Towards a Cutting-Edge Criteria for Aggressive Driving Behavior Recognition

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***Abstract*—Driver behavior (DB) plays an important role in both road safety and vehicle energy management. Better understanding of how drivers respond to actual driving environments, as well as how their driving style affects road traffic safety, fosters the development of driver behavior monitoring systems that enhance Intelligent Transportation Systems (ITS). However, a literature review shows a lack of integrated and robust systems capable of providing reliable driving assistance in the field that accounts for the uniqueness in driving style and risk profiling assessments. This work aims to showcase a research taxonomy[1] for aggressive driving behavior recognition, which relies on a context-aware, personalized, and real-time assessment. These findings will be used to highlight the importance of incorporating contextual and personalized assessments into driver behavior monitoring systems, paving the way for more intelligent and proactive driving assistance solutions.**

***Index Terms*—Aggressive Driving Behavior; Connected Vehicle Data; Machine Learning; Road Safety; Systematic Review Mapping; Intelligent Transportation Systems; Contextual-Awareness; Personalized Feedback; Real-time Prediction.**

I. Introduction

Road safety is a global critical concern, deeply related to the rapid urbanization and increased mobility over the past years [1], in a scenario where over one million people are either killed or injured on roads around the world [2]. More recently, the World Health Organization (WHO) announced an ambitious resolution called ”Decade of Action for Road Safety 2021-2030” that contains several approaches to reduce road crash deaths and injuries worldwide by at least 50% by 2030 [2]. In this context, road safety has been a major focus for transport researchers and engineers, leading to a significant trend in publications over the past years.

Crash prevention is understood as a proactive approach aimed at minimizing the occurrence and severity of vehicle crashes on the road [1]. A key area of investigation includes analyzing driver behavior (DB), as how drivers operate their vehicles during a certain driving scene and surrounding environment [3], [4]. Different types of DB can be perceived as the outputs of a driving style (DS), which is affected by several different factors (e.g., environmental and human factors) [5] and highly affects overall road safety.

[1]Definition of aspects that characterize the cutting-edge field of research.

The literature reveals that driver behavior strongly correlates with road crashes and fatal injuries, resulting in over 90% of all cases involving transportation [6], and standing as a major field for transport engineers and researchers nowadays [1], [4]. Aggressive driving refers to driving behaviors that increase the risk of traffic accidents and necessitate targeted intervention, such as harsh acceleration, sudden braking, abrupt lane changing, and speeding [1]. Analyzing DB could aid driver performance assessments, enhance traffic safety and fuel efficiency, as well as support intelligent and reliable transportation systems development [4].

The objective of this study is to develop a research taxonomy of cutting-edge criteria for aggressive driving behavior systems. The results suggest a desired criterion for robust and reliable systems that rely on context awareness of the driving conditions, personalized driving assessments, as well as real-time recognition to support crash prevention.

The remainder of this study is organized as follows: Section II provides the structure of the systematic literature mapping. Section III discusses results and the cutting-edge criteria. Section IV highlights the related works on aggressive driving recognition that met the personalized and real-time criteria. Lastly, Section V offers the conclusion and draws future studies from research findings.

II. Survey Methodology

Systematic Literature Mapping (SLM) studies offer an extensive overview of a particular research field and assess what is available in the literature [7], [8]. These studies facilitate an in-depth analysis of evidence across defined domains. Their outcomes can recognize suitable subjects for systematic reviews and reveal gaps that necessitate primary research.

The current SLM aims to gather information about driver behavior studies that assess aggressive driving. Furthermore, the SLM obtains information about the different methodologies applied to Intelligent Transportation Systems (ITS) to detect aggressive driving, which data-driven approaches are employed, and the cutting-edge criteria to accomplish a reliable and robust solution. Limitations and gaps were found in the literature, and opportunities for future studies were noted.

A. Search String and Selection Criteria

To create the search string for the automatic search in multiple databases, it is important to define the keywords and their synonyms. The choice was made based on reference studies in road safety [1], driver behavior [4], and aggressive driving [9]. Thus, the keywords are:

- **machine learning / connected vehicle / aggressive driving behavior / road safety**

For the automatic search based on the search string, the selected databases were Scopus, IEEE Xplore, and Science Direct, given that these databases are relevant in the area of Computer Science according to specialists. Over 1,074 distinct studies returned from the automatic search string in the databases, as input to the study selection process.

The selection process targets studies that refer to human interactions with the vehicle, corresponding to manual driving behaviors that are not ruled by autonomous driving. Also, the review consists of evaluating studies regarding the use of vehicle telematics and on-board devices to characterize certain driving events, avoiding the use of intrusive sensors that capture driver characteristics. Lastly, the inclusion criteria focused on studies addressing data-driven methods to infer driver behavior (e.g., Artificial Intelligence, Machine Learning, analytical methods), as they solve a major challenge of handling massive sets of naturalistic driving data in real-world environments, along with a strong capability to represent the complexity of human driving behavior more accurately.

