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Design of Cooperative Advanced Driver Assistance System based on Artificial Intelligence Models aware of driving profiles and the environment surrounding the vehicle

Profesor supervisor: PhD. Miguel E. Figueroa Toro
Departamento de Ingeniería Eléctrica
Facultad de Ingeniería
Universidad de Concepción
Profesor co-supervisor: PhD. Samuel Montejo Sánchez
Instituto Universitario de Investigación y Desarrollo Tecnológico
Universidad Tecnológica Metropolitana

Tesis para optar al grado académico de Doctor en Ciencias de la Ingeniería con mención en Ingeniería Eléctrica

Juan Felipe González Saavedra
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Prefacio

Esta tesis es presentada como parte de los requisitos para optar al grado académico de Doctor en Ciencias de la Ingeniería con mención en Ingeniería Eléctrica, de la Universidad de Concepción, Chile, y no ha sido presentada previamente para la obtención de otro grado en esta Universidad u otras. La misma contiene los resultados obtenidos en investigaciones llevadas a cabo en el Departamento de Ingeniería Eléctrica, durante el período comprendido entre el año 2018 y 2025, bajo la dirección de los Doctores Samuel Montejo Sánchez y Miguel E. Figueroa Toro.

Juan Felipe González Saavedra
juanfegonzalez@udec.cl
Departamento de Ingeniería Eléctrica
Facultad de Ingeniería
Universidad de Concepción
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Dedicatoria

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List of Acronyms

5G-Advanced	Fifth generation wireless communication technologies Advanced
ABS	Anti-block system
ACC	Adaptive cruise control
ADAS	Advanced driver assistance systems
AEB	Autonomous emergency braking
AI	Artificial intelligence
AR	Augmented reality
ASIRT	Association for Safe International Road Travel
ASR	Automatic speech recognition
BSW	Blind spot warning
C-ADAS	Cooperative advanced driver assistance systems
CAN	Controller area network
CARLA	CAR learning to act
CAV	Connected and autonomous vehicle
CNN	Convolutional neural network
DSRC	Dedicated short-range communication
EAS	Electronically assisted steering
ECG	Electrocardiography
ECU	Electronic control unit
EEBL	Emergency electronic brake light

EEG	Electroencephalogram
EMG	Electromyography
ESC	Electronic stability control
ETSI	European Telecommunication Standards Institute
FCC	Federal communications commission
FCW	Forward collision warning
GMM	Gaussian mixture model
GPS	Global positioning system
GP	Gaussian processes
GRU	Gated recurrent unit
HMI	Human-machine interface
HMM	Hidden Markov model
HUD	Heads up display
IBK	Instance based learner
IEEE	Institute of electrical and electronics engineers
IMU	Inertial measurement unit
IoT	Internet of things
IoV	Internet of vehicles
ITS	Intelligent transportation systems
K-NN	K-nearest neighbours
LCA	Lane change assistance
LDW	Lane departure warning
LED	Light emission diode
LIDAR	Light detection and ranging
Li-Fi	Light fidelity
LIN	Local interconnect network
LKA	Lane keep assistance
LMT	Logistic model tree
LRR	Long range radar

LSTM Long short term memory

LTE Long term evolution

LTE-A Long term evolution advanced

LWL Locally weighted learning

MBC Model based communication

MOST Media oriented systems transport

MPC Model predictive control

MR Mixed reality

NGSIM Next generation simulation

NIR Near infrared

NLP Natural language processing

NTSC National Transportation Safety Council

OBD On-board diagnostic

OEM Original equipment manufacturers

OGF Occupancy grid filtering

OHMD Optical head-mounted display

PER Packet error rate

PERCLOS Percentage of eyelid closure over the pupil over time

PLR Packet loss rate

PTE Packet tracking error

RGB Red green blue

RMSE Root mean square error

RNN Recurrent neural network

RSA Road safety applications

RSS Road safety system

SAE Society of Automotive Engineers

SDT Signal detection theory

SL Simple logistic

SMAC Secuential model-based algorithm classification

SPMD	Safety pilot model deployment
SRR	Short range radar
SVM	Support vector machine
TTC	Time to collision
TOPS	Trillions of operations per second
URLLC	Ultra reliable and low latency communications
V2I	Vehicle to infrastructure communication
V2N	Vehicle to network communication
V2P	Vehicle to pedestrian communication
V2V	Vehicle to vehicle communication
V2X	Vehicle to everything communication
VANET	Vehicular ad-hoc network
VR	Virtual reality
VRU	Vulnerable road users
WAVE	Wireless access vehicular environment
WEKA	Waikato environment for knowledge analysis
XAI	Explainable artificial intelligence

Abstract

The design of driver assistance systems to improve road safety has been present since the beginning of the automotive industry itself. These systems have evolved, in close relationship with technological advances in the areas of electronics, computer systems and telecommunications. Different stages have marked this evolution, from the emergence of the first passive systems, the transition from these to the so-called active assistance systems and more recently the appearance of cooperative assistance systems, which incorporate communication elements. The design of these systems has a close and direct relationship with the main aspects related to road safety: the driver, the vehicle, and the environment. The absence of any of these elements or the failure to consider the interrelations between them contributes to a deterioration in road safety.

The driver is a relevant element for road safety. Although the first steps are being taken in the implementation of autonomous driving, the current transition stage that involves the coexistence and interaction of autonomous vehicles with traditional vehicles driven by a human driver seems to be far from being concluded in the short and medium term. Therefore, it is relevant to consider the study of the driver and his different driving profiles in the design of assistance systems, both to assist the driver in non-autonomous vehicles and to incorporate this information related to human drivers in autonomous vehicles, favoring their integration in the road scenario where they must coexist with the rest of the non-autonomous vehicles. The more autonomous vehicles know human drivers, the better they will be able to interact with them, which contributes to promoting road safety. One of the most widely used methods in the literature to address the study of driver profiles is the analysis of the vehicle's trajectory. Lane-changing maneuvers on highways are particularly a risk factor for road safety, given the high driving speeds of these scenarios. These maneuvers allow the analysis of the bidirectional behavior of vehicle movement and thus enrich the study of bidirectional driving profiles of drivers.

In this thesis, we present a study on the design of Cooperative advanced driver assistance systems (C-ADAS) and propose a conceptual architecture that includes the main elements related to road safety: the driver, the vehicle, and the environment, as well as the interrelation between these through a holistic and systemic approach. In this architecture, the remote operation of this C-ADAS based on the Internet of vehicles (IoV) paradigm is also considered, as well as the enabling technologies involved, the main evaluation mechanisms, and the performance metrics used in these systems. From data on real trajectories, we analyze bidirectional driving profiles in lane-changing maneuvers on highways, grouped according to the vehicle's longitudinal and lateral movement behavior. We obtain an analytical description of these driving profiles, through logistic models, which describe the drivers' behaviors during the execution of these maneuvers. This information improves the prediction

accuracy of the most probable trajectory of the vehicle when drivers change lanes. These models were evaluated for many time windows of historical trajectory data, right and left turn maneuvers, different driving profiles for each type of maneuver, and various traffic lane configurations, the results obtained showed an accuracy greater than 92% in the detection of driving profile and greater than 99.1% in the particular driver detection.

Resumen

El diseño de sistemas de asistencia a la conducción para mejorar la seguridad vial ha estado presente desde los inicios de la propia industria automovilística. Estos sistemas han evolucionado en estrecha relación con los avances tecnológicos en las áreas de electrónica, informática y telecomunicaciones. Diferentes etapas han marcado esta evolución, desde la aparición de los primeros sistemas pasivos, la transición de estos a los llamados sistemas de asistencia activa y, más recientemente, la aparición de los sistemas de asistencia cooperativos, que incorporan elementos de comunicación. El diseño de estos sistemas guarda una relación estrecha y directa con los elementos principales relacionados con la seguridad vial: el conductor, el vehículo y el entorno. La ausencia de alguno de estos elementos o la no consideración de las diferentes interrelaciones entre ellos, tributan a una degradación de la seguridad vial.

El conductor es a día de hoy un elemento relevante para la seguridad vial, si bien se están dando los primeros pasos en la implementación de la conducción autónoma, la etapa actual de transición que involucra la coexistencia e interación de los vehículos autónomos con los vehículos tradicionales conducidos por un conductor humano, parece estar lejos de concluir en el corto y mediano plazo. Por ello es relevante considerar el estudio del conductor y sus diferentes perfiles de conducción en el diseño de los sistemas de asistencia, tanto para asistir al mismo en los vehículos no autónomos como para incorporar esta información relacionada a los conductores humanos en los vehículos autónomos, lo cual favorecerá la integración de estos en el escenario vial donde deben coexistir con el resto de los vehículos no autónomos. En la medida en que los vehículos autónomos conozcan mejor a los conductores humanos, mejor podrán interactuar con estos, lo cual tributa a favorecer la seguridad vial. Una de las formas más empleadas en la literatura para abordar el estudio de los perfiles de un conductor, es mediante el análisis de la trayectoria del vehículo. Las maniobras de cambio de carril en autopistas, constituyen particularmente un elemento de riesgo para la seguridad vial, dadas las altas velocidades a las que se circula en estos escenarios. Estas maniobras, permiten analizar el comportamiento bidireccional del movimiento del vehículo y con ello, enriquecer el estudio de perfiles de conducción bidireccionales de los conductores.

En esta tesis, presentamos un estudio sobre el diseño de C-ADAS y proponemos una arquitectura conceptual que incluye los elementos principales relacionados con la seguridad vial: el conductor, el vehículo y el entorno, asi como la interrelación entre estos mediante un enfoque holístico y sistémico. En esta arquitectura, se considera además la operación remota de este C-ADAS basado en el paradigma de IoV, así como las tecnologías facilitadoras involucradas, los principales mecanismos de evaluación y métricas de desempeño empleados en estos sistemas. Analizamos a partir de datos de trayectorias reales, perfiles de conducción bidireccionales en maniobras de cambio de carril en

autopistas, agrupados según el comportamiento del movimiento longitudinal y lateral del vehículo. Obtenemos una descripción matemática de estos perfiles de conducción, mediante modelos logísticos, que describen el comportamiento de los conductores durante la ejecución de estas maniobras. Esta información mejora la precisión en la predicción de la trayectoria más probable del vehículo cuando los conductores cambian de carril. Estos modelos fueron evaluados para diferentes ventanas de tiempo de datos históricos de trayectoria, maniobras a la derecha y a la izquierda, diferentes perfiles de conducción para cada tipo de maniobra y distintas configuraciones de carril de circulación, los resultados obtenidos mostraron una precisión superior al 92% en la detección del perfil de conducción y superior al 99,1% en la detección de un conductor en particular.

1 Introduction

1.1 General introduction

Road safety is a major issue in modern society. Statistics from Association for Safe International Road Travel (ASIRT) indicate that in 2021, traffic accidents caused the deaths of nearly 1.19 million people. Since 2019, they have been the leading cause of death in children and young people aged 5 to 29 and the twelfth leading cause of death across all age groups. Two-thirds of the deaths are in people of working age (18 to 59 years), which causes enormous harm to society in economic, social, and health terms [1]. More than 90% of road accidents are related to human-caused errors due to factors such as drowsiness, fatigue, irresponsible behavior, or driver distraction [2]. To improve traffic safety, numerous researches have focused significantly on the development of Advanced driver assistance systems (ADAS).

The history of research on assistance systems for driving safety is almost as old as the rise of the automobile industry itself. One of these first systems was implemented as standard equipment by Volvo in 1959 when it began to install seat belts with a three-point system in its vehicles, patented in 1962 [3] and later became the universal standard used by commercial vehicles today. Different road safety mechanisms have been incorporated over the years in the development of the automotive industry to provide a higher level of road safety to traditional transport systems. These mechanisms constitute technological implementations of concepts that the European Telecommunication Standards Institute (ETSI) has subsequently defined as road safety applications, which can be grouped into primary road safety applications (equivalent to the so-called active road safety systems) and secondary and tertiary road safety applications (equivalent to so-called passive road safety systems)[4]. The former focuses on collision avoidance as its primary mission, while the latter aims to lessen the severity of potential injuries to vehicle passengers or Vulnerable road users (VRU) after the collision. Specific bumpers designed to keep pedestrians safe, airbags, and seat belts are some of the well-known examples of passive safety mechanisms. Others like Anti-block system (ABS), Lane change assistance (LCA), or Forward collision warning (FCW), are examples of active safety systems. The development of these assistance systems, from the perspective of road safety as a complex and systemic phenomenon, has reflected to date some limitations in the design approaches. In some cases, the influence of the main elements associated with it has not been considered: the driver, the vehicle, and the surrounding environment, in others, even having taken into account the presence of these three elements, the bidirectional interrelation that develops between them has not been analyzed in depth. This is a relevant element to consider in the design of these ADAS, which contributes to increasing road safety levels. Let us consider, for example, autonomous driving systems, where the influence of the driver is intended to be removed. Although these systems have been shown to surpass human driving capabilities in numerous scenarios, in areas such as executing turns or operating in low visibility conditions, they show significantly lower performance. Likewise, these autonomous systems are very limited when trying to infer social signals and/or understand the psychological behavior of other road users such as pedestrians, cyclists or other human drivers. In these environments, human drivers have a manifest superiority [5].

The lane change maneuvers are driving actions that involve crossing from one lane to another and constitute a risk to road safety. In the particular scenario of highways, a relevant element is speed, where high values are a distinctive characteristic, which relates a high frequency of maneuvers of this type with risky situations that cause traffic accidents [6]. They are grouped into two types of maneuvers: mandatory [7] and discretionary [8]. These maneuvers involve two important aspects: lateral movement, which is the change of position between lanes, and longitudinal movement, oriented in traffic direction. The speed factor affects the perception of available space in the destination lane and the decision threshold for initiating the maneuver. Maneuvers performed at higher speeds take less time to complete but involve greater risk and difficulty, which influences the safety margins that different drivers are willing to assume. The study of these elements constitutes a critical dimension for improving road safety by analyzing the factors and models that influence the lateral and longitudinal movement of vehicles when changing lanes on highways [9].

During the execution of lane change maneuvers, there may be significant differences between different drivers. There are drivers with a driving profile associated with performing smooth and safe maneuvers, who signal in advance, check side mirrors, and analyze blind spots before executing the maneuver. On the other hand, some drivers have a more aggressive driving profile, characterized by performing unexpected or sudden maneuvers, blocking the passage of other drivers in the destination lane, or making frequent lane changes, assuming higher levels of risk during the process. Knowledge of these driving profiles can benefit the modeling of the lateral and longitudinal movement of the vehicle and the accuracy of the estimation of the most probable trajectory during a lane change. Incorporating the heterogeneity and variability of driving behavior can improve the explanatory and predictive power of lane change models by adding relevant information about the driver [10].

The prediction of the most probable trajectory, considering the driver's driving profile during the execution of lane change maneuvers on highways, is a crucial task to guarantee road safety. To further analyze lateral and longitudinal movement in lane change maneuvers, we consider logistic modeling. These models are a type of data-driven algorithm that uses binary or multinomial logistic regression to predict the probability of lane change events or types by fitting input data to a sigmoid curve. XAI is a field within AI models that aims to make these systems transparent, interpretable, and accountable to humans. This is particularly relevant for road safety, where traffic accidents and loss of human life must be dealt with. In this sense, logistic models provide some advantages in trajectory estimation during lane change maneuvers on highways, such as simplicity, flexibility, scalability, and robustness. They are generally simple models, with few parameters that can be easily adjusted in the training stages, they are interpretable, easy to explain by humans, and require fewer computational resources than deep learning models.

Many existing methods for vehicle trajectory prediction employ sensors such as cameras, radars, and LIDAR to detect and track the motion of surrounding vehicles [11]. However, these methods face several challenges, such as occlusions, sensor failures, and lack of line of sight due to congested traffic scenarios. In general, these methods tend to ignore driver profiles, which can provide valuable information about driver behavior and intention. Other methods, for example, address the existence of driving profiles but do not consider the relationship between driver behavior and the direction of motion to which drivers are subjected during maneuver execution, such as the bidirectional motion present in lane change maneuvers. Therefore, there is a need for more advanced and robust methods that can analyze and incorporate the driver profile into the vehicle trajectory prediction process, considering the analysis and influence of bidirectional motion present, for example, in the execution of lane change maneuvers on highways, on the driver's behavior.

1.2 Hypothesis and research questions

The hypothesis that was tested during this doctoral thesis is:

The design of cooperative advanced driver assistance systems, based on artificial intelligence models aware of driving profiles and the environment surrounding the vehicle, contributes to improving the performance of cooperative road safety applications; providing the system with relevant information associated with the drivers' behaviors; thus increasing the predictive horizon of the trajectory models and the robustness of the information exchanged in the vehicle network.

The research questions driving this thesis are:

i) How to integrate the relationship of the main elements of a road safety system in the design of a C-ADAS?

ii) How to design artificial intelligence models, using appropriate computational simulation tools to process and analyze real vehicle trajectory data on highways?

iii) How to obtain relevant information related to driver behavior to improve the performance of trajectory models and the robustness of the information exchanged in vehicular networks?

1.3 Objectives

General objective

Design C-ADAS based on Artificial intelligence (AI) models, aware of driving profiles and the environment surrounding the vehicle, which contribute to improving the performance of cooperative Road safety applications (RSA).

Specific objectives

i) To propose a general architecture of a C-ADAS, which considers the interrelation between the elements associated with road safety.

ii) To model driving profiles associated with lane change maneuvers on highways based on real trajectory data.

iii) To design models based on previously identified driving profiles, to predict the most probable trajectory when performing lane change maneuvers on highways.

1.4 Author contributions.

i) General design architecture of C-ADAS. In studying C-ADAS, this work emphasizes a comprehensive approach that integrates the driver, vehicle, and environment, highlighting their mutual interactions. It presents a conceptual architecture that enables remote C-ADAS operations via the IoV supported by critical enabling technologies, assesses current advancements, addresses research challenges, and outlines key evaluation methodologies essential for quantifying C-ADAS performance.

ii) Bidirectional driving profile models that characterize the behavior of lane change maneuvers on highways. This work focuses on improving road safety through analyzing high-risk lane change maneuvers on highways by extracting, clustering and mathematically modeling the bidirectional driving profiles from real trajectory data, which can used to better predict the driver behavior during lane changes.

iii) Trajectory prediction models based on relevant information associated with the driver to assist in lane change maneuvers on highways. Development of models that improve the predictive character of trajectory estimation mechanisms. The obtained models based on the driver's profiles previously detected, were evaluated across various time windows and lane configurations, and achieved over 92% accuracy in predicting the most probable vehicle trajectories and greater than 99.1% in the particular driver detection.

1.5 Journal papers and conference presentations.

The following journal papers and conference presentations were obtained as a result of this thesis, and they allowed the dissemination of this research work:

i) González-Saavedra, J.F.; Figueroa, M.; Céspedes, S.; Montejo-Sánchez, S. Survey of Cooperative Advanced Driver Assistance Systems: From a Holistic and Systemic Vision. Sensors 2022, Vol. 22, Page 3040 2022, 22, 3040.

ii) González-Saavedra, J.F.; Figueroa, M.; Céspedes, S.; Montejo-Sánchez, S. Accurate Lane Change Prediction on Highways through Bidirectional Driving Profile Modeling (under review). IEEE Transactions on Intelligent Transportation Systems.

1.6 Thesis Manuscript Structure

The thesis manuscript presented here is organized as follows: Chapter 2 presents a general discussion of related work in the area of this study and the current challenges. Chapter 3 presents a systematic analysis of C-ADAS design and how the inclusion and interaction of road safety elements in design architectures have been addressed. In addition, a general C-ADAS design architecture is proposed, which seeks to address the challenges found in the consulted literature. Chapter 4, proposes and evaluates mechanisms for the extraction, clustering, modeling, and detection of bidirectional driving profiles in lane change trajectories on highways, to assist in the estimation of the most probable trajectory according to the previously identified driving profile and the detection of the most probable behavior of the driver, for different instances of execution of the lane change maneuver. Finally, chapter 5 discusses the conclusions and contributions of this study, as well as future research work in line with the results obtained.

