creating a specific instance for each driver. Adaptation is achieved by collecting telemetry data while the driver is using the vehicle (thanks to the use of a cloud-based, connected-vehicle platform) and periodically updating the model offline (i.e., remotely). The adapted model is then deployed onboard to update the previous version.

The DSE module is implemented as an Embedding Extractor obtained by a Deep Neural Network trained on an auxiliary task (i.e., the driver state estimation itself, if the ground-truth is available in the experimental setup). The extracted embeddings constitute data points living in a latent space, i.e., a manifold in which the distance embodies a semantic similarity. Hence, embeddings that are close to others in this space represent similar driving styles. On top of this, functional drift detection is implemented by means of an Anomaly Detection algorithm that identifies impaired driving situations as outliers with respect to the nominal model of the driver. This combination allows to exploit the power of feature extraction of a supervised learning model, with an unsupervised algorithm on top. Through the latter, it is possible to exploit the huge amount of unlabelled telemetry data generated on a daily basis while traveling. The Anomaly Detection model represents the component that is periodically updated over more recent data.

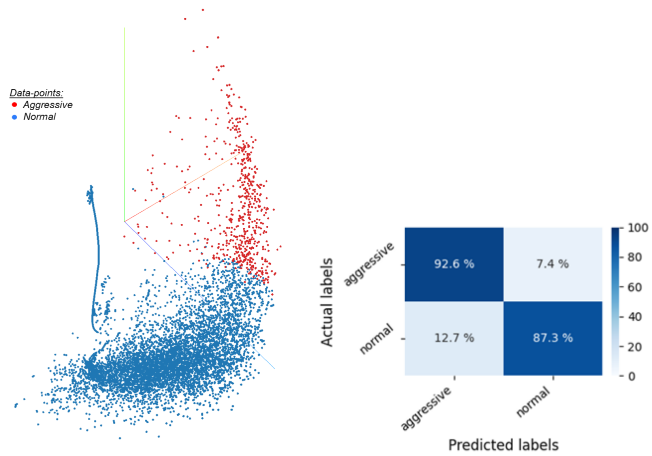
This approach can be applied also for the other types of impaired driving mentioned above, by computing drift detection (tuned on the specific target) with respect to the nominal driver behavioural model.

IV. Evaluation

The feasibility of indirectly estimating the driver state by exploiting vehicle variables has been evaluated over an aggressive driving detection use case. To this purpose, we considered the Aggressive Driving Detection (AD^2) dataset [11], which contains experimental data on naturalistic driving behaviors for driving event analysis. It contains vehicle signals (such as triaxial accelerations, engine RPM, and vehicle speed) together with the annotation of performed maneuvers and the related level of aggressivity. The dataset was augmented with feature engineering techniques by computing the longitudinal jerk (i.e., the first derivative of the acceleration) that has been proven to be an effective parameter for aggressive driving detection [12].

The detection of the aggressivity level was selected as the auxiliary task. The obtained embeddings reside in the latent space shown in Fig. 2a, where it is possible to observe a central cluster of nominal driving style instances (in blue), as well the functional drift (the elongation, in red).

The Anomaly Detection algorithm was trained over the data points processed by the Embedding Extractor. Its performance, summarized in Fig. 2b, reaches an accuracy of 92.6% in detecting the positive class (i.e., aggressive driving) by analyzing a time window of one second. Such a limited amount



(a) Latent space visualization (b) Confusion matrix normalized

Fig. 2: Aggressive-driving detection results

of needed data allows a fasten response of the system. It is also interesting to notice that the false-positive rate, which is considered as a key parameter for a reliable and robust DSM system [6], is quite low (12.7%).

V. Conclusion

In this paper, we introduced a method for monitoring the driver state by relying solely on vehicle data (i.e., no biometric information is used, with clear advantages from a privacy perspective). The performance of the model, measured on an aggressive driving detection task, demonstrates the feasibility of indirectly estimating human-related parameters by analyzing the vehicle response to the driving style.

Future work will include extending the proposed approach to further categories of impaired driving situations, such as distraction and drowsiness.

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