To promote a deeper understanding of what might contribute to this present study, the proposed methodology of each study was thoroughly reviewed to ensure that it relates to an aggressive driver behavior recognition system. At the end, 87 studies passed the overall study selection process, of which 21 were secondary studies (e.g., surveys, literature reviews).

III. Synthesis of Results

The complex nature of road safety and driver behavior analysis is evident in several literature reviews. Most of the secondary studies on driver behavior analysis (DBA) investigate different data sources, features, and methodologies used to identify driving styles, summarizing which key trends and patterns to follow [6], [10]. Important steps and procedures in the development of driving recognition systems are often required to provide reliability and customer acceptance in the field.

The integration of various data collection methods, such as onboard devices and vehicle perception information, reveals strong capabilities for capturing comprehensive driving behavior data [5], [11], due to their wide-range applicability, low cost, and advantages in privacy and information security [6], [10]. Understanding the surrounding environment during a driving event (e.g., road characteristics, time of the day) along with the vehicle's motion (e.g., acceleration, braking, and turning), enables a contextual understanding of the driving state [5], [11]. Recognizing and adapting to these conditions promotes a more accurate classification in DBA and an effective implementation of advanced driver assistance systems, which is particularly in accordance with the Driver-Vehicle-Environment (DVE) concept [4], as highlighted in the context environment in Figure 1.

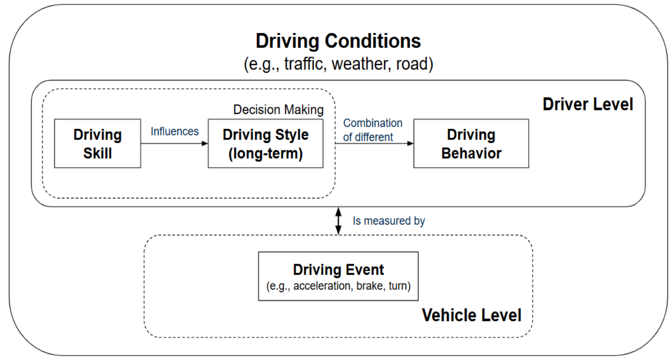

Fig. 1. Driving style environment and terminology

Real-time recognition in automotive applications is crucial as it allows immediate response to driving conditions and behaviors [12]. This is particularly more urgent for safety systems, where delays in recognition could lead to road accidents or inefficient vehicle operation. In this matter, reference [6] argued that real-time driver behavior detection is a key aspect for crash prevention and the quality of driving. By recognizing driver behavior in real-time, ITS can be designed to provide timely intervention and support, thereby reducing the risk of accidents caused by aggressive driving behaviors [6].

Among all primary studies found in the previous selection process, the majority rely on having a "ground truth" concerning the driver behavior. This concept refers to the use of *a priori* known information on driver behavior, which is provided by direct observation instead of inference [13]. Several of them rely on different supervised learning methods and are usually developed using available open-source naturalistic driving datasets. SHRP2[2], UAH-DriveSet[3], and 100-car[4] are strong examples of fused sensors studies that support driving style recognition and risk assessment [14]–[17]. These datasets contain months of driving data collection from thousands of participants, often exhibiting labels related to each driver's behavior or crash risks.

Despite the usability and scientific benefits of those datasets, there is a significant challenge to replicate those methods on a large scale, as it carries several constraints related to the subjective assessment of individuals on labeling, as well as the lack of generalization outside the driving conditions previously collected [18]. Thus, the development of DBA under uncontrolled driving environments becomes promising and allows a more robust and reliable modeling for real-world driving. While the former refers to the use of supervised machine learning methods, the latter is commonly assessed with clustering, hybrid, and rule-based algorithms.

[2]https://insight.shrp2nds.us/
[3]http://www.robesafe.uah.es/personal/eduardo.romera/uah-driveset/
[4]https://www.nhtsa.gov/sites/nhtsa.gov/files/100carphase1report.pdf

In this context, the deployment of intelligent systems for driving risk assessment becomes even more important. The concept of driving style (DS) refers to the combination or distribution of different driver behaviors [19], as each driver holds their own and unique driving style, reflecting the specific driving scenarios they have experienced. This understanding strongly supports driving score calculations and a more robust driver risk profiling, which reflects both short-term and long-term driving styles [12], [19].

With the aforementioned results found in the systematic review, the cutting-edge research on driver behavior recognition relies on assessing (i) contextual information (i.e., driving conditions awareness), (ii) personalized driving aspects (e.g., driving scores and individual assessments on driving behavior), and (iii) real-time detection to enhance road safety.