2

State-of-the-art in ADAS

2.1 Introduction

Safe mobility is an essential element of the fundamental rights of every human being, which must not and need not, come with a tragic cost in human lives. The increasing urbanization and increase in the world population entails a growing demand for mobility, which in turn tends to overwhelm current transport systems, particularly those that rely heavily on private vehicles. The proliferation of motor vehicles has redoubled the efforts of countries to design transport systems for cars, not for people, to the detriment of the latter's safety. Some of the main advances have been achieved where the safe system approach has been applied to road safety. This holistic approach to mobility places people and safety at the center of attention. As previously mentioned, in the design of Advanced driver assistance systems (ADAS) elements such as the vehicle, the driver, and the road environment must be considered, which makes these systems complex. Therefore, in this chapter we aim to address the importance and the main elements of road safety and how these can be integrated into current transport systems through the design of ADAS systems from a holistic and systemic approach, which involves the interrelationship between these elements. In addition, topics related to road safety in driving, the modeling of driver behavior through trajectory prediction, as well as some challenges that persist today, according to the literature consulted, will be discussed.

2.2 Road Safety in Driving

Driven by technological developments in the electronics field, the automotive industry has evolved from traditional mechanical control to electronic control of the vehicle's main internal functions, primarily related to acceleration, braking, gear shifting, suspension, and ignition/alternator integration [12, 13]. The principal elements of this evolution are the Electronic control unit (ECU) and the management of the information flow between ECU, for which bus communication protocols like the Controller area network (CAN) bus [14, 15], or Local interconnect network (LIN) are employed. These developments allowed the implementation of safety systems such as the Anti-block system (ABS), the Electronic stability control (ESC), or the Electronically assisted steering (EAS). The introduction of on-board sensors such as radars, ultrasonic, cameras, Light detection and ranging (LIDAR), Global positioning system (GPS), Inertial measurement unit (IMU), enables the development of driving assistance systems more oriented to the sensing and interaction of the vehicle with the surrounding environment to help the driver in the driving process [16]. Initially, these safety systems were oriented to the longitudinal control of the movement of the vehicle, such is the case of the Adaptive cruise control (ACC) system, Forward collision warning (FCW) and Autonomous

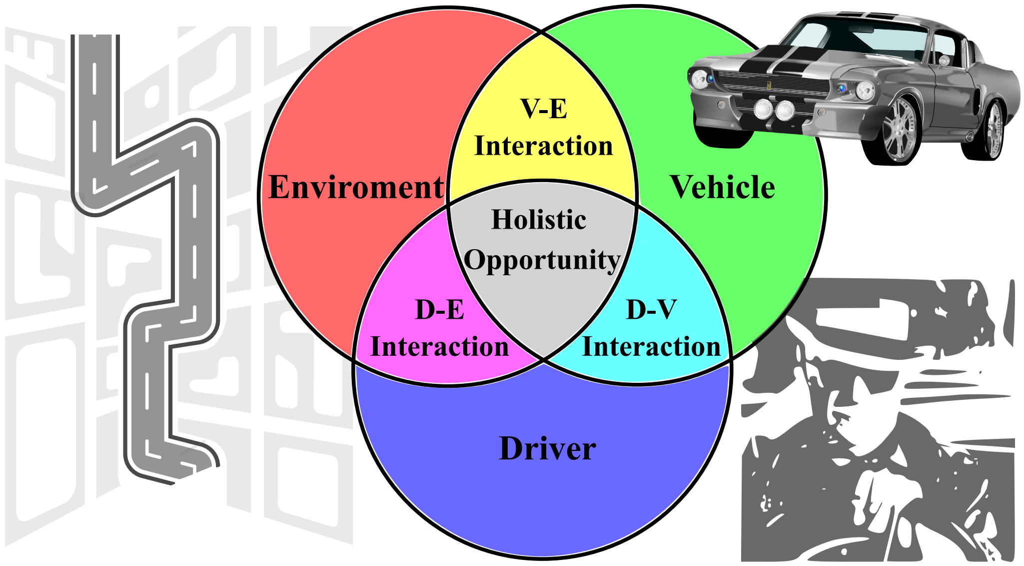


Figure 2.1: Main elements involved in a Road safety system (RSS) : environment, vehicle, and driver. Interactions between these elements: vehicle-environment (V-E) interaction, driver-environment (D-E) interaction, and driver-vehicle (D-V) interaction. At the center is reflected the holistic relationship between elements and the opportunity in the C-ADAS design.

emergency braking (AEB) [17]. Later, lateral control-oriented systems emerge, such as Lane departure warning (LDW) [18], Blind spot warning (BSW) [19], Lane keep assistance (LKA) [20] or Lane change assistance (LCA) [21]. Although these sensor technologies represented a benefit for the surrounding awareness knowledge of the vehicle in terms of road safety, their short range and line-of-sight obstruction problems limit their ability to sense the environment. A new generation of ADAS, named Cooperative advanced driver assistance systems (C-ADAS) [22, 23], has started to be developed, which also incorporates wireless communication devices. The main distinguishing factor between the C-ADAS and ADAS is the visibility of the system. C-ADAS can know the traffic situation miles ahead, while conventional systems know of a few meters around the vehicle. The extended visibility is possible not only due to Vehicle to vehicle communication (V2V) communication but also to Vehicle to infrastructure communication (V2I) and Vehicle to everything communication (V2X) communication [24].

Road safety is an area where internal and external elements converge and interact. Figure 2.1 shows the main elements involved in a RSS: the environment, the driver, and the vehicle. The design criteria of ADAS that do not consider the presence of all these elements, as well as the bidirectional interaction that occurs between them, reduce their level of effectiveness to react in certain dangerous situations and contribute to a degradation of the level of road safety.

An important aspect for the proper functioning of C-ADAS is the performance of the vehicular communication networks, which must be able to guarantee the timely exchange of sensitive information for road safety. Vehicular ad-hoc network (VANET) [25] are powered by vehicular communications and further provide enhancement in driving experience by improving security, infotainment, and robustness. Many researchers have contributed and explored this concept, but due to many security and privacy-related issues, the implementation stage has not matured enough. Only in the last few years has there been a growing commercial interest from the automotive industry in the area of vehicular communications. A considerable volume of research in this field has led to a move from conventional VANET to the Internet of vehicles (IoV) [26]. The fusion between the traditional concepts of VANET and the most recent concepts linked to the Internet of things (IoT), has promoted a very tempting research area today. The IoV concept materializes this integration process between VANETs, IoT, and mobile computing. In this sense, the so-called intelligent vehicles are defined, which are equipped with Internet connection devices to collaborate through data exchange and can even interact with other road users such as pedestrians or roadside units through the exchange of information about the road environment. Under this concept, a traffic management system can be established based on communication and cooperation between the vehicles, the road infrastructure, and the rest of the actors present in the road environment. On-board sensors and processors with remote connection capacity are required in each element of the network, where the information exchange must be managed efficiently to guarantee that the system is useful and capable of providing a road safety benefit.

2.3 Modeling driver behavior through trajectory prediction

Lane change maneuvers on highways present a significant risk to road safety due to their inherent complexity. A comprehensive analysis of such maneuvers requires a holistic modeling approach that accounts for the interdependence between lateral and longitudinal vehicle dynamics. While existing literature has extensively employed unsupervised machine learning techniques to identify driving profiles during lane changes [27], many studies fail to capture the nuanced distinctions between lateral and longitudinal driving behaviors.

Several works leverage clustering algorithms, such as fuzzy c-means [28] and k-means [29], alongside dimensionality reduction methods like factor analysis [28], to classify driving behaviors without relying on labeled data. For instance, [28] proposes a personalized lane change assistance system that categorizes drivers as aggressive, normal, or cautious using factor analysis and fuzzy c-means clustering. These classifications are then used to trigger personalized alerts via back-propagation neural networks. However, this approach does not distinguish between lateral and longitudinal driving styles, which may vary independently—e.g., a driver could exhibit aggressive longitudinal acceleration while remaining cautious in lateral movements.

Recent advances in data-driven lane-change prediction have introduced more sophisticated frameworks that enhance both safety and trajectory forecasting. Notably, [30] proposes a Responsibility-Sensitive Safety model that integrates lane-change intention prediction with real-world driving data to dynamically assess risk and adjust safety margins based on real-time maneuver intent. While this framework improves risk evaluation, it does not explicitly model driver-specific behavioral variations. Similarly, [31] employs driving micro-data and deep learning to predict lane changes and vehicle trajectories, demonstrating high accuracy in maneuver detection. However, like many data-driven approaches, it treats driving behavior as homogeneous rather than accounting for individual driving styles.

Other studies focus on maneuver recognition rather than driver profiling. The work in [32] employs a K-nearest neighbours (K-NN) algorithm to detect lane-keeping, left lane changes, and right lane changes using acceleration and speed data from the Highway Drone dataset [33]. Although this model analyzes both lateral and longitudinal dynamics, it does not differentiate between driving styles during execution. Similarly, [34] introduces a lane change prediction model based on macroscopic cell-based lateral movement analysis, yet it neglects the longitudinal component and disregards variations in driver behavior.

A growing body of research explores intention inference and trajectory prediction in mixed traffic environments. For example, [35] develops a probabilistic model for lane-change intention inference and trajectory prediction, leveraging vehicle interaction patterns on highways. While effective in maneuver anticipation, the model does not adapt to driver-specific execution patterns. In contrast, [36] proposes a dual-transformer architecture to simultaneously predict lane-change intentions and trajectories, improving robustness in heterogeneous traffic conditions and capturing inter-dependencies between human-driven and autonomous vehicles. Nevertheless, the study does not explicitly incorporate driver behavioral traits into its predictions.

Recent works have also investigated early detection of lane changes and diverse trajectory forecasting. In [37], the authors present a method for predicting multiple possible lane-change trajectories based on early behavioral cues, enhancing adaptability in dynamic environments. This aligns with the need for holistic profiling, though the study lacks granularity in style-based trajectory differentiation. Meanwhile, [38] introduces an efficient environment representation combined with deep learning for lane-change prediction, reducing input dimensionality while preserving contextual fidelity through deep learning. This work highlights the trade-offs between real-time processing and predictive accuracy, yet like others, it omits driver-behavior clustering as a preprocessing step for trajectory customization.

The personalization of driver assistance systems has gained traction in recent years, yet challenges remain in ensuring dynamic adaptability to the driver's state and reactions [39]. In the context of autonomous driving, [40] investigates the impact of environmental awareness and V2V data on overtaking performance, modeling lane changes via a linear function. While this approach simplifies trajectory prediction, it lacks realism in vehicle positioning and overlooks driver profile variability—a critical consideration, given the ongoing coexistence of human-driven and autonomous vehicles.

To better emulate human-like control, [41] applies a polynomial model for autonomous lane changes but disregards inter-driver behavioral differences. Similarly, [42] employs fourth and fifth-degree polynomial models to estimate lateral and longitudinal trajectories in virtual environments. While these models improve trajectory prediction, they do not incorporate driver-specific behavioral traits, limiting their applicability in mixed-traffic scenarios.

Analyzing the human factor during the execution of lane change maneuvers on highways, through the study of different driving profiles, constitutes a relevant element when explaining the differences reflected by various drivers or the same drivers in different situations when executing these maneuvers. Considering the existence and mutual dependency of driving profiles associated with lateral and longitudinal movement of the vehicle is an element that enriches the precision with which human driver behavior can be described when executing this type of bidirectional maneuver. This last element allows for obtaining better results in predicting the most probable trajectory of the vehicle during lane change maneuvers on the highway.

2.4 Previous work on ADAS

There are several published surveys on ADAS in Connected and autonomous vehicle (CAV) with different design perspectives. Despite the latent need and challenge of integration and bidirectional interaction of the three subsystems analyzed, to the best of our knowledge, these aspects have not been addressed in the scientific literature. However, some surveys have stood out for the rigor and depth with which they address some of these elements. In this Section we present the aspects in which each one of them stands out, to later point out the shortcomings and discuss the current challenges in the subject.

i) Pathan *et. al.* [43] provide a review of the proposed techniques to implement C-ADAS and intelligent traffic management systems, comparing pros and cons, and also looking at the practically feasible features.

ii) Hasenjäger *et. al.* [39] provide a review of personalization for ADAS and propose a general conceptual framework of personalized ADAS and Human-machine interface (HMI) which can be expected to continuously adapt in interaction with the driver.

iii) Martinez *et. al.* [27] provide a survey on driving style characterization and recognition revising several algorithms, with emphasis on machine learning approaches.

iv) Xing *et. al.* [44] present an overview of the driver intention inference, which mainly focuses on the lane change intention on highways.

v) Bila *et. al.* [45] provides an overview of information and communication technologies-based support and assistance services for the safety of future connected vehicles, given from the perspective of vehicle detection, road detection, lane detection, pedestrian detection, drowsiness detection, and collision avoidance.

vi) Siegel *et. al.* [46] summarize the state of the art in connected vehicles, reviewing the architectures, enabling technologies, applications, and development areas.

vii) Wang *et. al.* [11] focus on heterogeneous multi-sensors fusion technologies, including radar, camera, LIDAR, ultrasonic, GPS, IMU, and V2X, analyzing the necessity of fusion strategies since the limitations of sensors.

viii) Martí *et. al.* [47] proposes an overview of existing and upcoming sensor technologies, applied to common perception tasks for ADAS and automated driving. Specifically focus on artificial vision, radar, and LIDAR technologies of exteroceptive sensors applied in tasks as *(i)* automatic traffic sign detection and recognition, *(ii)* perception of the environment, and *(iii)* vehicles, pedestrians, and other obstacles detection.

ix) Kaiser *et. al.* [48] carries out an author-centric literature review to illustrate the opportunities in using smartphones to detect driver distraction. The authors have reviewed several papers and summarized their application cases, smartphone sensor data used, methods, and results.

x) Arumugam *et. al.* [49] survey driver behavior analysis based on the use of big data. Works related to monitoring driving patterns and fatigue, detecting drowsiness and driver distraction, are discussed.

xi) Zhang *et. al.* [50], investigate mean take-over times from 129 studies with Society of Automotive Engineers (SAE) level 2 automation or higher. How quickly drivers take over control of the vehicle in response to a critical event or a take-over request is an important question in automated driving research.

xii) Sarker *et. al.* [51] review the principal aspects of the sensing and communications technologies, human factors, and controller aspects for information-aware CAV.

Table 2.1 Summarizes these works and shows that none of them have described the ADAS architecture from a holistic and systemic perspective; evaluation mechanisms are hardly mentioned; and only one of them has addressed the interaction between the three subsystems, but not bidirectionally in all cases.

The directionality of the interactions between the vehicle, environment, and the driver is very relevant. For example: consider a situation where a driver approaches an intersection, in which the traffic light just switched to red. In this scenario, the environment is issuing a notification about

Table 2.1: Analysis of the main characteristics and limitations of other published surveys and our proposal in terms of architecture, system evaluation, and interactions between elements, considering D-V interaction, D-E interaction, and V-E interaction; specifying whether this relationship is bidirectional ($<->$) or unidirectional ($->$). Symbol ($*$) represents that this item has not been addressed in the consulted literature.

Articles	Architecture	D-V Interaction	D-E Interaction	V-E Interaction	System Evaluation
[43]	*	**D<−>V**	*	**V<−>E**	*
[39]	**Modular**	**D<−>V**	*	*	**Mechanisms**
[27]	*	**D<−>V**	*	**E−>V**	*
[44]	**Modular and relational**	**D<−>V**	**D<−>E**	**E−>V**	**Mechanisms and metrics**
[45]	*	*	**D<−>E**	**V<−>E**	*
[46] [11]	*	*	*	**V<−>E**	*
[47]	*	*	*	**E−>V**	*
[48]	*	*	**D<−>E**	*	*
[49] [50]	*	**D<−>V**	**D<−>E**	*	*
[51]	**Modular**	**D<−>V**	*	**V<−>E**	*
Our proposal	**Modular, holistic and systemic**	**D<−>V**	**D<−>E**	**V<−>E**	**Mechanisms and metrics**

the state of road safety, representing a form of interaction in the direction environment $->$ driver (E$->$D) and environment $->$ vehicle (E$->$V). This notification can be captured correctly or not by the driver. The vehicle, through its onboard sensors, could detect the red light and then calculate the distances between the elements of the environment, *e.g.* the predecessor vehicles and the intersection. Besides, the surrounding situation is transmitted to other road users through messages corresponding to the V$->$E interaction. On the other hand, the vehicle can sense the driver's reaction to surrounding stimuli by monitoring the driver through on-board devices, which is a form of D$->$V interaction. The system alerts the driver through the V$->$D interaction if his/her reaction is not as expected and communicates to other road users the potential risk, as a V$->$E interaction form. Additionally, the vehicle captures the driver's reaction to the C-ADAS alert notice, like a D$->$V interaction form. Consequently, the C-ADAS takes the vehicle control to guarantee road safety, if the driver's reaction is not as expected, which is a form of V$->$E interaction. In this way, it is observed how the C-ADAS system is responsible for assisting the driver promptly on road safety risks, guaranteeing the correct closure of the cycle started with the notification of the environment to the driver on the red light, E$->$D interaction, and finished with a correct response in the reaction that the driver should have in this situation, D$->$E interaction, to preserve road safety or with the intervention of the C-ADAS at different levels to guarantee road safety. This shows how C-ADAS can mitigate a poor reaction on the part of the driver, resulting from a wrong interpretation of the situation or after the driver's inability to react.

2.5 General considerations of the chapter

A holistic approach to the system in the interaction between vehicle-environment, vehicle-driver, and driver-environment, essential for improving road safety, has not been sufficiently addressed in the literature consulted. Holistic is an adjective that indicates that something is relative or belongs to holism. Holism is a concept created by Jan Christiaan Smuts [52] that he described as “the tendency of nature to use creative evolution to form a whole greater than the sum of its parts.” In general terms, holistic indicates that a system and its properties are analyzed as a whole, in a global and integrated way, through the multiple interactions that characterize them. Holism assumes that all the properties of a system cannot be determined or explained as the sum of its elements, highlighting the importance of the interdependence of those elements. The term systemic is used in the literature with a similar meaning to the term holistic, however, in this work when referring to a systemic perspective we focus mainly on the structural aspect of the system, in the analysis of each of the elements that compose it, and in the bidirectional study of the interactions that occur among them.

Analyzing the human factor during lane change maneuvers on highways, from different driving profiles, constitutes a relevant element when explaining driver behavior. Considering the existence and mutual dependency of driving profiles associated with lateral and longitudinal movement of the vehicle is an element that enriches the precision with which human driver behavior can be described when executing this type of bidirectional maneuver. This last element allows for obtaining better results in predicting the most probable trajectory of the vehicle during lane change maneuvers on the highway. In our work, we highlight the importance of extracting, classifying, and modeling driving profiles of real trajectories associated with lane change maneuvers on highways, considering different behaviors in both directions of movement, which has not been the case sufficiently addressed in the literature.

In this sense, the design of current ADAS has a variety of potential difficulties: reflecting the effects of all kinds of traffic factors on driving safety; describing the interactions between the characteristics of the driver’s behavior, the state of the vehicle and the road environment; or providing an accurate basis for vehicle control. Existing systems that assess driving safety may not work properly if they consider only a limited number of factors and their interactions. Driving is a complex decision-making process due to the intricate relationships between the main elements (vehicle, environment, and driver) and the dynamic nature of these elements. In the driver-vehicle-road closed-loop system, the driver is a crucial component, with unique driving characteristics that vary from driver to driver or even for the same driver in different conditions or days. In the next chapter, we analyze the relationship between the principal elements of RSS and the directionality within each relationship.

3

Systemic analysis of C-ADAS architectures

3.1 Introduction

In this chapter, a systemic analysis of the design of C-ADAS is developed. The inclusion of the aforementioned elements of a road safety system is investigated, as well as how the different bidirectional interactions between each of these elements are manifested. The scientific literature in the area is analyzed, focusing on the proposals for the design architecture of C-ADAS. As a result of this analysis, some limitations in the scope of these works are evident in relation to how the design of these C-ADAS is approached, and a general design architecture for C-ADAS is proposed, which involves in a holistic and systemic way the elements present in road safety and their interrelations. These shortcomings today constitute an unmet need in terms of road safety. Hence the importance of considering, from the design, a holistic and systemic approach that involves the elements of road safety and their interrelations.

3.2 Vehicle-environment interaction

The analysis of bi-directionality in the study of the interaction between driver and environment (V-E) is relevant to all ADAS. If we analyze, for example, the information coming from the environment, we find that the C-ADAS can receive it in several ways: (i) directly, through the information captured by the set of sensors and communication devices that are found on board the vehicle (E $\rightarrow$ V) or else (ii) indirectly, at first through the information captured by the driver through their sensory elements and later, through the information partially captured by devices on board the vehicle in charge of monitoring the status and behavior of the driver as a reaction to the stimuli that he perceives from the environment (E $\rightarrow$ D $\rightarrow$ V). This alternative path of redundancy is relevant to consider, given that sensors and communication devices present limitations and challenges for their optimal operation. This degree of redundancy can only be achieved if the design of the C-ADAS is approached from a holistic and systemic perspective, where the study of directionality in interactions is considered. The works of the state of the art that are described in this section, fundamentally contribute to the first of these two ways (directly).

The main elements associated with the assisted perception module of the surrounding environment are described in this Section, as well as the signaling devices, sensors and communication technologies involved with the operation of this module. On the one hand, this perception "assists" the driver in acquiring information from the environment in which he/she operates. On the other hand, the vehicle, through its signaling and communication devices, communicates to the surrounding environment information on its movement state and also information related to the intention and actions of the driver. In general sense, the sensors and communication technologies improve the range and precision of the information that the driver can perceive, especially in variables that are difficult to estimate such as distances, speeds and relative accelerations between vehicles and other actors in the environment.

With the use of communications, high-level information can be incorporated with a high predictive degree, which allows anticipating changes in the dynamics of vehicle movement before they materialize and can be perceived by drivers. In the same way, the range of perception coverage can be extended and information can be obtained beyond the local environment of the vehicle, associated with scenarios where there are no direct line of sight conditions.

3.2.1 Current state

The discussion of this section begins by grouping the works that use vision and infrared cameras to capture the information from the vehicle-environment interaction, a method that is currently widely used in the automotive industry, but with limitations related to adverse weather conditions, lighting deficient and the high computational cost of image processing algorithms, to name a few. L.Xin *et. al.* [53] propose an intention-conscious model to predict the trajectory based on the estimated lane-change intention of neighboring vehicles, using an architecture with two Long short term memory (LSTM) networks. The first one receives as input sequential data that characterizes the lateral movement of the vehicle to infer the driver's intention to stay in the lane, turn left or turn right. Once the target lane is detected, this indicator is passed as an input to the second LSTM network, which also receives the sequential data of the longitudinal movement of the vehicle, to finally predict its position. From the view point of the ego vehicle, only the features that can be feasibly measured using on-board sensors, such as LIDAR and radar, are used as input. An ego vehicle is a vehicle that has sensors that perceive its environment and is the primary focus in testing, trailing, or operational scenarios. The database used in this paper is from the Next generation simulation (NGSIM)[54].

N.Deo *et. al.* [55] design an LSTM encoder-decoder model that uses convolutional social grouping layers as an enhancement of social grouping layers for robust learning of inter-dependencies in vehicle movement. The social grouping is defined by a structure called the social tensor, which groups the LSTM states of all the agents located around the predicted agent. This is done by defining a spatial grid around the agent being predicted and filling the grid with LSTM states based on the spatial configuration of the agents in the scene. The encoder is an LSTM network with shared weights that learns vehicle dynamics based on trajectory histories. The output of the LSTM decoder generates a probability distribution on future movement for six maneuver classes and assigns a probability to each maneuver class. A lot of complementary information can be captured using visual and map-based cues. For the experiments, they use the publicly available in NGSIM database. N.Deo *et. al.* [56] propose a variation of the architecture designed in [55], using an LSTM network as an intermediate layer to classify and assign a probability to the maneuvers, instead of the convolutional social grouping layer. The results of these analyzes evidenced the importance of modeling the movement of adjacent vehicles to predict the future movement of a given vehicle, as well as the importance of detecting and exploiting common vehicle maneuvers for the prediction of future movement. They use the publicly available NGSIM database for the experiments.

J.Kim *et. al.* [57] present a collision risk assessment algorithm that quantitatively assesses collision risks for a set of local trajectories through the lane-based probabilistic motion prediction of surrounding vehicles. Initially, the target lane probabilities are calculated, representing the probability that a driver will drive or move into each lane, based on lateral position and lateral velocity in curvilinear coordinates. Is assumes that the lateral offset of vehicles with respect to the road center-line is measured from a suitable sensor suite such as a camera, radar, or LIDAR. To estimate the collision probability, the collision risk is assumed as a metric, which is modeled as an exponential distribution, dependent on the Time to collision (TTC). The prediction performance of the lane-based probabilistic model is first validated by comparing the model probabilities from the probabilistic target lane detection algorithm against the maneuver probabilities obtained from real-world traffic data, the NGSIM database.

Y.Hou *et. al.* [58] propose a model of mandatory lane change (maneuver of incorporation into the vehicular flow of a highway) that considers as input variables data associated with the distances and relative speeds between the vehicle that is going to carry out the maneuver and the front and rear vehicles in the lane to which it is intended to enter, in addition to the distance the vehicle has traveled on the merging lane. Bayesian classifiers and decision trees are used to predict the driver's decision to carry out the maneuver or not, determining as the most relevant variable the relative speed between the vehicle carrying out the maneuver and the vehicle in front on the line to which it is intended to enter and, in general, the greater relevance of relative speeds over relative distances. Detailed vehicle trajectory data from the NGSIM database were used for model development (data of U.S. Highway 101) and testing (data of Inter-state 80). Y.Liu *et. al.* [59] develop a deep learning model to evaluate discretionary lane change maneuver decision-making. The model is based on deep neural networks and with the exception of the instantaneous states of the subject and the surrounding vehicles, the historical experience of the drivers and the memory effect from vehicle to vehicle are also taken into account for the final evaluation of the maneuvering situation of change of lane, considering the analysis of time series of trajectory data as part of the historical behavior of drivers. The classifier used is a Gated recurrent unit (GRU) neural network, which is a type of Recurrent neural network (RNN). They use the traffic data of NGSIM database to train and test the model.

A.Benterki *et. al.* [60] present a system for predicting lane change maneuvers on motorways. These maneuvers are classified into left turn, right turn, and lane keeping, using two machine learning techniques: Support vector machine (SVM) and neural networks. The system also estimates, with a time window in advance, the time in which the lane change maneuvers will take place. The lane change process is subdivided into three stages: preparation of the lane change, active execution of the lane change, and completion of the lane change, therefore the system proposes to exploit the changes that occurred during the lane change preparation stage to premature detection of maneuvers. The real driving data of NGSIM database is used for training and testing. W.Ding *et. al.* [61], propose a method that combines high-level policy anticipation with low-level context reasoning. An LSTM network is used to anticipate the vehicle's driving policy (go ahead, yield, turn left, turn right) using its sequential historical observations. This policy is used to guide a low-level optimization-based reasoning process. In this reasoning process, cost maps are defined to represent the context information, associated with certain characteristics of the road such as lane geometry, static objects, moving objects, area enabled for driving, and speed limits. The open-source urban autonomous driving simulator CAR learning to act (CARLA) [62] is adopted to collect the driving data, with the use of a Logitech G29 racing wheel.

H.N.Mahjoub *et. al.* [63] propose a stochastic hybrid system with cumulative relevant history based on Gaussian processes (GP). This design is used within the context of Model based communication (MBC) to jointly model driver/vehicle behavior as a stochastic object and obtain accurate predictive models for mixed driver/vehicle behavior trends in the short and long term (within 0-3 seconds) of the critical dynamic states of the vehicle, such as its position, speed, and acceleration, within the discrete modes of the system, which are equivalent to different long-term behaviors (maneuvers) of the driver. The lane change maneuver is selected as a specific long-term driver behavior, and the lateral position of the vehicle is modeled, through an available set of your already observed instances. This is done by building a cumulative training history of on-the-go maneuver-specific data from identical or relevant maneuvers observed in the driver's recent driving history, and then feeding this training data to the model inference block, such as your initial training set. To evaluate the proposed method, real trajectory data of forty lane change maneuvers from the NGSIM database were used. As a recommendation for network situations with a high degree of congestion, where frequent reception of messages is difficult, a model that combines the constant speed model with the proposed Gaussian regression model, would ensure prediction for both the near future (less than one second), as well as for the far future (between one and three seconds).

The following describes the works that use more specific sensors, of greater complexity and economic cost, such as radar, LIDAR, GPS, and IMU to capture the information from the interaction with the vehicle environment. These devices, on the other hand, have disadvantages due to direct line of sight obstruction problems, in the case of LIDAR radars, and in general to unfavorable environmental conditions. F. Batsch *et. al.* [64] propose a classification model using a GP for the problem of detecting the presence or absence of risk of collision between a vehicle and the vehicle that precedes it, which circulates at a slower speed as a result of being part of a traffic congestion scenario that includes several vehicles. To train the system they use data produced by CarMaker simulation software [65]. The tests are conducted in an automated vehicle equipped with a radar sensor, neglecting the sensor uncertainty in the velocity and aperture angle measurement. A.Zyner *et. al.* [66] present a method based on recurrent neural networks to predict driver intention, by predicting multi-modal trajectories that consider a level of uncertainty. To deal with data sequences of different lengths, sequence fill techniques are introduced, taking as reference the last known position of the vehicle. The data analyzed contains the lateral and longitudinal position track history, as well as heading and velocity. S.H.Park *et. al.* [67] employ the use of LSTM networks to predict the future trajectory of surrounding vehicles based on a history of their past trajectory, formulating the vehicle trajectory prediction task as a multi-class sequential classification problem. For the evaluation of the system, real vehicle trajectory data from a highway environment was employed. To capture the vehicle-environment interaction data, the test vehicle use radar sensors and the IMU sensors.

Next, the works that use, together with the use of cameras, the incorporation of sensors such as radar, LIDAR, GPS, and IMU are grouped to capture the information from the interaction with the vehicle environment. It is worth noting the fact that by using a greater number of sensors of different technologies, a greater degree of robustness of the system is achieved due to the redundancy in the information that can be received, but on the other hand, a greater degree of processing is necessary to data from diverse heterogeneous sources, which increases the computational cost. Y.Liu *et. al.* [68] establish an autonomous lane change (discretionary maneuvering) decision-making model based on benefit, safety, and tolerance functions that analyze not only lane change factors in autonomous vehicles associated with route planning and monitoring but also in addition to the lane change decision-making process. The benefit function considers the relative speed and distance data between the vehicle and the predecessor vehicles in the same lane and the target lane. The safety function considers a minimum safe distance between the vehicle and the successor vehicle located in the target lane, in addition to the relative distance and speed values between the two. Finally, the tolerance function considers relative distance and speed values between the vehicle and the predecessor vehicle in the same lane, avoiding frequent lane changes if the distance between them is too great. In order to verify the effectiveness of the model in real scenarios, is realized a test verification in vehicles. The test vehicle used is equipped with Mobileye, millimeter wave radar, mobile station GPS, AutoBox dSPACE, IMU, and other devices.

In this site are grouped the works that exclusively employ the use of Dedicated short-range communication (DSRC) to capture the information from the interaction with the vehicle environment. Although the use of communications manages to fundamentally compensate for the range limitations presented by the use of sensors and cameras, providing greater flexibility in terms of the road safety information that can be exchanged, there are also a series of limitations associated with all technologies. of wireless communication, such as packet loss, transmission errors and communication delay, to name a few. Y.P.Fallah *et. al.* [69] use the MBC scheme in cooperative FCW system using the example of CAMPLinear and specifically, the collision detection algorithm proposed in [70] and later refined in [71]. This algorithm uses speed and acceleration information as input, both from the following vehicle host vehicle and from the remote vehicle, that is the vehicle ahead in its own lane. The model used to estimate remote vehicle mobility data belongs to the family of follower car models, specifically the model introduced in [72] is used. The concept of hybrid automaton is used [73], which is a well-known method for modeling mixed systems of discrete and continuous states. To evaluate the MBC approach, two configurations are presented (MBC1 and MBC2), which are compared with traditional communication schemes that directly transmit speed and acceleration data. In both MBC1 and MBC2, each vehicle sends its movement models once at the start of the test and then periodically transmits the updates of the model inputs (speed and acceleration). In the case of MBC2, more sporadic additional messages associated with the change in the movement pattern are also transmitted. It is precisely this second configuration that obtains the most accurate results when tracking the movement of a vehicle.

C.L.Huang *et. al.* propose [74] and develop [75] a mechanism based on the real-time estimation of the position tracking error of neighboring vehicles, to manage the cooperative information exchange in the vehicle communications environment. They first evaluate decentralized information dissemination policies for tracking error dependent multiple dynamic systems and then use collision error dependent policy to obtain better tracking performance, finally the transmission probability is calculated for each vehicle each fifty milliseconds based on expected tracking error. Upon receiving information from the channel, each vehicle updates its estimated states of neighboring vehicles using a first-order kinematic model, *i.e.* a constant speed predictor. The main concept of measurements in these algorithms is that the generation of messages from the receiver and the timing of the communication must be determined so that the position tracking error is reasonably limited. A local copy of the neighboring estimators is executed at each local estimator. The sender compares the output of this simulated estimator with its actual state, thus estimating the Packet tracking error (PTE), and determines whether remote vehicles need updated messages from the sender. The decision is made by comparing the PTE with a configurable error threshold, generally defined according to the requirements of the cooperative Road safety applications (RSA).

H.N.Mahjoub *et. al.* [76] propose a technology-independent hybrid model selection policy, based on the MBC scheme, for V2X. The core idea is to implement a hybrid modeling architecture that switches between different modeling subsystems to adapt to the dynamic state of the vehicle. In this particular case, two modeling states are used: one governed by GP, which uses two kernels: one linear and one radial basis function. The another modeling state is defined by the constant velocity kinematic model. A tracking error threshold is used as a selection element when using these models. The results show the effectiveness of the proposed communication architecture both in reducing the required message exchange rate and in increasing the accuracy of remote vehicle tracking. The greater tracking accuracy of the MBC scheme can be attributed to its ability to capture higher-order vehicle dynamics as a result of harsh braking maneuvers and lane-change maneuvers.

H.N.Mahjoub *et. al.* [77] explode the modeling capabilities of the non-parametric Bayesian inference method: GP, integrated into the MBC design scheme, to accurately represent different patterns of driving behavior using only a bank of GP kernels of limited size. To do this, a group of representative trajectories from the Safety pilot model deployment (SPMD) data [78], were selected and the properties of the required kernel bank were explored, to be modeled within of the GP-MBC scheme. The two fundamental metrics used to evaluate the proposed system are: the length of the transmitted message (related to the size of the kernel bank) and the message transmission rate (related to the persistence of the model). The existence of such a kernel bank allows transmitting entities to send only the kernel ID instead of the kernel itself, which consequently reduces the length of the packet. Persistence of the model is understood as the time in which a model remains valid for the prediction, *i.e.* obtaining a margin of error in the prediction lower than the threshold established by the RSA requirements. The results obtained showed the feasibility of using a group of GP kernels of finite size to predict with the precision required by the RSA, the future position of the vehicle through an indirect prediction method, *i.e.* by predicting the values of the time series of the future speed and direction of the vehicle. Indirect position estimation (speed, direction or acceleration) achieves superior results than direct position estimation.

A.Vinel *et. al.* [79] design an analytical framework that considers the behavior of cooperative RSA considering the performance of V2V. The relationship between the characteristics of V2V associated with the probability of packet loss and the packet transmission delay, with the physical mobility characteristics of the vehicle, such as the inter-vehicle safety distance, is analyzed. The case of the cooperative RSA of Emergency electronic brake light (EEBL) defined by the European Telecommunication Standards Institute (ETSI) is analyzed.

Finally, the jobs that use, together with the use of vehicular communications DSRC, the use of cameras and sensors such as radar, LIDAR, GPS and IMU are grouped to capture the information from the interaction with the vehicle environment. Which favors the complement between communication and sensor technologies, taking the best of both and guaranteeing a more complete performance and greater possibilities of facing the challenges in the area of road safety. H.N. Mahjoub *et. al.* [80] design a system for the prediction of the lateral and longitudinal movement of the vehicle. For the prediction of the longitudinal trajectory, nonlinear auto-regressive exogenous models based on neural networks are used. In the case of lateral trajectory prediction, RNN are used. The system use two main sources of information: (i) cameras and on board detection devices such as radars and LIDAR are assumed as the primary information providers for CAV applications an (ii) V2V, which is obtainable using DSRC devices, is regarded as an important supplementary information source whenever it is accessible. The performance of the system is evaluated not only in ideal communication conditions, but also in the presence of scenarios with up to forty percent losses. In this case, a zero hold estimation method is included to combat packet loss or sensor failure and to reconstruct the time series of vehicle parameters at a predetermined frequency. Its evaluation is simulated using real communication scenarios with data extracted from SPMD [78]. H.Du *et. al.* [81] develop a network architecture called vehicular fog computing to implement the cooperative data census of multiple adjacent vehicles circulating in the form of a platoon. Based on this architecture, a greedy algorithm is used to maximize the census coverage (associated with the area ratio and total ratio parameters) and minimize the overlap coverage (associated with the efficiency parameter), enhancing the parallel calculation through of the distributed management of the computational resources of the platoon members. A SVM algorithm is used to merge the census data of multiple vehicles and obtain precise information on the status of the vehicles. Through Occupancy grid filtering (OGF) of the on-board sensors (LIDAR, cameras), the environment is mapped as occupancy states. These OGF maps are integrated into the head vehicle and by means of SVM it is classified when a grid is occupied by a vehicle. To train the SVM classifier, the GPS position data extracted from the NGSIM database is used to locate the vehicles on the OGF map. Finally, the result of the merger of the census data of multiple vehicles (location of the vehicles on the OGF map), feeds the algorithm of a light GRU neural network to predict the discretionary maneuvers of change of lane to classify them into lane-keeping maneuvers or lane-change maneuvers.

E.Moradi-Pari *et. al.* [82] use the MBC scheme to design a small-scale and large-scale modeling strategy of the dynamics of vehicular movement. The representation model of the system to describe the behavior of the vehicle is based on the representation of stochastic hybrid systems, where: (i) small-scale evolution represent actions of braking and acceleration, represented by exogenous auto-regressive models and (ii) large-scale evolution, that include lane change maneuvers and free circulation flows, are represented by coupling these models within a Markov chain. At each model calculation time, all currently available states of the latest version of the model must be explored, and the best-fit parameter values must be found for each of them according to the new observation element. If at least one of these states satisfies the error threshold specified by the application using its new parameter values, the current model is assumed to be fully descriptive for the entire observation sequence received. However, if the minimum error reached given by the current model exceeds the required threshold, it is necessary to introduce a new state to represent the new observation segment and describe the last maneuver of the driver. To evaluate the performance of the proposed models and adaptive cruise control methods, various scenarios were simulated with different realistic data sets, including data from SPMD [78] and driving cycles for environmental protection agency standards testing [83].

We want to emphasize that cooperative driving can significantly contribute to the development of C-ADAS, since this is the most important result of detection, communication, and automation technologies and, in turn, significantly influences the behavior of drivers. Z. Wang *et. al.* [84] provide a review of the literature associated with cooperative multiple CAV longitudinal motion control systems, with an emphasis on the architecture of several cooperative CAV systems. An in-depth discussion of control aspects of CAV systems is carried out, highlighting the main challenges generated by the existence of different information flow topologies, mainly focused on: string stability, communication issues, and dynamics heterogeneity. H. Zhou *et. al.* [85] present a literature review of learning-based longitudinal motion planning models for autonomous vehicles, focused on the impact of these models on traffic congestion. There are surveyed the non-imitation learning method and imitation learning method, and the emerging technologies used by the principal automakers for implementing cooperative driving are described.

Multiple research works have investigated in the context of cooperative driving the design of control systems that favor the management of traffic and/or the crossing of intersections. B. Zu *et. al.* [86] propose a cooperative method for CAV that controls the timing of the traffic lights and manages the optimal speed at which the vehicles should circulate. The optimization of the traffic light times and the calculation of the arrival times of the vehicles at the intersection allows to minimize the total travel time for all the vehicles and individually the fuel consumption of the vehicles. Y. Zheng *et. al.* [87] establish analytical results on the degree of stability, controllability, and accessibility of a mixed traffic system composed of autonomous vehicles and human-driven vehicles. The proposed system allows the flow of traffic to circulate at a higher speed and shows that autonomous vehicles, along with cooperative driving, can save time and energy to smooth traffic flow and reduce traffic undulations. J. Wang *et. al.* [88] propose a cooperative platoon system for CAV, based on a Model predictive control (MPC) with real-time operation capability, to efficiently manage the vehicle tracking behaviors of all CAV in a platoon. The constant time advance method is used to adjust the balance gap between successive vehicles. A. Zhou *et. al.* [89] introduce a smooth-switching control-based cooperative ACC scheme with information flow topology optimization to improve riding comfort while maintaining string stability. A Kalman filter-based predictor is used to estimate the state of the preceding vehicle, suppressing the noise in the measurement and estimating the acceleration of the vehicle, in the event of communication failures.