IV. Related Works: Taxonomy

This review proposes a taxonomy to characterize the cutting-edge criteria for recognizing aggressive driving behavior, specifically techniques applied in personalized and real-time assessments. The application of this taxonomy uncovered a major research gap: of the 66 primary studies examined, only 4 (detailed in Table I) satisfied all three criteria found in the SLM, revealing that current literature largely fails to integrate key components for a robust crash prevention solution. Consequently, this review focuses on this shortfall to guide future works toward real-time, personalized systems for driving risk profiling and crash prevention. Contextual data serves here as a supplementary feature to enhance model performance.

Many studies applied unsupervised pattern recognition to evaluate driver behavior in real-world environments when ground-truth data is unavailable. A prominent trend is the development of driving scores for personalized feedback and driving profiling. However, a significant gap exists in several advanced models; while methods like hybrid systems [20], Latent Dirichlet Analysis [19], and clustering techniques [21] offer detailed assessments, they often fail to incorporate the context of the driving environment. In contrast, another set of cutting-edge studies successfully integrates this information. Using rule-based methods [22], [23] and different clustering approaches [18], [24], these studies deliver aggressive driving recognition that is contextual, personalized, and real-time. Therefore, it is crucial to analyze these successful methodologies to understand how they meet the criteria for robust, real-world applications.

The SenseFleet platform, detailed in [22], employed a fuzzy logic system on smartphones to detect risky maneuvers, including over-speeding, hard acceleration, hard braking, and aggressive steering, by analyzing fused data from the phone's GPS and inertial sensors. The study utilized a trip-based driving score that started at 100 and was reduced based on detected events. The scoring model leveraged contextual information, such as road topology and weather conditions, to dynamically penalize behaviors that were more dangerous in specific situations. Validation confirmed a clear distinction in scores between calm and aggressive driving.

Reference [23] proposed a context-aware system using a two-level fuzzy logic model to classify driving styles, such as aggressive or non-aggressive, based on vehicle speed and fuel consumption data from the OBD system. Contextual information, specifically road occupancy percentage in the SUMO simulation environment, was leveraged to provide drivers with personalized suggestions for speed adjustments. While validation showed a significant reduction in traffic incidents, the system's reliance on simulated road occupancy data presents a notable constraint for real-world and large-scale implementation.

In [24], a recognition system was developed to investigate driver behavior by leveraging road type (highways, commercial, and residential streets) as the primary contextual factor. The technique quantified driving style using "temporal volatility," a surrogate safety measure derived from Basic Safety Messages (BSM) using connected vehicle data. For profiling, a clustering method was used to classify drivers into aggressive, normal, or calm categories specific to each road type. A continuous driving score was also proposed to provide a more granular assessment of the observed driving behavior, as referenced in Table II.

The framework proposed by [18] utilized a G-G diagram to identify risky acceleration, braking, and turning maneuvers. The system involved a two-stage clustering process: first, Hierarchical Clustering identified the overall percentage of risky maneuvers and a driving instability index, and second, a unique Gaussian Mixture Model (GMM) was fitted to each driver to create a detailed profile with eight distinct risky driving patterns. A driving score was then calculated to quantify the frequency and severity of these behaviors. Finally, the system leveraged spatial information to identify behavioral hotspots, enabling proactive warnings before a driver enters a high-risk location.

V. Conclusions & Future Studies

This review presents the foundation for future applications in driver behavior recognition, discussing pivotal criteria to develop a reliable and robust intelligent transportation system (ITS) for real-world driving. The cutting-edge criteria emphasize the importance of contextual information, such as environmental and road factors, in accurately recognizing aggressive driving behavior and better understanding the context in which aggressive behaviors occur. Personalized mechanisms are also important to evaluate long-term driving style analysis, and they account for individual and subjective driving habits. This is of paramount importance to allow acceptance and understanding of improvements in driver behavior over time. Lastly, real-time recognition is an essential aspect for crash prevention, as it provides timely feedback to drivers to enhance road safety.

Major challenges for future applications mostly rely on (i) integrating contextual information for real-time applications in crash prevention; (ii) adequately estimating the long-term driving score to preserve plasticity in overall driving style,

TABLE I
CUTTING-EDGE AGGRESSIVE DRIVING TAXONOMY

Ground truth on DB	Studies	Technique	Contextual?	Personalized?	Real-time?
Yes	[25] [27]	Hybrid	No	Yes	Yes
	[17] [26] [28]	Hybrid	Yes	Yes	Yes
No	[20]	Hybrid	No	Yes	Yes
	[19]	Latent Dirichlet Analysis			
	[21]	Clustering			
	[23] [22]	Rule-based	Yes	Yes	Yes
	[24] [18]	Clustering			

TABLE II
CONTINUOUS CATEGORIES OF DRIVING SCORE

Categories	Score
Very Poor	1.0
Poor	1.5
Fair	2.0
Good	2.5
Excellent	3.0

and (iii) promoting a robust personalized aggressive driving recognition for uncontrolled driving environments with unsupervised learning methods.

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