A. Zhou *et. al.* [90] propose a hybrid cooperative intersection control framework to manage the entrance and exit of a group of vehicles to an intersection. A virtual platoon is defined as a group of these vehicles according to their proximity to the entrance of the conflict zone of the intersection, the location assignment of the vehicles within the virtual platoon differs from their real relative locations. This virtual platoon is obtained by linearly projecting the distances at which the vehicles are from the center of the intersection, and then platoon control rules are applied to manage the movement of vehicles approaching the intersection.

The management of the flow of information exchanged in a V2V environment has been addressed in [91]. Wang *et. al.* develop mathematical modeling based on queues to manage the transmission of information of multiple classes, with different levels of delay, according to the cooperative RSA. These authors also addressed traffic management in mixed environments with the presence of human-driven vehicles and CAV, analyzing the differences in the principles of route choice and the traffic patterns followed by human-driven vehicles and CAV in [93] and considering the use of preferential circulation lanes with free access to CAV in [92].

Table 3.1 summarizes the main works consulted that address elements of the vehicle-environment interaction. The directionality in which this interaction is approached is analyzed, as well as the way in which it is implemented.

3.2.2 Challenges

The addressed challenges in this section are focused on the sensors and communications technologies. The main challenges about sensors technologies are:

i) The sensor occlusion with respect to the line of sight of the objects and other road actors. The good performance of these technologies is affected under various climatic and environmental conditions, such as roads with markings covered by snow, heavy rain, or dense fog. Objects, people, and animals located in the vicinity of the vehicle, or obstructing each other, represent serious security problems for detection by these devices. This phenomenon is not so serious when the objects are located at greater distances, where the processing algorithms can help the sensing devices improve detection tasks. These drawbacks can be minimized by sensor redundancy as in [94], where a 360-degree vision system is used for parking assistance.

ii) The high computational resource consumption of image processing algorithms present in camera-based sensors. Detection at distances greater than 200 meters requires the use of ultra-high resolution cameras for the sensing of small details in the target image. Therefore, powerful image processing algorithms are required to analyze the high volume of image data and extract useful information from the noise associated with it [95], which continues to represent a limitation to the adequate processing in real time that road safety demands.

iii) The high cost of specific hardware technologies. Some well-established technologies in the market, such as vision cameras or radars, have managed to establish themselves in large-scale production, lowering their production costs. This situation, however, differs from other more specific technologies for the automotive industry, such as LIDAR devices, whose standard incorporation in vehicles considerably increases their price, depending on various factors such as the type of use for the one that the vehicle is destined for, or the sensing capabilities in 2D or 3D.

The main challenges about communications technologies are:

Table 3.1: Works in which vehicle-environment interaction is addressed. The “ideal” behavior means that the authors do not consider the losses of the communication channel. The works that are not grouped within “ideal” behavior or “non-ideal” behavior, are those in which the use of communications is not considered for the design of ADAS.

Articles	**Directionality**		**Implementation of the interaction**			**Communications**	
	V− >E	**E− >V**	**Data source**	**Data type**	**Environment**	**“non-ideal” behavior**	**“ideal” behavior**
[80]		X	Cameras, radar, LIDAR and DSRC	Real	Real	X	
[64]		X	Radar	Simulated	Simulation		
[53] [55] [56] [57] [58] [59] [60]		X	Cameras	Real	Real		
[61]		X	Cameras	Real	Simulation		
[66]		X	LIDAR	Real	Real		
[67]		X	Radar	Real	Real		
[68]		X	Cameras, radar, GPS and IMU	Real	Real		
[81]	X	X	Cameras, LIDAR and DSRC	Real	Real and Simulation		X
[69]	X	X	DSRC	Real and simulated	Simulation	X	
[63]	X		Cameras	Real	Real		
[82]	X	X	Cameras, radar, LIDAR and DSRC	Real and simulated	Simulation		X
[74] [75] [79]	X	X	DSRC	Simulated	Simulation	X	
[76]	X	X	DSRC	Real and simulated	Real	X	
[77]	X		DSRC	Real	Real	X	
[84]	X	X	DSRC	Real and simulated	Real and simulation	X	
[85]		X	Cameras, radar, LIDAR	Real and simulated	Real and simulation		
[86]	X	X	DSRC	Simulated	Simulation	X	X
[87]	X	X	DSRC	Simulated	Simulation		X
[88]	X	X	Cameras, radar, LIDAR, DSRC	Real and simulated	Simulation		X
[89]	X	X	Cameras, radar, LIDAR, DSRC	Real and simulated	Simulation	X	
[90]	X	X	DSRC	Simulated	Simulation	X	
[91]	X	X	DSRC	Simulated	Simulation	X	
[92]	X	X	DSRC	Simulated	Simulation	X	
[93]	X	X	DSRC	Simulated	Simulation	X	

i) The scarce deployment of network infrastructure in the road environment. The massive implementation of V2I technologies is an expensive and time-consuming task. Various costs must be assumed depending on the location environment, such as the installation of nodes, bandwidth, and energy support, and the subsequent maintenance of the installed equipment. An important aspect is the traffic capacity of these networks, given that cooperative road safety applications require a high degree of penetration of vehicles with installed connection capabilities, *e.g.* in the case of the cooperative collision warning application, a density greater than 60 % of the total connected vehicles is desirable [96].

ii) The robustness of current communications networks to operate in a vehicular environment, evidenced by loss of transmitted packets and other problems, such as communication channel congestion, transmission delay, fading, and shadowing in signal propagation. The reliability and accuracy of the exchanged data is vital to ensure the proper functioning of cooperative applications, as inaccurate data can ruin bad judgment when making a decision related to road safety. These networks must guarantee robustness against sending duplicate messages or false positives in the issuance of alerts. Furthermore, even when the data exchanged is accurate, the freshness of the information is required, due to the importance of the temporal component of road safety data. It is not enough to detect a risk situation on the road and communicate it accurately, it is also required that this information arrives in time to be able to react appropriately to said danger and thus guarantee the good global operation of cooperative security applications. In this sense, emerging technologies such as Fifth generation wireless communication technologies Advanced (5G-Advanced) can provide greater capacity and reduced latency when exchanging this sensitive information and it will provide by enabling vehicles to communicate directly with each other V2V, transportation infrastructure V2I, and Vehicle to network communication (V2N). [97] [98]. With the progressive increase in the volume of data, the need arises to have tools and algorithms capable of efficiently processing them. Raw data handling is becoming less feasible and more expensive. Dimensionality reduction techniques are required to identify patterns in data and achieve more scalable developments [99].

iii) The security and privacy of the information exchanged represent an important challenge to consider when designing C-ADAS. As in any communication network where private information is exchanged, the issue of data security and integrity is vital, but in these networks in particular it is even more important since people's lives are at stake and in a sense overall road safety. Hacking activity in networks without adequate protection can cause attackers to take control of a vehicle's security systems causing traffic diversions or the activation of the emergency braking system, stealing personal data from users, and in the worst case scenario, causing the conditions for the occurrence of traffic accidents. These challenges are part of the Original equipment manufacturers (OEM) and after-sales connectivity systems [100], which are especially sensitive in automated vehicles with electronic control of their actuators. Another current problem is that network security approaches can, on occasion, compromise vehicle security due to the overload of exchanged security information, generating excessive delays in communications, associated with authentication mechanisms, validation, and security certificates.

The shortcomings that still persist, in the study and achievements related to the V-E interaction, are the inability to operate bidirectionally, the lack of holistic integration between the detection, communication, and processing technologies, as well as the joint operation with the driver subsystem, which allows exploiting the use of these redundant pathways to obtain information from the environment. In addition to this, there are also the challenges associated with the functioning and operation of these sensing (e.g. resolution and scope) and communication (e.g. reliability and delay) technologies, which undoubtedly limit the effectiveness of the current implementation of the proposed C-ADAS.

3.3 Driver-vehicle interaction

The analysis of bidirectionality when studying the interaction between driver and vehicle (D-V) is relevant for proactive decision-making in a vehicular context. Let us consider an example where the driver is developing aggressive driving on the road, and the C-ADAS detects this behavior (D $\rightarrow$ V interaction). This characterization of the driver will allow the C-ADAS to estimate possible risk situations when this vehicle approaches other aggressive or extremely conservative drivers. Given such knowledge, convenient and personalized messages could be sent to moderate the conduct of those involved, which is a more complex form of interaction (D $\rightarrow$ E $\rightarrow$ V). This redundancy alternative path is relevant to consider, given that HMI devices have limitations and challenges for optimal performance in cooperative environments and sometimes limited customization features. This degree of redundancy can only be achieved if the design of the C-ADAS is approached from a holistic and systemic vision, with bidirectional interactions among subsystems.

The D-V interaction describes the main elements related to the HMI module. This area is in charge of presenting the driver with the information about the environment acquired by the sensors and communication technologies and the information of the vehicle itself, obtained from the internal communication ways like the CAN Bus. Similarly, it is also necessary to sense the driver's reaction to the operation of the assistance system. At the same time it is in charge of materializing, through the vehicle operation, the driver's actions on the environment that surrounds him. As an "assistance" system, its first function should be to learn about the particular characteristics of the driver, understand their actions, and be able to model their behavior (instantaneous and historical), to identify the "particular assistance needs" that the driver requires. It must also be able to communicate that knowledge acquired to the rest of the actors on the road, as part of the concept of cooperative knowledge. Note that, the warnings and vehicle take-overs should be limited to situations evaluated with a high degree of certainty and personalization. The redundant information in terms of sources, modules, and communication paths, as well as the prior and continuous characterization of drivers and their driving styles, prevents unnecessarily modifying the driving styles and regulating those, in which aggressive behavior represents a danger.

3.3.1 Current state

The discussion of this section begins by grouping the works that use the devices that allow the driver to operate the vehicle while driving to capture the information of the driver-vehicle interaction, obtained through the internal communication buses of the vehicle, for example, the CAN bus. Although this information is present in most modern vehicles, it is not currently sufficiently exploited by the automotive industry to establish a personalized interaction between vehicle and driver. W.Wang *et. al.* [101] propose a method to predict the driver's braking intention in car-following scenarios from a perception-decision-action perspective according to his/her driving history, considering the following variables: vehicle speed, distance between the host vehicle and vehicle preceding, relative speed between them and TTC. The system combines Gaussian mixture model (GMM) with Hidden Markov model (HMM) to infer the driver's braking action given the state of the driving situation, using data from the CAN bus, cameras, and radars installed in the vehicle. R.Dang *et. al.* [102] design an ACC system with a LCA. First, the risk associated with the lane change is analyzed by calculating the minimum safe space between the host vehicle and the surrounding vehicles. To calculate this risk, a driving style factor is introduced, which modifies the calculation of the minimum safety distances between the vehicle performing the maneuver and neighboring vehicles. The value of this factor is set by the driver, values greater than one indicate conservative conductors, and lower values indicate aggressive conductors. Finally, a coordinated control algorithm is developed using predictive model control theory that limits the longitudinal acceleration of the vehicle, to guarantee better performance in terms of comfort in movement.

B.Zhu *et. al.* [28] propose a personalized driver assistance system that includes driver profile identification for lane change assistance. Initially, the data obtained through driving simulators are analyzed and statistically processed to select the most relevant variables. With these results, the fuzzy c-means clustering algorithm is used to extract different conduction profiles. Three clusters are generated, which are associated with aggressive, normal, and conservative profiles. A neural network classifier, optimized by a particle swarm algorithm, is used to detect these conduction profiles. According to the profile of the driver identified by the system, preset values are determined for the execution time of the lane change maneuver and the minimum safety distance margin required with the preceding vehicle in the lane to which the change is made, to avoid a forward collision. These personalized values are included in the analytical model to calculate the risk of collision associated with lane change and subsequent behavior of the following vehicle in the destination lane. C.Su *et. al.* [103] design a forward collision system that employs a method to recognize driver intent and driving behavior, based on the GMM. The proposed system has the advantages of adapting the model and the ability to generate probability densities in arbitrary shapes. In addition, it allows real-time implementation and has high precision. A precise recognition model of the driver's driving behavior is first established and verified in a real-time driving simulator with 36 drivers as samples. Then, an FCW algorithm is designed with a braking execution strategy and alarm classification based on the results of the driver's driving behavior recognition. Drivers are classified as conservative, normal, and reckless. Mantouka *et. al.* [29] identify driving styles based on unsupervised classification techniques, using acceleration and speed data collected through the use of smartphones. Initially, the styles are grouped into aggressive and non-aggressive behaviors, to subsequently analyze additional unsafe behaviors associated with distraction and risk-taking. Once the driving profiles have been detected, the driver's average behavior and its persistence or volatility in different situations are analyzed.

Works that use vehicle driving devices to capture the information of the driver-vehicle interaction have been grouped here, including the use of devices that emit visual, sound, or vibrotactile alerts to the driver and analyze their reaction to these alerts. Although the use of devices that alert the driver is increasingly being addressed by the automotive industry in modern vehicles, the personalized interaction between vehicle and driver, which also includes the issuance of personalized warnings according to the driver's behavior, continues to be a challenge in this area. W.Yang *et. al.* [104] proposes a collision warning system based on V2V. The algorithm initially detects the intention of the driver of the preceding vehicle, which is transmitted, together with other movement parameters of said vehicle, to the following vehicle through the V2V module. Finally, the safety application that runs in the following vehicle estimates the risk of potential collision with the information received through V2V and with the movement parameters of the vehicle itself, to alert the driver, outperforming systems based on TTC thresholds. J. Bavendiek *et. al.* [105] present a HMI design method based on the concept of metaphors to analyze and improve the vehicle-driver interaction through the design of HMI interfaces. This methodology, whose best-known example is the design of computing machines based on the desktop interface, enables a friendlier relationship between man and machine, achieving improvements in the design of the HMI interface installed in the vehicle. The study focuses on describing a procedure to identify metaphors in the HMI environment of the automobile. Subsequently, the development of new HMI concepts based on the identified metaphors is proposed.

Table 3.2: Works in which driver-vehicle interaction is addressed. The type of personalization described in the consulted works is analyzed from 2 approaches: (i) the action that the driver exerts on the driving elements of the vehicle (described as an action on the vehicle) and (ii) the reaction that the driver adopts before the notices and alerts sent by the system (described as a reaction to ADAS).

Articles	**Directionality**		**Implementation of the interaction**			**Personalization Types**	
	V− >D	**D− >V**	**Data source**	**Data type**	**Environment**	**Action on the vehicle**	**Reaction to ADAS**
[101]		X	CAN bus	Real	Real	X	
[102]		X	CAN bus virtual	Real	Simulation	X	
[28] [103]		X	CAN bus virtual	Simulated	Simulation	X	
[29]		X	Smartphone sensors	Real	Real	X	
[104] [105]	X	X	CAN bus and warning indicator	Real and simulated	Real and simulation	X	X
[106] [107] [108]	X	X	CAN bus and warning indicator	Real	Real	X	X
[109]	X	X	Eye-tracker and warning indicator	Real	Simulation	X	X

S.M.Iranmanesh *et. al.* [106] design a FCW system that considers the driver's historical braking profile in the face of previous alert events to establish a reaction threshold. The time of advance (time headway) for a vehicle is understood as the time it would take for the vehicle to travel, circulating at its current speed, and the distance between its front part and the front part of the vehicle that precedes it. The main metric is the alert activation defined as a warning triggering threshold, considered as the normal level of risk tolerance, to determine the need to issue an alert to the driver in the event of a possible dangerous situation. The caution deceleration threshold is also defined to avoid false alerts and discard situations outside a dangerous situation, such as stops or turns in the presence of traffic lights. The system continuously monitors driver distraction through data obtained from the CAN bus associated with the state of the acceleration pedal, speed, acceleration, and turning angle, among others. Detection of driver distraction is performed by SVM classifiers and multi-layered perceptron neural network. Q.Sun *et. al.* [107] propose a LCA system based on the identification of the individual driving profile, determining an optimal alert threshold that varies as the characteristics of the individual profile change. The authors use the Signal detection theory (SDT) to develop a method to determine the characteristics of the driver in a lane change maneuver. The target signal is defined as the operation to complete the maneuver by the driver and as a noise signal the operation to abandon the maneuver, which is associated with warning and non-warning criteria for the lane change warning system. The warning threshold is adjusted in real time, according to the particular characteristics of each driver during the maneuver. According to the authors' definition, those who complete the lane change maneuver even in the presence of the safety system warning signal are grouped as aggressive drivers, and those who abandon the lane change execution even in the absence of the system alert signal are grouped as conservative drivers. Based on the analysis of the existing warning criteria, variables such as the TTC and the relative distance between the subject vehicle and the rear vehicle in the destination lane were used as warning indicators, while the initial warning threshold according to the difference the speed of the subject vehicle was selected for the adaptive algorithm.

J.K.Choi *et. al.* [108], propose a personalized design of the next generation HMI interfaces, where the driver can personalize the way in which he/she interacts with the vehicle and, in turn, it responds in a personalized way, identifying the characteristics and the state of the driver in a given situation. The proposed system consists of elements such as sensors embedded in the car, an adaptive inference engine that analyzes the driver-vehicle interaction, and an advanced digital platform in the vehicle cabin, which accesses the data obtained from this interaction. K.Dargahi Nobari *et. al.* [109] proposes a control scheme with feedback that considers the state of the driver as an input element for the system that analyzes the driver-vehicle interaction. Sensors such as (*e.g.*, eye-tracker, physiological sensors) are used to detect the state of the driver. This result is compared with previously established situations to then design a policy that regulates the generation of stimuli tending to reduce the degree of criticality of the traffic situation. Table 3.2 summarizes the main works consulted that address elements of the driver-vehicle interaction. The directionality in which this interaction is approached is analyzed, as well as the way in which it is implemented.

3.3.2 Challenges

The current challenges of this section are focused mainly on the personalization of the ADAS and the motion modeling.

i) The personalization of the ADAS, which should consider the driving profile, preferences, and peculiarities of the driver. In the design of HMI devices, not only the driver's action on elements of the vehicle that determine its state of movement should be considered but also feedback elements through visual or sound information that alert the driver about the consequences of his/her action and that of the other actors in the environment around road safety. There is a common assumption in the personalization of ADAS systems that the driver is more comfortably adjusted to systems that implement a driving style similar to his/her own, but in practice, determining the optimal driving style for each individual driver is a very challenging task. In current systems, the process of interaction between driver and vehicle through the HMI limits the driver's ability to correct and shape the system to establish a driving style that provides greater comfort. This interactive exchange phase between vehicle and driver requires further development. Another aspect to deal with in greater depth is the fact that the personalization process must be conceived as a continuous process. It is not enough to limit the customization process to obtaining and establishing a personalized system, since the drivers, influenced by various internal and external factors present on the road, can modify their preferences and driving styles in certain situations. For this reason, this phase of interactive exchange between driver and vehicle must last over time as a continuous process, improving its usability characteristics and finally, its benefit for road safety.

ii) Modeling the longitudinal and lateral motion is a challenging task, which includes predicting the driver's intention in response to the dynamics of the surrounding environment. Accurate sensing of the surrounding environment and prediction of the intent of neighboring vehicles represent the biggest challenges for modeling the lateral and longitudinal motion of a vehicle by considering human driving preferences in the process. When the distances between vehicles, pedestrians, and objects are small, the degree of precision of on-board sensors must be very high. Similarly, if we take into account that the movement of vehicles on the road is a complex scenario of interaction between several actors, it is crucial to have tools that allow us to infer the intention and future behavior of neighboring vehicles. The failure of any of these two elements can lead to a tragic result, dynamic instability of the vehicle, and even a traffic accident. When dealing with a high risk of collision, the development of conservative algorithms is chosen, even if this sacrifices aspects of the system such as efficiency, comfort and acceptance of drivers and passengers. Incorporating V2V and V2I communications into the system can overcome these limitations and inefficiencies of non-cooperative systems [110].

iii) Vehicles with SAE level 3 automation allow the driver to freely participate in tasks not directly associated with driving, but the driver is required to be able to disconnect from these tasks to regain manual control whenever required by the system. This requirement, related to the term takeover, represents a challenge to consider in the study of D-V interaction. This capability demands that the driver carry out this process of returning to driving tasks, ensuring a smooth, and at the same time, safe transition towards taking control of the vehicle. This challenge requires a novel design when addressing the D-V interaction (between the driver and the automated system), which considers the driver's ability to take control in real-time [111]. Situational awareness may be diminished in highly automated driving environments compared to manual driving environments, if drivers are engaged in non-driving tasks [112]. In [113] the authors present a novel predictive haptic takeover controller to further explore the safe and smooth interaction mechanism during the takeover of autonomous vehicles.

The works described do not show the required bidirectionality between driver and vehicle, nor a holistic integration between subsystems, which is essential for information redundancy and system reliability. But the more specific challenges, in D-V interaction, are associated with the degree of customization of these HMI devices for the timely display of alerts to the driver, high-precision modeling and prediction of the driver's intentions, and the execution of the maneuver, and guarantee the safe takeover transitions. Note that these interaction challenges not only limit the implementation of the proposed C-ADAS but also the progress in autonomous driving.

3.4 Driver-environment interaction

The analysis of bi-directionality in the study of the interaction between driver and environment D-E is relevant for the C-ADAS to be aware of how attentive drivers are to the environment and how they react to eventual risk situations. Let us analyze, for example, the information provided by the environment and directed toward the driver, which can be a stop warning signal. This information can be received: (i) directly by the driver (E $\rightarrow$ D), or (ii) indirectly, via a stop notification issued from a roadside unit and notified by the vehicle to the driver (E $\rightarrow$ V $\rightarrow$ D). Regardless of the way in which the driver perceives the stop order, the C-ADAS must guarantee the vehicle's stop. In this sense, it is vital to determine as soon as possible if the driver is aware of his surroundings and will carry out the braking maneuver effectively. For this purpose, the C-ADAS must continuously monitor the driver's behavior through sensors, cameras, and wearable devices on board the vehicle (D $\rightarrow$ V). In this particular case, if the driver does not react adequately, then the C-ADAS itself can issue an alert to stop, contributing as a redundancy path that guarantees that the information that the driver should receive is received satisfactorily (D $\rightarrow$ E, D $\rightarrow$ E), but if the risk situation cannot be fully mitigated by warning or vehicle takeover, then a general stop warning should be issued to alert other drivers and vehicles of the situation (D $\rightarrow$ V $\rightarrow$ E). It is important to consider this redundancy route by the C-ADAS, given that there may be innumerable occasions in which the driver fails to perceive relevant information in terms of road safety, either due to distraction or due to impairments in his/her driving operational capacity. This degree of redundancy can only be achieved if the design of the C-ADAS is approached from a holistic and systemic perspective, where the study of bi-directionality in interactions is considered. The works of the state of the art that are described in this section, fundamentally contribute to the indirect ways of obtaining this information and in this sense, they are relevant in terms of the use of sensors, cameras, and wearable devices to monitor the status and behavior of the driver.

The importance of the natural perception module lies in the fact that the drivers form a personal reality about their surrounding environment, make their own assessment of risk situations, and the interaction between the different actors on the road, and based on this determines their primary behavior, before interacting with the ADAS. This module of natural perception has an amazing capacity to process large volumes of very diverse data, this versatility of processing in humans still represents a challenge for the computer systems that exist in the present. However, it also has real limitations regarding the level of precision when estimating kinematic variables associated with the movement of vehicles, something that is vitally useful in potential risk situations on the road. This can be seen reflected in the deficient calculation of the adequate distances to carry out lane change or overtaking maneuvers, maintain an adequate safety distance with the vehicle in front, and detect the presence of vehicles approaching from behind in adjacent lanes, among other common situations that arise daily. As an active element within the dynamics of the road environment, the drivers modify the state of said environment through their actions and reactions. The use of various signals by the drivers represents how they interact with the surrounding environment, among these we can mention: (i) visual signals through the vehicle's lighting devices, such as turn signals, position indicator lights, or stop lights, (ii) sound signals through the use of the horn and (iii) body signals through gestures or so-called "hand signals" of the drivers. The technological development associated with the infotainment area, together with the challenges imposed by the increase in the complexity of the road infrastructure and the increase in traffic congestion, have shown a growing use by drivers of navigation applications through the use of maps for route planning, which to some extent conditions their future behavior and mobility.

3.4.1 Current state

The discussion of this section begins by grouping the works that use cameras to capture information on the driver-environment interaction, a method that is currently widely used in the automotive industry to analyze the behavior of the driver inside the vehicle. Qiao *et. al.* [114] propose a fatigue detection system using images of the driver's face, eyes, and mouth, obtained by a smartphone camera. Signals of fatigue such as blinking of the eyes are detected using a Haar qualifier [115], while sudden movements of the head are captured by calculating the variance of the centroid of the face. Yawning is detected by measuring changes in the geometry of the mouth, through the Canny active contour method [116]. Mandal *et. al.* [117] proposes a fatigue detection system for bus drivers, using a Percentage of eyelid closure over the pupil over time (PERCLOS) method to determine the level of eye-opening. Initially, the system locates the position of the driver's head in the incoming image, to detect the location and orientation of the eyes. Yuen *et. al.* [118] proposes a system to monitor the driver's activity during driving, analyzing information related to facial reference points, which is used for the detection of the face and the position of the head. Its performance is analyzed under various lighting conditions and the degree of occlusion of the driver's face, which enables the system to be able to detect when there are occluded parts of the face and consequently achieve better estimation results in this situation.

Next, the works that use smartphones to capture the information of the driver-environment interaction are grouped together, a method that allows, in addition to the use of the smartphone camera, the use of various sensors embedded in it, which allows obtaining various physical variables that favor a more complete analysis of the driver's actions while driving. One of the principal causes of vehicle accidents is the distraction during the driving process. Eraqi *et. al.* [119] presents a vision-based system that uses Red green blue (RGB) images obtained from the rear camera of a smartphone to recognize distracted driving postures, composed of a face detector, a hand detector, and a skin segmenter. The proposal is implemented using Convolutional neural network (CNN), obtaining results of the order of 90 % accuracy, however, its performance overhead is higher in a real-time configuration. Janveja *et. al.* [120] present a smartphone-based system for the detection of driver distraction by analyzing gaze tracking through the left and right rear-view mirrors and for fatigue detection by monitoring yawning and eye blink frequency. The system is designed to operate in low light conditions using two configurations: in the first, a Near infrared (NIR) Light emission diode (LED) coupled to a smartphone is used; and in the second, a generative adversarial network is used to synthesize a thermal image obtained from the RGB camera of a smartphone. The results show a better behavior of the system when NIR images are used. Kapoor *et. al.* [121] designed a smartphone-based driver distraction detection system capable of operating in real-time, which alerts the driver with a beep once distracted behavior is detected. The ten classes of distracted behavior are drawn from the State Farm distracted driving database [122], which is used for fine-tuning the four pre-trained CNN models, namely MobileNetV1, InceptionV3, VGG-16, MobileNetV2. Xie *et. al.* [123] present a system for the detection of driver distraction based on the use of data from GPS and IMU sensors of a smartphone, during the performance of turning maneuvers, lane change, lane maintenance, stop and near stop. According to the results published by the authors, the best performance of the distraction detector, in terms of the F1 score metric, is obtained for lateral maneuvers (turn and lane change), this is assumed since the data used are more sensitive to this type of movement. This metric is defined by the authors themselves, using sliding windows to extract the temporal characteristics of the data obtained from the sensors and weighting the classification result of each sliding window according to the number of normal driving or distracted driving labels.

Next, we describe a work that uses the devices and internal sensors of the vehicle to capture the information of the driver-environment interaction, through physical variables that they describe as the result of the driver-environment interaction directly in the vehicle. Hu *et. al.* [124] present a system to detect abnormal driving behaviors, such as recklessness, fatigue/drunkenness, and use of the smartphone. Unlike other works where the driver's activity is monitored by cameras that capture the image and movements of the driver while driving, in this study the authors analyze vehicle movement patterns, such as sudden acceleration and braking with a delayed response to traffic conditions, to detect abnormal driving behavior. To quantitatively assess these behaviors, a driver abnormality index is proposed. Qi *et. al.* [125] presents a passenger and driver activity detection system by means of acoustic recording devices for the recording and inference of activity inside the vehicle and by means of IMU and GPS sensors, including On-board diagnostic (OBD)-II [126] data for human activity detection and for the detection of vehicle movement patterns, like braking, lane changes and turns.

The works that use wearable devices and biomedical sensors have been grouped to capture the information of the driver-environment interaction, which allows a deeper analysis from the biological and physical point of view of the behavior of the driver during driving. The use of these devices, however, presents a challenge to the design of less invasive systems for the driver, with the aim of not distracting them or making them uncomfortable during the driving process, together with the necessary medical restrictions so as not to compromise the driver's health. Rohit *et. al.* [127] exploit the use of wearable Electroencephalogram (EEG) sensors for real-time detection of driver drowsiness. An SVM classifier is used to detect drowsy states, by means of a spectral analysis of the EEG signals obtained from the drivers. Additionally, the blink duration parameters were extracted and analyzed, which were less favorable than the spectral analysis for the detection of drowsiness. Li *et. al.* [128] develop a system for early detection of driver drowsiness using not only the signal obtained from a wearable EEG sensor but also incorporating a gyroscope coupled to the driver's head to analyze the movement of the driver's head. Different from previous works, this study analyzes the feedback of the system when stimulating the driver by means of transcranial direct current, to improve their state of alertness in real-time while driving. In the same way, visual and vibrotactile alerts are presented to the driver to combat the different levels of drowsiness detected by the system. Guo *et. al.*[129] present a study to analyze the transition process of the driver's intention, caused by the driver's emotions. Various visual, olfactory, and auditory stimuli are used to generate emotions in the driver before driving tests and maintain them during the driving process. The results show high accuracy and reliability in estimating the driver's intention through the evolution of his/her emotions, and this system can be used to design personalized driving alerts in the human-machine interfaces of modern vehicles.

Finally, the works have been grouped in which the driver plans his/her future route through the selection of points of origin and destination, which may undergo modifications according to the dynamic characteristics of the environment. Through the ADAS assisted by navigation maps, the driver is an active agent that modifies the environment, through route planning the state of the road environment is modeled. An assistance opportunity could be designed based on specific sections present in the routes defined by the driver, such as traffic between roads with different vehicle flow capacities, entering roundabouts, overpasses, joining or exiting motorways, lane changes, turns at intersections, among others. All these maneuvers involve risk and through cooperative knowledge of the pre-established routes, this risk can be minimized at these critical points for road safety. In these cases, an explicit notification prior to carrying out maneuvers at these points could mean the difference between the occurrence or not of a road accident. Xu *et. al.*[130] present a study focused on improving intelligent transport management, to combat the problem of predicting road congestion levels in real time. To do this, they develop an analysis method implemented in big data and cloud computing platforms, which enriches the traditional method based only on the use of historical driving data, also incorporating the users' travel plans, contained in the vehicle navigation information associated with route planning. The system visualizes the data from this analysis by means of heat maps and sends personalized notifications to drivers according to the particular situation of their road environment.

Withanage *et. al.*[131] develop a personal navigation system that simplifies the user's interpretation of the translation of voice commands and visualization of the routes in the navigator. During this process, the system initially translates the audio files into text using Automatic speech recognition (ASR), then uses Natural language processing (NLP) techniques to retrieve previously undetected navigation information, and finally displays the generation of trajectories on the map using the development interface provided by Google map. Keerthana *et. al.*[132] designed a navigation assistant based on voice instructions as a human-machine interface, to guide the user to the requested destination through text-to-speech techniques to show the source and destination addresses on the map, allowing the planning algorithms to get route information by recognizing the user's voice instructions. The addition of voice recognition techniques represents an improvement to the navigation tools for an individual client who needs to navigate in an obscure landscape. Zhou *et. al.*[133] propose a system for planning tourist routes by correlating data associated with tourist places with precise data on the personal interest of the individual. To do this, it studies the behavior and personal needs of tourists and based on this, it proposes tourist places with views and characteristics that are related to the interests previously analyzed. This method allows us to obtain a more personalized route planning and its viability is testified through the design and execution of experiments with real data. Rathnayake *et. al.*[134] present an interactive system for planning and evaluating travel routes, which analyzes the distances and weather conditions of the moment to carry out the evaluation of the trip previously established by the user. As a result of this analysis, recommendations and improvements to the initial travel plan are established, guaranteeing optimization of the journey in terms of distance and coverage of the different destinations selected a priori by the user.

Here, we consider driving behavior by capturing and detecting from on-board sensors the bodily and physiological reaction that the driver manifests to stimuli from the environment. The knowledge of the D-E interaction can be correlated with the knowledge of the D-V interaction to be able to conclude about the ability or not of the driver to respond to certain events. Through V2V communication, the C-ADAS knows that the ego vehicle is approaching the vehicle in front of it (E-V interaction), simultaneously, through on-board cameras, it perceives drowsiness in the driver (D-E interaction) and, in turn, low pressure on the brake (D-V interaction). Consequently, the intervention of the C-ADAS in driving is required to avoid the accident, given the inability of the driver to react appropriately.

3.4.2 Challenges

The current challenges of this section are focused mainly on capturing the information associated with the driver's natural perception process and minimizing the degree of distraction to the driver.

i) Determining the main implicit and explicit characteristics that allow capturing the information associated with the driver's natural perception process about the road environment. Actually, the most used explicit characteristics to describe the driver's status are the movement of the eyes, head, hands, and feet, which reflect the state of attention of this and the body's actions of reaction to the traffic's dynamic. These are mostly monitored through vision and infrared cameras installed inside the vehicle, which is susceptible in many cases to adverse environmental conditions and poor visibility conditions.

ii) How to make the sensing of these characteristics as less invasive as possible, to minimize the degree of distraction to the driver. On the other hand, the implicit characteristics are related to drunkenness, drowsiness, blood pressure, or heart rate, among others, which can be obtained through various types of biomedical sensors attached to the driver. In this case, the installation of these devices sometimes has a reduced degree of flexibility in terms of driving dynamics and even a possible element of distraction and discomfort for the driver. It is in this last aspect that we refer to the fact that conventional biopotential measurement systems require in most cases that the electrodes are in contact with the human body, which can disturb the operation of the driver during the driving activity and cause some distraction or physical discomfort. Even the use of more recent devices, including capacitive electrodes for sensing biopotentials, presents some limitations in integration with the elements of the vehicle's internal structure.

iii) To address in greater detail the study of the influence that the driver exerts during the driving process on the road environment, an aspect that is evidenced in Table 3.3 with the reduced number of works that consider the directional interaction D$-$ >E.

iv) The integrated and complementary approach for the natural context perception module. In this process, the obvious physical limitations of the driver must be considered to analyze aspects related to the calculation of distances and relative speeds between the different vehicles, pedestrians, and objects on the road. It is necessary to establish a holistic approach to develop a comprehensive surrounding environment model, from the vision through the sensors and the vision through the driver. This integration to analyze the driving behaviors in the dynamics of

Table 3.3: Works in which driver-environment interaction is addressed. In this work we decided to analyze two of the characteristics most addressed in the literature consulted on the detection of the driver state: (i) monitoring of driver fatigue or drowsiness (fatigue monitoring) and (ii) driver distraction. Also, we analyze the works in which the driver has an active role in the modification of the environment's state through the planning of his/her future route.

Articles	**Directionality**		**Implementation of the interaction**			**Driver status**	
	E− >D	**D− >E**	**Data source**	**Data type**	**Environment**	**Detection of the driver state**	**Trajectory planning**
[114] [117]	X		Camera	Real	Real	fatigue monitoring	
[127]	X		EEG and wearable sensors	Real	Simulation	fatigue monitoring	
[128]	X		Bluetooth sensor and smart watch	Real	Real	fatigue monitoring	
[124]	X		CAN bus	Simulated	Simulation	fatigue monitoring, driver distraction	
[119] [121]	X		Smartphone camera	Real	Real	driver distraction	
[120]	X		Smartphone and NIR LED	Real	Real	fatigue monitoring, driver distraction	
[125]	X		Microphone and CAN bus	Real	Real	driver distraction	
[123]	X		Smartphone sensors	Real	Real	driver distraction	
[129]	X		Visual, auditory and olfactory stimuli	Real and simulated	Real and simulation	driver distraction	
[118]	X		Cameras	Real	Real	driver distraction	
[130]		X	Map display device	Real	Real		route planning
[131]		X	Smartphone	Real	Real		route planning
[132]		X	Smartphone	Real	Real		tourism guidance
[133]		X	Map display device	Real	Real		tourism guidance
[134]		X	Non specified	Real	Real		tourism guidance

the environment will allow a significant increase in the prediction horizon and the precision in the prediction of the driver's intention.

Studies related to the D-E interaction have addressed to a very low degree the correlation between the interpretation of the environment by the driver and the notification to the environment of this, which would undoubtedly modify the situation of the environment itself. The proposed C-ADAS architecture could take advantage of situations of vehicular congestion, unfavorable weather conditions, or dangerous situations of an effective bidirectional interaction between the driver and the environment, which would moderate the behavior of all drivers and consequently mitigate the risks in the environment. In addition to this, there are also the challenges associated with the use of these wearable devices and other on-board sensors and cameras and the way in which they are implemented, so as not to generate distraction or discomfort in the driver, while being able to obtain diverse information with a high predictive value in terms of inferring its future actions. The current state of progress made in the interaction between the driver and the environment, as well as the latent technological challenges, still limit the potential of the proposed C-ADAS.

3.5 System evaluation

This section presents aspects related to the evaluation of C-ADAS in the field of road safety, the main mechanisms used, the evaluation environments, as well as the main evaluation metrics used. We also include some of the challenges associated with the limitations in the use of simulators and evaluation metrics employed in order to meet the design requirements of a C-ADAS proposal such as the one presented.

3.5.1 Evaluation mechanisms

Road traffic represents a complex system made up of multiple independent and interrelated elements. In terms of safety, economy, and fluidity, the evaluation of transport can be associated with the performance of certain main factors, which can be grouped into elements such as the driver, the vehicle, and the road environment. For the most part, the interrelationship between these elements is highly variable and random in nature. The behavior of transport, from the mathematical point of view, can be associated with a stochastic process, where each of its elements can be represented as random variables. An in-depth study of the complexity of this system requires tools that allow achieving a certain degree of reproducibility of the real characteristics present on the roads. To this end, driving simulators have been developed, which are devices used to simulate the driving of a vehicle in an environment with conditions similar to the real characteristics of road traffic. These devices are an effective tool in the training and study of driver behavior, but they also play a very important role in the design and improvement of the HMI elements present in vehicles.

Among the many advantages of using these devices, we can mention the possibility of studying the driver's behavior in situations that may arise while driving and even emulate this behavior in situations that are legally prohibited, such as driving under the influence of alcohol, or cell phone use while driving. Another of the advantages of using simulators corresponds to the reduction of the economic costs associated with carrying out tests in real environments, generating high volumes of data from very diverse situations for the training of artificial intelligence models, guaranteeing reproducibility conditions, necessary for statistical analysis of the same. However, the main limitation is that in these scenarios, drivers are not exposed to a fundamental element: the real risk present on the roads. This can distort the analysis and modeling of the behavior of drivers in real situations.

In the same way, other elements of distraction and influence that are only present in real scenarios are not considered within the simulators, which shape the behavior of drivers and their reaction to risky situations.

Musa *et. al.* [135] points out that vehicle manufacturers develop and test ADAS technologies following the V-model, conventionally used for automotive electronics. The development steps consider the model-in-the-loop and software-in-the-loop tests, while in the validation the hardware-in-the-loop, vehicle-in-the-loop, and driving tests can be performed. In addition, MPC-based strategies represent interesting solutions for ADAS evaluation. Vehicle-in-the-loop tests may be useful to evaluate the effective responses of vehicles in safety-critical scenarios and to test them with real V2X systems. The combination of hardware-in-the-loop and driving simulator is useful for taking into account human error.

3.5.2 Performance metrics

The overall performance of a C-ADAS system must consider not only the precision in estimating the location of remote vehicles but must also the impact of the communication schemes used and the performance of the communication network. The first step in determining this performance is to define a metric that can directly indicate how the security algorithm is performing quantitatively. Generally, for the evaluation of this type of situation, classification metrics are used. Table 3.4 summarizes the most used metrics in the review of the literature consulted, grouping them fundamentally in regression, classification, and communication performance metrics. The accuracy of hazard detection algorithms to classify situations as dangerous is one such metric. [137]. The security algorithm generally runs periodically and at each run-time instance, it determines whether a threat exists. The ratio between true positives plus true negatives within the total number of execution instances of the algorithm is defined as the precision. PTE, which describes the mean or ninety-fifth percentile of the error in tracking a remote vehicle's position, is used to ensure accuracy in position estimation, which is an independent metric of the C-ADAS that is running. Warning detection is performed at the same time as position tracking. The overall performance of C-ADAS depends on the accuracy of the alerts, which depends on the accuracy of tracking the position of the remote vehicles, and this, in turn, depends on the performance of the communications. To analyze this performance, metrics such as the PER are used, which is the number of packets received incorrectly divided by the total number of packets received. Another metric that can be used to model the robustness of the communications network is the PLR, equal to the number of packets not received divided by the total number of packets sent. In this sense, we analyze the evaluation metrics employed in the surveyed works, grouping them in *(i)* regression metrics, *(ii)* classification metrics, *(iii)* communication performance metrics. The fulfillment of this task requires the use of evaluation metrics that consider all the elements of the system, focused on the requirements associated with RSA, described mainly in terms of road safety. Robustness of the information refers to guaranteeing the reliable delivery of the road safety information required by the RSA (low rates of losses and transmission errors). The freshness of the information meets the delay requirements to guarantee the usefulness of the same in terms of road safety.

Through the analysis shown in Table 3.4, we can observe as a flaw present in most of the analyzed works, that the consideration, and even more so the evaluation of the behavior of the communications, has not been sufficiently addressed. We assume that this is due to the fact that currently there is a majority trend in the automotive industry to bet on the use of different sensor technologies on board vehicles, capable of self-supporting the development of the ADAS implemented in these, without considering the cooperative operation of these systems between different vehicles and/or with the road infrastructure.

Table 3.4: Classification of the consulted works according to the evaluation metrics used.

Articles	**Regression**	**Classification**	**Communication**
[80]	90 percentile position error		Packet loss rate (PLR)
[53] [61] [55] [56]	Root mean square error (RMSE) position error		
[66]	total euclidean error sum, horizon euclidean error, modified Hausdorff distance [136]		
[67]	mean absolute error		
[57]	collision risk probability		
[58] [68] [114] [106] [103] [119] [121] [129]		accuracy	
[59]		accuracy, true positive rate, true negative rate	
[60]		recall, accuracy, precision and F1-score	
[81]	absolute position error	accuracy	
[69]	95 percentile of velocity and acceleration error	accuracy	Packet error rate (PER), transmission rate
[63]	95 percentile of absolute position error		
[82]	spacing position error and velocity tracking error		
[74] [75]	95 percent cutoff Euclidean position error		transmission rate, percentage of packet losses
[76]	90 percentile position tracking error		transmission rate, PER
[77]	90 percentile position tracking error, average model persistency		packet length, transmission rate
[79]	probability of safe breaking		maximum communication delay, bit error rate
[101]		accuracy, sensitivity, specificity	
[102]	tracking position error		
[104]		accuracy, premature, timely and late warning rate	
[107]		accuracy, false positive rate, false negative rate	
[28]	tracking position error	accuracy	
[29]	Driver's behavior volatility	Calinski-Harabasz, silhouette and Dunn's index	
[117]	average error of eye-openness	detection rate	
[127]		precision, recall, accuracy	
[124]	abnormal driver behavior index		
[120]	normalized mean squared error	accuracy, precision, recall and F1-score	
[125]		accuracy, precision, recall	
[123]		precision, recall, F1-score	
[118]	mean and standard deviation of yaw angle absolute error	detection rate, success rate	

3.5.3 Challenges

An important aspect in the evaluation of the C-ADAS systems is the fact of considering their operation and degree of customization as a continuous process. In this sense, systems designed to operate in real-time must have the capability to adjust dynamically with the new real data. Together with this, it is also important to consider the use of real databases obtained in field measurement campaigns, to provide the system with a priori knowledge, which can be complemented with the processing of data obtained in real-time during the tests of system operation. Nowadays, there is a lack of development of integral evaluation systems, in order to be able to evaluate our proposal. Note that, it is impossible for a current simulator to fully replicate real-world driving scenarios, especially from a vehicle and traffic perspective, since there are a set of events and random variables that are difficult to model such as catastrophic, climatic, environmental and political-social-cultural events, but these events have a high incidence on vehicular traffic, the environment and drivers. However, several of the interactions should be evaluated beforehand, such as the interaction of vehicles with each other as a result of collaborative actions and the communication delays between them. Besides, we consider that it is essential, for the effective implementation of the proposed C-ADAS, to run many tests in controlled scenarios, but as real as possible. Probably in the short or medium term, these tests must be executed in hybrid environments where there are vehicles with sensing and communication capabilities and others with the absence of some or none of these capabilities. The latter shows the current relevance of the driving assistance systems, even though there is a growing development in the area of autonomous driving.

3.6 Commercial Systems of ADAS

This section presents a brief study of the main ADAS currently implemented in commercial vehicles, describing the predominant technologies, as well as the main car manufacturers, technology companies, and future trends of the automotive industry.

The rapid growth of driver assistance systems has not only improved driving comfort and experience in recent years, but has also positively impacted road safety. Many of these systems now include driver status monitoring [138], [139],[140]. EyeSight (Subaru), for example, is a driver assistance system that uses dual stereo cameras to detect vehicles, obstacles, and traffic lanes, improving driving safety and comfort. DriverFocus is one of the safety functions offered by EyeSight. Its system monitors the drivers with a near-infrared camera and alerts them about distraction events. Additionally, scan and recognize up to 5 drivers and remember their preferences like seat position, climate settings, and outside mirror position, previously stored manually [138]. Super Cruise (General Motors) is an advanced driver assistance technology that enables hands-free driving on compatible roads. It works in conjunction with the adaptive cruise control system, using cameras, sensors, GPS, and LIDAR map data to keep the vehicle centered in its lane and make lane changes under certain conditions. Among its main features, we can mention the driver attention camera, which monitors the driver's head position and gaze to ensure they are attentive to the road [139]. Drive Pilot (Mercedes-Benz) is an automated driving system designed to operate under specific conditions on controlled highways. This system allows the user, known as the "fallback-ready user", to delegate driving to the vehicle while remaining available to resume control when necessary. The HMI incorporates continuous driver monitoring to ensure responsiveness [140]. The degree of customization of these systems has also evolved; however, some challenges persist, along with other more technical ones associated with sensors such as cameras, radars, lidar, etc., which have meant, for example, that these systems have not yet achieved a level of total autonomy.

During the operation of systems such as emergency braking, forward collision warning, or adaptive cruise control, criteria are used to establish a certain safety distance, which, in most cases, is calculated based on kinematic and dynamic movement criteria. Other systems such as lane keeping systems, lane change assistance systems, or blind spot detection systems also establish strict criteria for calculating the safety distance between the vehicle equipped with these systems and neighboring vehicles traveling in its own lane or adjacent lanes. It is worth asking whether these systems consider driver characteristics such as reaction time and visual acuity, constant monitoring of driver activity, or even the condition of the road at any given time when calculating these safety distances. In [141] the author performs a comparative analysis of the main driver assistance systems currently available, highlighting that none of them make a car fully autonomous. Aspects such as capability and performance in steering tests, speed control, ease of use of the system, keeping the driver safe and engaged while driving, and the system's response to distracted drivers are evaluated. The interaction of the aforementioned systems with systems such as the driver monitoring system or the drowsiness and distraction detection system is particularly important. Ultimately, since these are not considered fully autonomous systems, they must be able to occasionally allow the driver to take control. However, if the driver is not in optimal condition, this decision can be counterproductive to road safety. These driver monitoring systems are limited to perceiving the driver's response capacity in emergencies, but they do not use this monitoring data, for example, to dynamically build a driver profile based on the evolution of their driving activity. This information would be useful for more personalized adjustments to the operating parameters of the system itself, something that, according to the literature, has not yet been achieved.

In recent years, the automotive industry has undergone a significant transformation through the integration of artificial intelligence into advanced driver assistance systems and autonomous vehicles. The future of artificial intelligence in automotive applications presents a dynamic landscape of technological advancements and societal adaptation: (i) the automotive AI market is projected to grow at a compound annual growth rate (CAGR) of 25.8% through 2030; (ii) autonomous vehicle systems are expected to require computing capabilities exceeding 300 TOPS by 2027; (iii) test scenario coverage must reach 99.99% for SAE Level 4 and 5 autonomy certification; (iv) consumer confidence in autonomous vehicle technology increased from 42% in 2022 to 58% in 2024 [142].

The BMW Group, together with Amazon Web Services (AWS) and Qualcomm Technologies, are partnering to develop a next-generation automated driving platform [143]. This system, which will be implemented in vehicles of the new "Neue Klasse" line starting in 2025, will integrate advanced generative artificial intelligence, IoT, machine learning, and cloud storage capabilities. Through Qualcomm's Snapdragon Ride Vision platform, 360-degree perception is implemented in vehicles. This cloud-based system will improve real-time driver warnings in dangerous situations, as well as navigation assistance, while facilitating the management of large volumes of data generated by automated on-board functions during driving. Cases like this mark the current state and future trends in the automotive industry, representing a qualitative advance toward software-defined vehicles with scalable architecture designed to enhance safety, comfort, and the driver experience.

3.7 Proposed General Architecture of a C-ADAS

This section describes our C-ADAS architecture proposal from a holistic and systemic vision. The systemic vision considers the relevance of the three main elements that make up the RSS (driver, environment, and vehicle). For its part, the holistic vision also reflects the relevance of considering the dependence and interrelationship between these elements, as essential requirements for the system´s functioning as a whole. Additionally, we establish a comparative analysis between this proposal and the architectures proposed in the previous reviews, describing its main characteristics and limitations. Figure 3.1 present our C-ADAS architecture proposal.

This architecture considers the presence of the three main elements of an RSS, as independent and closely interrelated subsystems, which influence and determine the state of road safety. The driver subsystem includes everything related to the actions and reactions of the drivers during the driving process, conditioned by their physical and psychological characteristics such as age, gender, mental state, driving skills, experience, and driving profile. The vehicle subsystem considers aspects related to the electromechanical characteristics of the vehicle, braking behavior, acceleration, sensing, and communication technologies embedded on board, among others. Finally, the environment subsystem takes into account the rest of the elements outside the vehicle and the driver; among them, we can mention the elements of the road structure, the physical conditions of the road, the weather conditions, as well as other vehicles, pedestrians, animals or obstacles on the road. We propose an integral communication system that seeks to leverage the advantages offered by the IoV concept, using data integration and the capacity for centralized decision-making. Note that considering C-V2X implies a high degree of redundancy so as not to lose communication and to have several sources through which redundant data may arrive. Also, the heterogeneity of networks and technologies may generate significant variations in the perceived delay and jitter among different communication paths, which becomes a very sensitive issue for RSA. That is why a C-ADAS must conceive minimum delay times for the security modules, which could imply that in some cases the information that causes an action could be only conditioned by messages received from neighboring vehicles in the vicinity of the ego vehicle. In [84], an in-depth discussion of control aspects of CAV systems is carried out, highlighting the main challenges generated by the existence of different information flow topologies, mainly focused on: string stability, communication issues, and dynamics heterogeneity. These aspects must be taken into consideration for a practical implementation of a C-ADAS, such as the one proposed here, since the heterogeneity in the network topology and high dynamism of vehicular networks can impose additional communication challenges. However, we are committed to the idea of conceptualizing the use of onboard communication devices with C-V2X functionality, framed within the IoV concept, given that current and future development points to the convergence of technologies. In this sense, 5G-Advanced is seen as a key technology to support the development of future vehicular networks, which presents low latency values in communications, which will undoubtedly help to compensate for the delays associated with the processing and control of communication schemes.

The proposed architecture includes three modules to capture the data from the bidirectional interaction between the three main elements of the RSS, these are the natural perception module, the assisted perception module, and the HMI module. Additionally, a main module is included in an upper layer that receives, processes, and stores the collected information by the lower modules to make decisions about the state of road safety. This is a modular architecture where the main module can be implemented both locally, inside the vehicle, and remotely, in a centralized management station within the environment of Intelligent transportation systems (ITS), under the IoV concept. In the latter case, the entire flow of information from the three data capture modules would be shared through the V2X devices on board the vehicle. In this sense, we conceive that our architecture can operate independently of the technology used for radio access. In this ITS environment, vehicles communicate with each other mainly through periodic messages called cooperative awareness messages (CAMs) in Europe [144] and basic safety messages (BSM) in the United States of America [145], to exchange kinematic information related to the state of their movement, such as: position, speed, acceleration and heading. However, sometimes it is required to exchange additional information to the kinematic parameters of the movement, related to the activity of perception of the environment, through different sensors located on board the vehicle, to increase the degree of situational awareness,

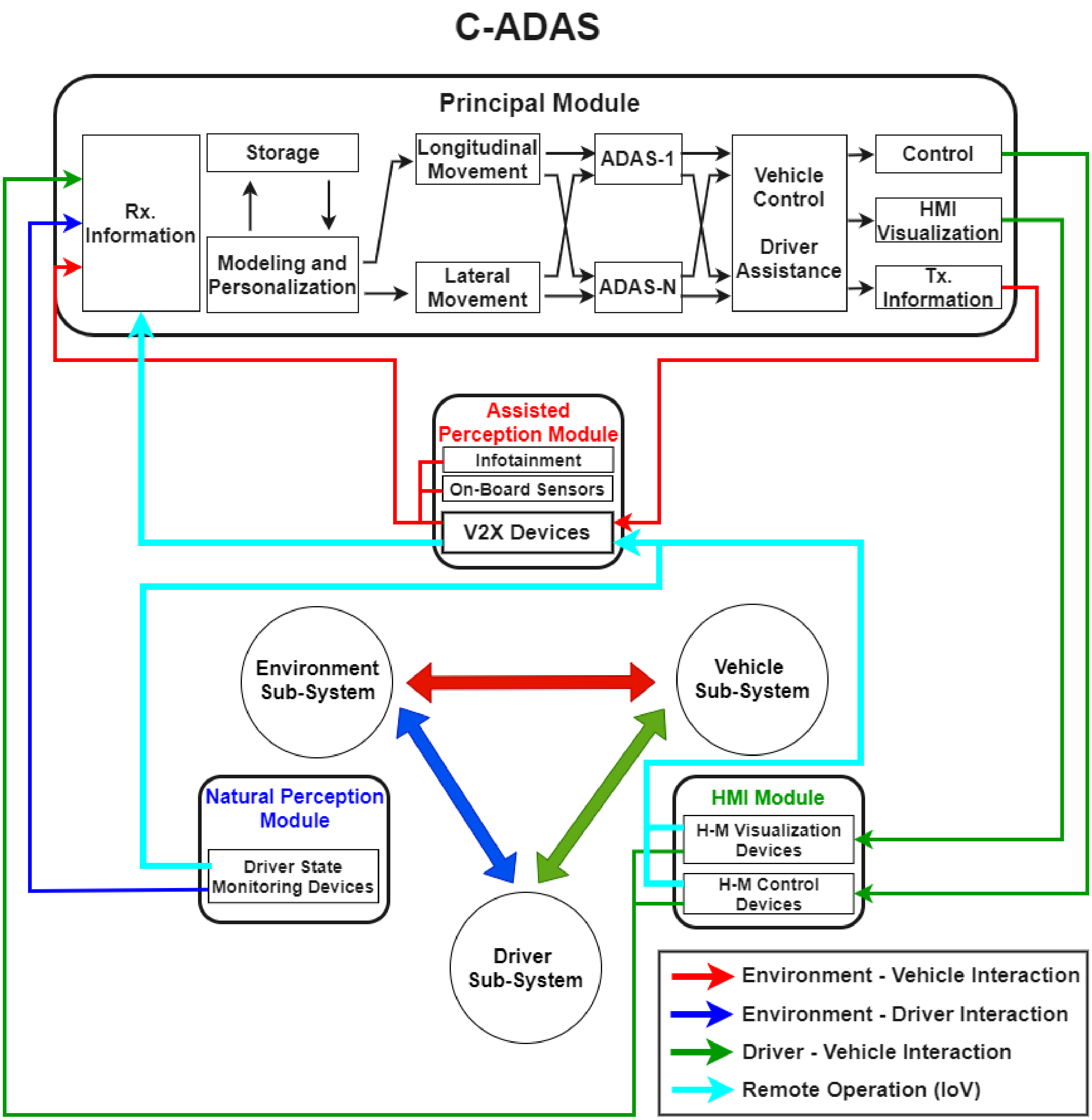


Figure 3.1: Conceptual architecture of a C-ADAS from the holistic and systemic vision. The red, green, and blue lines indicate the local operation of the principal module (inside the vehicle), while the cyan lines refer to the remote operation of the principal module through the vehicular network, under the IoV concept.

this is done through the so-called collective perception messages (CPM), specified according to ETSI [146]. These messages, for example, can be used to exchange information related to different driving profiles.

From the review of the state of the art in articles on enabling technologies, we can divide them into sensor technologies, wearable technologies, and communication technologies, which are related to each of the data capture modules and their connection with the main module. Although the most researched enabling technologies are those that intervene in the vehicle-environment interaction, it is also important to highlight those that are part of the vehicle-driver and driver-environment interactions, since all together allow closing the cycle in a holistic and systematic design of C-ADAS, where the three main elements of an RSS are present: driver, vehicle, and environment. In this sense, we have tried to list below the most relevant technologies (described repeatedly in many of the articles consulted), but at the same time to reflect, through an integrating spirit, the technologies present in each of the three areas of interaction between the three main elements of the RSS. For a greater level of detail, the reader can consult these technologies in [46, 47, 49, 51, 147, 148].

Sensor technologies:

i) Radar systems are classified into *(i)* Short range radar (SRR), which has a detection range of up to 20 meters, are based on single antenna and are not capable of detecting angular information; and *(ii)* Long range radar (LRR), which has a range of up to 150 meters and angular resolution of up to 2 degrees [149].

ii) Cameras embedded on vehicles are of two fundamental types: *(i)* stereo cameras used to obtain a wide panoramic vision in conditions of good visibility; and *(ii)* infrared cameras used in situations of reduced visibility at night or in the presence of adverse weather conditions [150].

iii) LIDAR uses laser signals to determine the relative distance of nearby objects from a vehicle. Laser signals are emitted and their respective echo signals are received to calculate these distances, with detection ranges between 10 and 200 meters [151].

iv) Acoustic sensors use an operating principle similar to that of radars and LIDAR, but using high-frequency sound waves (ultrasonic) to determine the distance of an object to the vehicle [152].

Wearable technologies (electronic devices designed to attach to the user's body, its classification depends largely on their functional properties:

i) Smartwatches are electronic devices with functionalities such as GPS, fitness/health monitoring, and waterproof operation [153].

ii) Wearable cameras are much more flexible and mobile than conventional cameras, as they focus on the first-person view and are often attached to eyeglasses, helmets, and caps [154].

iii) Smart eyewear used to provide information, notifications, and a three-dimensional view through Optical head-mounted display (OHMD), Heads up display (HUD), Virtual reality (VR), Mixed reality (MR), and/or Augmented reality (AR) [154].

iv) Fitness trackers are placed in different parts of the body to monitor the physical state of the individual during the performance of daily activities or exercise routines. Their measurements include parameters such as speed, heart rate, calories released, and a number of steps [155].

v) Smart clothing, usually shoes, hats, clothing, and helmets, incorporate cameras and sensors to monitor body signals and adapt their characteristics to the individual's state [156].

vi) Wearable medical devices made up of one or several biosensors are used to monitor the physiological activity of the individual for the purposes of prevention, diagnosis, and early treatment of diseases and health status abnormalities, by measuring temperature, heart rate, blood pressure, and glucose level, or performing Electrocardiography (ECG), EEG, and Electromyography (EMG). [157].

Communication technologies:

i) DSRC is a technology of fully integrated vehicular networking, implemented over the 75 MHz bandwidth (5.85–5.925 GHz) assigned for the Federal communications commission (FCC). The architecture and the services to enable this secure V2V and V2I communications, in the Wireless access vehicular environment (WAVE), are provided by the Institute of electrical and electronics engineers (IEEE) 802.11p and IEEE 1609 protocol suites [158].

ii) Light fidelity (Li-Fi) uses wireless communications in the visible light band for data transmission, by encoding the flashing states of LED [159].

iii) Long term evolution advanced (LTE-A) is part of the evolution of Long term evolution (LTE) networks in version 14 to ensure that V2X service requirements are supported by the LTE transport network. Different V2X application scenarios are defined, including V2V, V2I, Vehicle to pedestrian communication (V2P), and V2N [160].

iv) "5G-Advanced" 5G New Radio (NR) V2X technology permits the capacity to handle dense traffic, reduced latency for time-critical maneuvers, and higher bandwidth for sharing high-volume sensor data, including video and providing support for Ultra reliable and low latency communications (URLLC) scenarios [97] [98].

v) Internal communication network of a vehicle is composed of ECU, mechanical and electric sensors, and actuation devices to guarantee the correct vehicle operation. OEM today design proprietary devices and networks to share data through OBD hardware. Well-established technologies like CAN bus, Media oriented systems transport (MOST), LIN, and FlexRay are examples of resilience and flexibility. Other emerging technologies like vehicular Ethernet, support the growing communication capacity demanded for modern vehicles, and are discussed in [161].

The main module is in charge of using the information from the three data capture modules to analyze the state of road safety and make the best decision when it comes to assisting the driver or acting directly on the vehicle's safety systems in case of non-attention from the driver to warning notices or an imminent danger situation, with the aim to minimize the level of risk and traffic accidents. It is also in charge of sharing this information with the other actors in the road environment. The operation of this module begins with a reception information block that receives the data from the three capture modules. Once this data has been processed, models of driver behavior are established and stored, customized according to the characteristics of the driver. These models allow estimating the prediction of the longitudinal and lateral movement of the vehicle, information that can be used by different advanced driver assistance systems (ADAS-1 ... ADAS-N blocks) either to provide assistance to the driver or to take directly control the vehicle in case it does not respond adequately and in a timely manner to certain dangerous situations on the road. In this sense, the decision-making of the C-ADAS system may entail carrying out the functions of vehicle control, visualization through the HMI or the transmission of information related to road safety to the rest of the actors on the road or to the centralized management station in an ITS.

Under the IoV concept, different multi-layer architectures have been proposed and different types of interaction between the elements that compose it have been established [26, 162]. One of the layers that is commonly addressed is the centralized platform in the cloud (associated with the "intelligent brain" in the IoV architecture), in this the centralized processing of the road safety data obtained in lower layers is carried out, the global strategies and the management of road safety alerts, assisted automatic driving, intelligent navigation, among other functions. Centralized or distributed execution implies differences in signaling overhead and delay associated with decision-making, but the processing delay in the cloud is less than in computer equipment inside the vehicle. Some critical security applications will demand URLLC type communications, which will benefit from the growing development of the 5G-Advanced. The analysis of the local data allows guaranteeing the control of the main functions of the vehicle in real-time, while the remote analysis of the same, allows the creation of added value in the system to improve the reliability, efficiency, and performance of the vehicle, through the application of communications, computational processing, and distributed information on a large scale. To the extent that connectivity capabilities and computer technologies are developed and latency in the execution of applications is reduced, the use of aggregated data, obtained remotely, becomes more useful in the operation of these road safety applications in real-time. Vehicles do have limited computation and storage resources that may not be sufficient for road safety applications that need to process a large amount of data. Since they require big storage and complex computations, this vehicle to cloud computation helps by providing proficient support to these applications. In our architecture, the main module is flexible to operate with some of these functions, mainly oriented to the design of advanced driver assistance systems. Another layer that is described in an IoV architecture is the data acquisition layer, whose main function is to collect different types of data from different sources and digitize the data to ensure that it can be successfully transmitted and analyzed. In our architecture, this IoV layer is represented by the three data capture modules: the natural perception module, the assisted perception module, and the HMI module, described below.

The natural perception module is responsible for capturing the elements of D-E interaction during the natural perception process from the driver of the surrounding environment. Through devices implemented inside the vehicle, such as vision cameras, heart rate monitoring devices, and ethyl breath detection, the driver's behavior can be analyzed based on the monitoring of his/her activity on board and his/her reactions to the dynamics of the environment, which can help infer their behavior and future actions on the road [44].

The assisted perception module is responsible for capturing the elements of V-E interaction through sensors such as radars, ultrasonic, GPS, IMU, LIDAR and cameras, jointly with communications equipment, the state of the surrounding environment of the vehicle are sensed and its dynamic data are capture for the posterior presentation to the driver as additional information of his/her natural perception. This module is also responsible for communicating the driver's mobility and status information to the environment while driving, as well as ADAS alerts and warnings and the driver's reaction to them.

The HMI module is responsible for capturing the elements of D-V interaction during the driving process. It is composed of human-machine visualization devices like displays, vision cameras, or instrument panels and human-machine control devices like acceleration, brake and clutch pedals, steering wheel, switches, panel buttons, gear levers, etc. The four principal functions of this module are *(i)* sensing the physical actions of the drivers over the direct and indirect devices involved in the driving process: steering wheel, brake, clutch and acceleration pedals, transmission state, lights and others on board controls; *(ii)* display information about the vehicle status (from the internal modules of the CAN bus and GPS modules) and the surrounding environment (maps, routes, traffic signs, location of other vehicles, pedestrians and obstacles on the road); *(iii)* visualize alerts the driver over dangerous situations product of the analysis of data related to road safety; and *(iv)* sensing the driver's reactions to the alerts emitted by the assistance system.

Control systems refer to where C-ADAS processing and decision-making takes place, it can be locally in the vehicle itself or remotely, under the IoV concept. The modular structure describes the elements that make up the system and their functions. Personalization refers to the degree of mutual adaptation between the system and the driver during the vehicle-driver interaction, it includes the latter's actions during the driving process, as well as its reaction to the system alert notices presented through the HMI interface of the vehicle. Cooperative communication highlights the capacity of the system to communicate to other actors in the road environment about the information regarding the driver's actions and the result of the system's decision-making regarding the state of road safety. The assistance functions refer to assisting the driver or taking control of the vehicle's safety systems. It also highlights the system's ability to operate simultaneously with more than one ADAS (LCA, FCW, AEB, BSW, LDW, among others). However, monitoring the progress of these technologies, as well as the achievements and projections of the main automakers, will favor the implementation of a proposal close to this C-ADAS that efficiently exploits bidirectional interaction between the three subsystems to increase road safety. Table 3.5 resumes the analysis of architectures proposed in the surveys consulted and our architecture proposal, highlighting the control systems, the assistance functions, the degree of personalization and cooperation, as well as the main elements that compose them, describing also how the interaction between these elements is implemented.

3.8 General considerations of the chapter

The RSS consists of a driver subsystem, a vehicle subsystem, and a road environment subsystem. These three subsystems are essential to ensure the safe driving of automobiles. The "gaps" in the interaction between the three subsystems are causes of degradation in road safety. A fundamental element to fill the gaps in these interactions is the design of C-ADAS from a holistic approach that considers the presence and interaction between these different elements as a single system.

Recently, there have been situations in which the challenges faced by the automation of vehicle systems are emphasized and how the non-consideration of any of these elements can produce unfavorable results. Examples of this are some tragic accidents that occurred in Tesla vehicles [163, 164, 165], highlighting the serious consequences of life and death associated with failures or miscalculations that can occur with the vehicular systems. A Model X issued several audible and visual alerts before crashing into a concrete wall without the driver putting their hands on the wheel [163]. A preliminary report from the National Transportation Safety Council (NTSC) found that the driver of the vehicle activated Autopilot, which provides automatic driving functions, ten seconds before impact [164]. The document also indicates that the automatic system did not detect the driver's hands on the wheel in the last eight seconds and that it did not perform evasive maneuvers to avoid colliding with a truck. In [165], the Tesla driver acknowledged that he was watching a movie on his mobile phone at the time of the accident. However, the vehicle never got to take control of the situation, necessary in view of the evident state of distraction of the driver. In this particular case, perhaps the first and foremost thing is to slow down the rush to "remove the human being" from the equation. Officially, Tesla's autopilot was meant to aid the driver, not replace them. Human beings remain essential to driving and should continue to be so for some time until the technology matures. It is crucial to understand the surrounding cars with respect to the road context and interact with them harmoniously for the success of autonomous cars used in mixed urban traffic [166].

Similar examples can be evidenced by excluding any of the other two elements (vehicle and

Table 3.5: Analysis of the ADAS architecture proposed in the revised surveys and the architecture proposed in this work.

Articles	**Control System**	**Modular Structure**	**Personalization**	**Cooperative Communication**	**Assistance Function**
[39]	Local control	System composed of three main modules: ADAS module, personalization module and HMI module.	Personalization module that continuously adapts the ADAS to the driver's behavior through the HMI interface.	Cooperative communication is not explicitly considered.	Consider vehicle control and multiple driver assistance functions.
[44]	Local control	System composed of six main modules: environment perception module, vehicle dynamic module, driver behavior recognition module, driver intention inference module, lane change decision module and interaction module	The interaction module models the driver hand and foot dynamics as well as the dynamics of the vehicle control interface.	Cooperative communication is not explicitly considered.	Consider vehicle control and a single assistance function: lane change intention inference.
[51]	Local and remote control	System composed of three main elements: sensing and communication technologies, human factors, and information-aware autonomous vehicles controllers.	Human factor element: Design of a CAV system based on human driver expectation, and adaptation of the human driver to the designed CAV system.	It considers the exchange of environment information through the sensing and communication modules, but not the alerts and warnings generated for the ADAS system.	Consider vehicle control and multiple driver assistance functions.
Our Work	Local and remote control	System composed of three modules that sense the interaction between the three elements of road safety: the natural perception module, assisted perception module and HMI module. Besides, a principal module that receives, processes, storage, takes decisions and transmits the safety information.	Continuously adapt the ADAS by monitoring the driver's condition and his/her physical interaction with the vehicle's driving control elements, as well as its reaction to the information and alerts issued by the HMI module.	It considers the exchange of information through the communication devices on board the vehicle, both the information obtained by the three sensing modules and the alert or warning information generated by the main module of the system.	Consider vehicle control and multiple driver assistance functions.

environment) of the system in the design of C-ADAS. The increase in road safety has motivated progress in the area of safety systems. Depending on the degree of automation of these, their action can be limited to driver assistance tasks or even be of a more autonomous nature: acting directly on the components that modify the response of the vehicle such as the acceleration and braking pedals and/or the power supply, steering control. The complex interaction between these characteristics and the actions of drivers has led to numerous investigations on the human factors involved in motor vehicle accidents. Some of these factors are demographics, distraction, experience, fatigue, alcohol, stress, the tendency to risk behavior, and decision-making. At present, ADAS is a promising field of research in order to improve road safety.

While it is true that current projections on the levels of autonomy of modern vehicles tend towards a fully autonomous design, the fifth level according to SAE [167], the process of mass inclusion on the roads of fully autonomous vehicles and its coexistence with human-driven vehicles is not expected to end in the short term [168]. Moreover, it should be noted that the very process of development and improvement of the artificial intelligence systems that control autonomous vehicles requires continuous learning of the interactions with other drivers and road users, which is, in essence, learning to deal with human behavior. In the evolution of the levels of autonomy of vehicles, it is necessary to guarantee road safety, in order to preserve lives and limit economic losses through accident avoidance. To this end, the implementation and development of an effective ADAS that accompanies and assists the evolution and maturity of autonomous driving is essential.

The architectural proposal presented in this chapter addresses the challenges found in the literature on the design of C-ADAS and, in our opinion, constitutes a theoretical contribution to the design approach of these systems. These challenges present a deficiency and a latent need today because as long as the design does not contemplate the inclusion and bidirectional interrelation between the elements of the RSS, these systems will continue to have a limited scope and performance.

4

Influence of bidirectional driving profile knowledge on the vehicle trajectory prediction in highway lane change maneuvers

4.1 Introduction

In this chapter, we analyze one of the possible application scenarios conceived in C-ADAS architecture proposed in Chapter 3, highlighting the relevance of considering the driver element. This scenario has been the least addressed in the consulted scientific literature, as we can see comparatively in Tables 3.1, 3.2 and 3.3, and it is one of the areas where the most relevant challenges persist: around the degree of personalization achieved in current C-ADAS. In this scenario, the driver element plays a preponderant role, not only when considering vehicles driven by human drivers, but also semi-autonomous and autonomous vehicles. The current state of coexistence of these vehicles on the roads demands it. Traditionally, the study and modeling of driving profiles have been carried out by analyzing the movement and trajectory of vehicles as a tangible expression to infer driver behavior. Lane change maneuvers are high-risk situations for road safety on highways, scenarios characterized by high speeds and bidirectional vehicle movement. The analysis of these maneuvers allows for studying vehicle movement patterns during a lane change and extracting bidirectional driving profiles, associated with lateral and longitudinal movements, which describe driver behavior more accurately and improve the performance of trajectory prediction models. In this regard, we propose a system that exploits knowledge of driving profiles, obtained through real trajectory data and mathematically modeled, to improve inferences about a driver's behavior during a highway lane change maneuver. The parameterization of these models allows the acquired knowledge about the driver to be shared with other road users and promotes the design of collaborative strategies that minimize accident risks and contribute to increasing road safety. To do this, we analyze real data of lane change trajectories on highways, which are preprocessed and grouped into different driving profiles. These profiles are analyzed mathematically using logistic models, which will then be detected by classifiers that determine the most likely trajectory to be followed by the vehicle, given the type of driver performing the maneuver. Finally, we propose a model to detect a particular driver during multiple instances of maneuver execution.

4.2 System model

The proposed system model, illustrated in Figure 4.1, presents a comprehensive framework for ana-

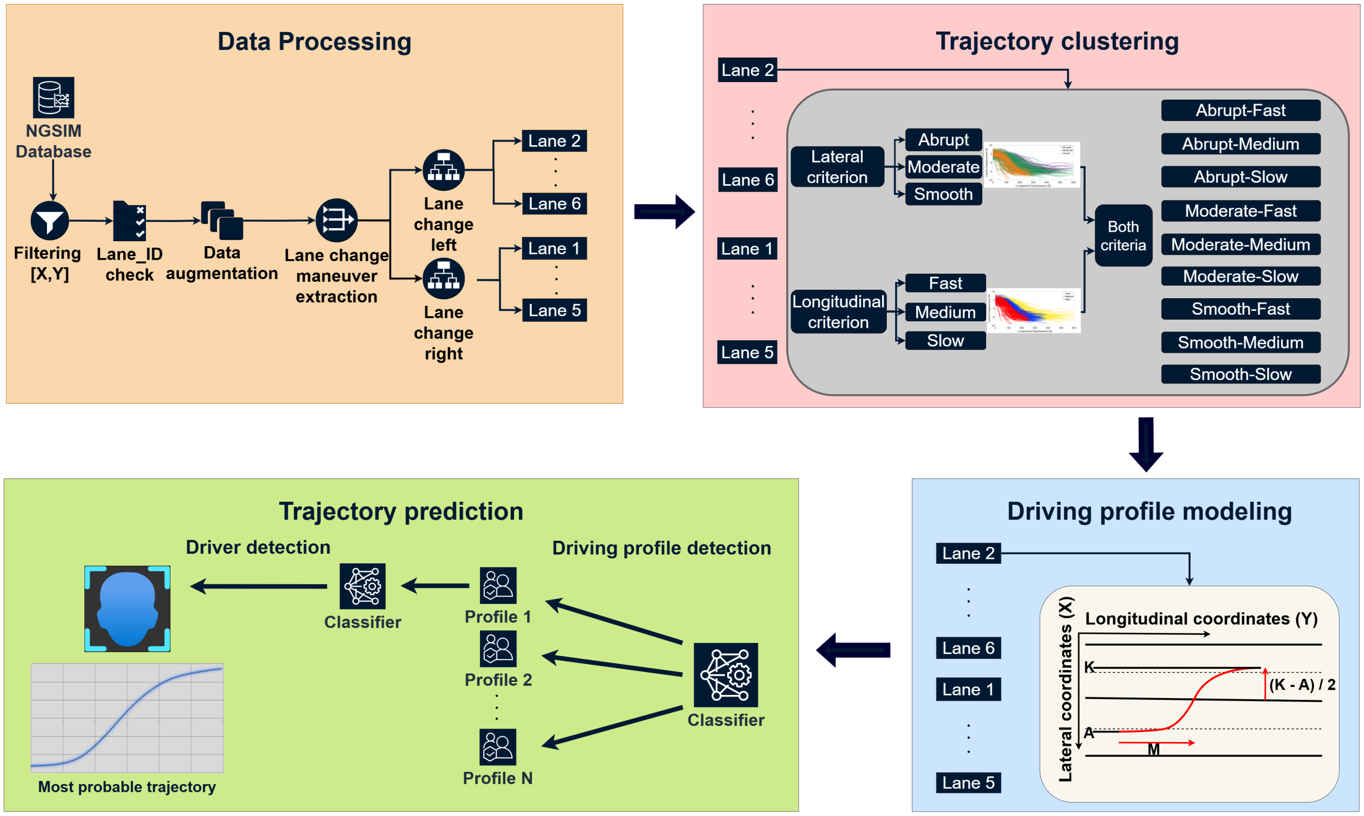


Figure 4.1: General diagram of the proposed system that considers the influence of bidirectional driving profiles in vehicle trajectory prediction.

lyzing the influence of bidirectional driving profile knowledge on trajectory prediction during highway lane change maneuvers.

The process begins with the real trajectory data extraction and filtering from the NGSIM database, where lane-specific trajectories, representing lane change maneuvers in both directions, are identified and augmented. Filtering and data augmentation are necessary to increase the robustness of the detection and prediction models, thereby minimizing the effects of noise present in these trajectory data. The extracted lane-change maneuvers are systematically categorized (e.g., left–to–right changes based on different highway lanes), allowing critical driving patterns to be isolated. Subsequent trajectory clustering further refines the dataset by grouping maneuvers according to kinematic characteristics associated with longitudinal movement (fast, medium, slow) and lateral movement (abrupt, moderate, smooth), which are critical for distinguishing between aggressive and conservative driving styles. This hierarchical data structure ensures that the model captures the intrinsic variability of driver behavior, which is necessary for accurate profile-aware trajectory prediction. The next phase of the model focuses on driving profile detection and its integration into trajectory prediction. A classification model identifies distinct driver profiles (e.g., Profile 1 to Profile N) by correlating clustered trajectories with longitudinal (X, Y) coordinates and lane–specific positional metrics. Notably, the model incorporates bidirectional knowledge|leveraging historical trajectory data and profile inferences|to enhance prediction robustness. For instance, the terms K and A exemplify the normalization of lateral deviations, which, when combined with profile–specific classifiers, refines the prediction of lane change maneuver execution. This dual emphasis on behavioral clustering and profile–aware modeling aligns with the article's core thesis: that bidirectional profile knowledge significantly reduces prediction uncertainty in complex highway scenarios, particularly during lane transitions. Finally, once the driver profile has been detected, our model focuses on increasing the degree of personalization of the system: classification models are trained to detect possible variations in the driver's behavior in different instances of executing the lane change maneuver. This model proposes a system capable of recognizing a driver whose driving profile has been previously identified, to model that driver's behavior under certain uncertainty limits and estimate the most likely trajectory with which the driver would execute the maneuver.

4.3 Data processing

4.3.1 Database

The analyzed road scenario is part of the NGSIM database [54], specifically we used the data related to the scenarios of the I-80 and US-101 highways. Figure 4.2 shows the two scenarios analyzed in this work. From the topological point of view, the I-80 has six freeway lanes, including a high-occupancy vehicle lane, in addition to an access ramp. On the other hand, the US-101 has five main lines and an auxiliary lane as a corridor between the access and exit ramps. For this study, the traffic on both highways is considered one-way roads, in accordance with the description of the data in the database used.

On both US-101 and I-80, the extracted lane change right maneuvers were grouped into five groups, based on the lane of origin, these groups encompassing maneuvers originating from lane 1 (LCR1) to maneuvers originating from lane 5 (LCR5). Similarly, the lane change left maneuvers were grouped into five groups, starting from maneuvers originating in lane 2 (LCL2) to maneuvers originating in lane 6 (LCL6). These extracted maneuvers in both scenarios were then merged, based on the different lanes and/or turn orientations. For example, LCR1 maneuvers on I-80 were merged with LCR1 maneuvers on US-101, thus forming a single LCR1 maneuver group. The remaining maneuvers were grouped similarly. These considerations were made based on two main assumptions: (i) the topological and structural similarity between both scenarios, about the type and use of roads, the number of traffic lanes and the location of the access and exit ramps, on the far right in the direction of traffic, for both highways, (ii) the possibility of having a larger amount of data and a greater probability of increasing the variety of driving profiles present in the real trajectory data. The number of extracted maneuvers varies depending on the scenario (I-80, US-101), the traffic lanes and the type of maneuver (lane change to the right and lane change to the left), obtaining a greater volume of data in the central lanes (lanes 3 and 4 in both scenarios) and a greater number of lane change maneuvers to the left than the total number of maneuvers to the right.

The nomenclature described above is illustrated in Figure 4.3. The selection of lane change left maneuvers in lane 4 (LCL4) to display the results of this chapter's different sections and subsections were motivated by obtaining a greater degree of representativeness of the total set of trajectories. This was the group with the highest number of trajectories extracted, together with the fact that it represents the maneuvers that began and ended in the central lanes of both highways (lanes 4 and 3, respectively), which allows for minimizing possible local effects associated with the extreme high-speed lanes and the merging/exiting lanes of the highways. Also related to this local effect of the end lanes, it was avoided to extract data from trajectories executed in the vicinity of the entrances and exits located between lanes 5 and 6, in both road scenarios, which are more related to mandatory maneuvers to enter or exit highway traffic.

Figure 4.2: Road scenarios analyzed in this study. (Up) Interstate I-80 highway. (Down) US-101 highway.

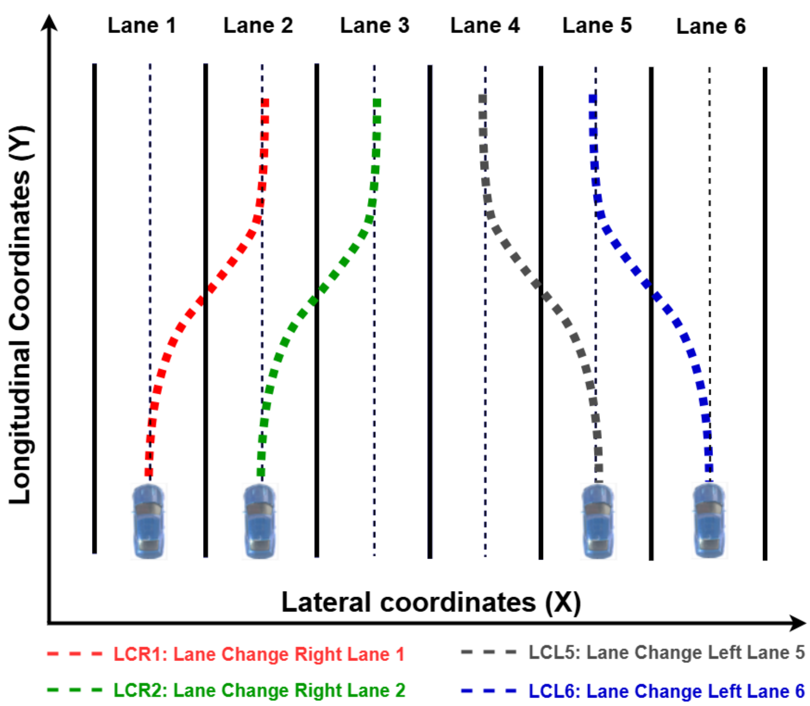


Figure 4.3: Nomenclature used to describe lane change maneuvers.

4.3.2 Pre-processing

The real trajectory data preparation cycle to obtain the driver's driving profiles is described below. That includes, initially, the pre−processing of the trajectory data and the extraction of maneuver data. The lateral and longitudinal position data used in this study refer to the variables LocalX and LocalY, respectively, described as follows, according to the documentation of the NGSIM database [54]. Local X is lateral coordinate of the front center of the vehicle in feet concerning the left−most edge of the section in the direction of travel. For its part, LocalY is longitudinal coordinate of the front center of the vehicle in feet for the entry edge of the section in the direction of travel. The rest of the data used were: VehicleID (Vehicle identification number, ascending by time of entry into section), FrameID (Frame Identification number, ascending by start time), vClass (we only employ vClass=2, cars), vVel (instantaneous velocity of vehicle in feet/second), vAcc (instantaneous acceleration of vehicle in feet/second square), LineID (current lane position of vehicle). Lane 1 is the farthest left lane, lane 5 is the farthest right lane. Lane 6 is the auxiliary lane between Ventura Boulevard on−ramp and the Cahuenga Boulevard off−ramp, according to Figure 4.2.

Once the data of position X (lateral position), position Y (longitudinal position), speed, and acceleration had been filtered, the angle of inclination of the vehicle to the direction of circulation was calculated. Once the lateral position values had been filtered, the traffic lane IDs were redefined for each instant of time considering a lane width of 12 feet, which is the lane width standardized by the U.S. Interstate Highway System. This angle of inclination was calculated as the slope between two consecutive pairs of coordinates [X, Y]. This assumption is considered reasonable since the position data is sampled every 100 milliseconds, during which time the kinematic variations of the vehicle are not so significant [169]. For the detection of lane change maneuvers, the value of the traffic lane ID is used and redefined after the filtering process. Once this identifier changes and is maintained in a sustained manner and a lateral displacement close to the width value of the lane is validated, the maneuver is considered completed. The data considered in this study for a lane change trajectory are composed of a set of 100 position data pairs of the lateral and longitudinal coordinates [X,Y]. Within this set, 50 data pairs [X,Y] correspond to position data recorded in the origin lane before crossing the dividing line between lanes. The remaining 50 data pairs are those recorded in the destination lane, once this line has been crossed. This is shown in detail in Figure 4.4. For lane change maneuvers this point is represented by the instant before the change in lane ID. These time series are equivalent to 10 seconds of trajectory, this particular value is selected based on similar analyses described in references of previous studies consulted [42], which is considered a satisfactory description to study the temporal evolution of these maneuvers.

To increase the number of trajectory samples for each lane, techniques were used to generate data synthetically from the real trajectory data. These techniques consisted of scaling the vertical and horizontal position data. Through each real trajectory, 4 synthetic trajectories are generated: two trajectories obtained by scaling the lateral coordinates by factors of 95% and 105% and another 2 trajectories obtained by scaling the longitudinal coordinates by factors of 95% and 105% of the real coordinates. The ranges for scaling the data were selected based on statistical criteria of variance of 5% around the real data, which can be based on assuming possible variations during the process of obtaining the real data itself through cameras installed on highways and subsequent image processing algorithms.

4.3.3 Lane change maneuver modeling curves

In this section, we include a brief description of the reference trajectory curves that are usually used to describe lane change maneuvers.

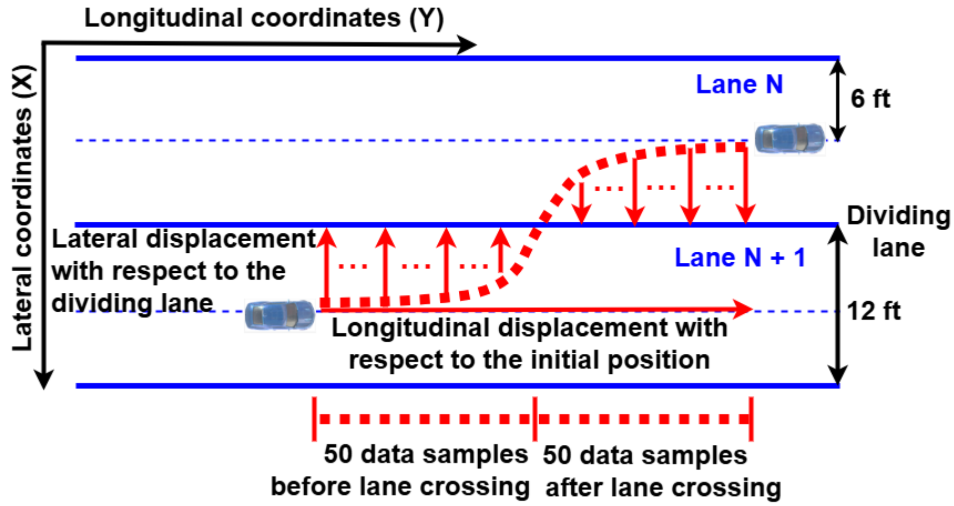


Figure 4.4: Data points considered to describe a lane change maneuver. In this case, the figure represents a lane change maneuver to the left.

The curves for modeling lane change maneuvers used in this article are the linear curve, the step curve, and the generalized logistic curve. A graphic description of each of them, as well as their main parameters, can be consulted in Figure 4.5. To try to capture the intrinsic behavior within each lane and the particularities of these depending on whether they are interior lanes or extreme lanes in the traffic flow, these 3 curves were generated for each of the maneuver groups of each lane separately: maneuvers to the right and maneuvers to the left for the case of the inside lanes (lanes 2 to 5), maneuvers to the right for lane 1 (high-speed lane) and maneuvers to the left for lane 6 (incorporation lane). In total, 10 sets of the 3 previously mentioned curves were generated.

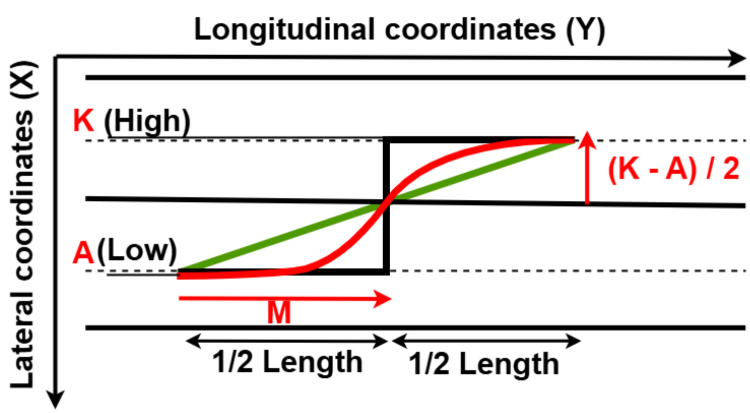


Figure 4.5: Graphic description and main parameters of the modeling curves used in this work: linear curve (green curve), step curve (black curve), and logistic curve (red curve). Parameters with red letters correspond only to the logistic curve. These representations are for lane change maneuvers to the left.

The procedure used for the design of the linear and step curves is described below: (i) Initially, a representative curve of the average trajectory of the lane is obtained, that is, all the lane change maneuvers were taken in one direction, and a synthetic trajectory was obtained whose data are the average values of the set of maneuvers. (ii) Subsequently, the [X, Y] coordinates of the starting point and the ending point of that average trajectory are determined, described by “High”, “Low”, and “Length”. These were the starting and ending points on which the linear and step curves were constructed. In the case of the step curve, the midpoint where the curve “jumps” was defined as the midpoint between the longitudinal coordinates of the initial and final points described above, described by “1/2 Length”. Finally, we use the generalized logistic function, similar to the one used in [170]. This function is also known in the literature as Richard’s curve [171]. A method for estimating the coefficients of various non-linear logistic models, including Richard’s curve, proposed in [172], is based on the calculation of partial derivatives, through the Marquardt regression method. However, in this study we carried out some algebraic work to adapt the mathematical expression according to the road environment where we will model our maneuvers, resulting in the following expression:

$$Y(X) = A + \frac{K - A}{1 + Q\mathrm{e}^{-B(X-M)}}, \tag{4.1}$$

where A is the lower asymptote, K is the upper asymptote, B is the growth rate, Q and M are constants related to the initial condition Y_0. With $X = M$ and $Q = 1$, the function has an inflection point, and its value reaches $(K + A)/2$. In our scenario, this occurs near the line change crossing point.

The procedure followed in this case was to carry out a logistic adjustment of the curve of the mean trajectory of the lane. In this work, some mathematical considerations and simplifications were used, motivated by the particular characteristics of the phenomenon to be modeled and the environment where it takes place, for example, the structure and dimensions of the roads, common driving habits when carrying out a lane change maneuver, among others. For example, the values of A and K are associated with the lateral coordinates of the initial and final points of the curve. The parameters C and v were set to the value 1, which is a typically used value, and, in our scenario, this assumption yielded good results. M represents the value of the longitudinal coordinate at the instant just before the lane crossing (the last of the 50 data points before the lane crossing). The B and Q terms of the equation were initially set with values of 0.03 and 1, respectively. During the logistic adjustment process, the parameters B, Q, and M were adjusted with the help of the Matlab 2022b software [173], which yielded particular values for each of the driving profiles obtained later. The latter are taken as the characteristic parameters of the driving profile.

Once these profiles are obtained and characterized, the next step is to design a classifier that is capable of correctly detecting the profiles and, based on this, predicting the most probable trajectory that the vehicle follows during the execution of the lane change maneuver. For the choice of the classifier, we use the design concept of Auto Machine Learning, it allows us to avoid possible biases associated with the manual selection and configuration of the classification models and, in the same way, allows us to obtain models that are more adjusted to the data we are working with. Specifically, the tool used for this purpose was the WEKA classification package called AutoWEKA [174], [175].

4.3.4 Results

In this section, the result of modeling the lane change maneuvers will be analyzed, according to the different modeling curves described in the previous section: the linear curve, the step curve, and the mean logistic curve of the lane. A representation of the left lane change maneuvers in lane 4, together with the respective modeling curves, can be seen in Figure 4.6.

To analyze the results of this modeling, the RMSE metric has been used, which has been widely used in the literature. In this work an analysis of the movement in both directions is made: the lateral movement and the longitudinal movement of the vehicle. Figure 4.7 shows the distribution of lateral error (RMSEx) obtained by modeling lane change maneuvers to the left of lane 4 using the

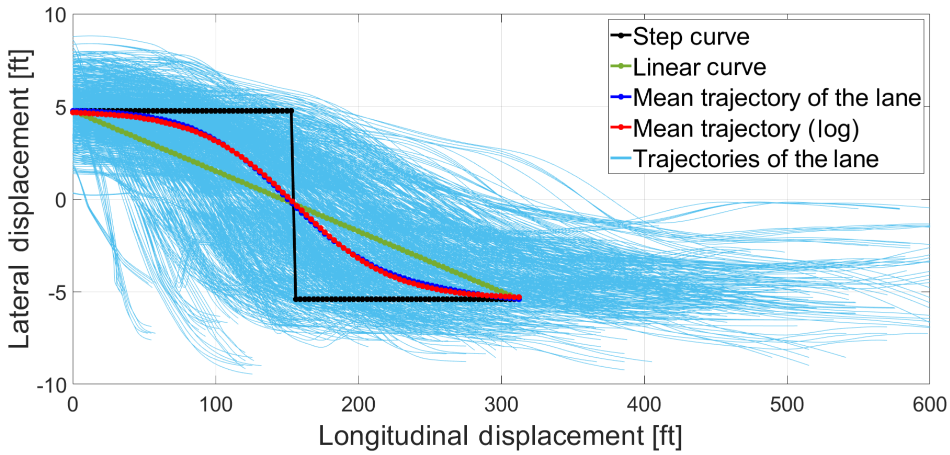


Figure 4.6: Lane change left maneuvers and reference trajectories of Lane 4.

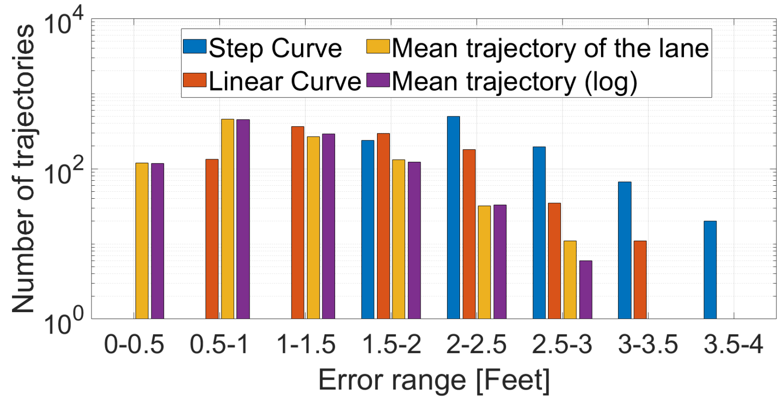


Figure 4.7: Lateral error distribution obtained by modeling lane change left maneuvers of Lane 4 using reference trajectories.

reference trajectories. For better visualization, the numbers of trajectories on the Y-axis have been represented on a logarithmic scale. As can be seen, the curve associated with the mean trajectory of the lane, as well as the curve obtained through the logistic fit of the latter, obtain better results than generic linear and step curves, evaluating the majority of trajectories with errors of less than 1 foot and, at most, less than 3 feet. The curve with the best modeling results, in terms of errors obtained, is the logistic curve that fits the mean trajectory of the profile. The opposite is observed with the performance of generic curves such as step and linear, which even obtain error values greater than 3 feet (within the range between 3 and 4 feet).

4.4 Trajectory clustering

Lane change maneuver clustering plays a pivotal role in extracting valuable insights from driving behavior and establishing comprehensive driving profiles. In the realm of autonomous vehicles and advanced driver assistance systems, understanding how drivers execute lane changes is crucial for enhancing safety and efficiency. By employing clustering techniques on lane change maneuvers, it becomes possible to identify distinct patterns and behaviors exhibited by drivers in various scenarios. These clusters not only provide a deeper understanding of driver decision-making processes but also aid in the development of more accurate predictive models. Furthermore, the utilization of lane change maneuver clustering contributes to the creation of tailored driving profiles, which can be employed for personalized assistance, optimizing route planning, and promoting adaptive driving strategies. In essence, the adoption of lane change maneuver clustering transforms raw driving data into actionable intelligence.

To obtain the different driving profiles related to lane change maneuvers, we consider it useful to section the analysis of the bidirectional movement of the vehicle. In the same way, we consider it useful to develop a particular analysis for each traffic lane, given that on a highway there are differences in terms of the use by drivers of the different lanes, there are high-speed lanes, central lanes, incorporation lanes and/or highway exit, each with different traffic patterns. In this study, we have decided to focus on the study of the central lanes, which is where the greatest number of lane change maneuvers are carried out and thus avoid the influence of undesired effects, such as the presence of entering and/or leaving maneuvers from the highway.

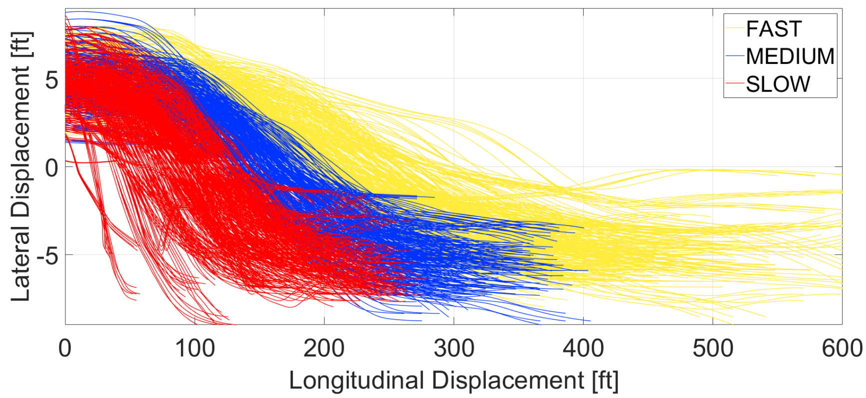
Initially, we analyzed the behavior of lateral movement, since it is highly relevant for this type of maneuver, as supported by numerous studies on the subject in the literature. In this analysis, variables such as lateral displacement and speed are considered, specifically the relationship between the lateral displacement and the longitudinal displacement of the vehicle is analyzed, to determine how abrupt the lane change maneuver is. More abrupt maneuvers are characterized by greater lateral displacement, together with less longitudinal displacement, characteristics that may be associated with more aggressive behavior on the part of drivers and more unsafe conditions for drivers who are driving in the traffic lane destination towards which the driver who is making the lane change is heading.

4.4.1 Results

In analyzing the longitudinal behavior of lane change maneuvers, we consider variables such as longitudinal displacement and speed. In the top side of Figure 4.8we can see the existence of three clusters, which we have associated with driving profiles defined as: “fast”, “medium” and “smooth”. On average, drivers with a slow profile complete the lane change maneuver in a longitudinal distance two and three times shorter than the distance used by drivers with a fast profile, for similar values of lateral displacement, which leaves less margin of reaction to the incorporation for drivers who circulate in the destination lane, with the consequent negative implications for road safety that this can cause.

Similarly, in the bottom side of Figure 4.8 we represent three driving profiles obtained for lane change maneuvers considering the lateral behavior. We have defined these lateral profiles as: “abrupt”, “moderate” and “smooth”. As can be seen, drivers with a steeper profile travel a greater lateral distance on average, which translates into greater obstruction to the use of the origin and destination lanes by other drivers.

In light of these results, we decided to go one step further to achieve a greater granularity in the differentiation of the different lane change profiles and we analyzed the joint behavior in both directions of movement, that is, obtaining profiles that describe both lateral behavior and the longitudinal behavior of lane change maneuvers. We have defined these profiles as: “abrupt-fast”, “abrupt-medium”, “abrupt-slow”, “moderate-fast”, “moderate-medium”, “moderate-slow”, “smooth-fast”, “smooth-moderate” and “smooth-slow”. The result obtained for the particular case of lane change maneuvers to the left of lane 4 can be seen in Figure 4.9, where seven of these driving profiles were obtained. For better visualization and analysis of the results obtained, the figure is subdivided on the right: for each of the three lateral profiles (smooth, moderate, and abrupt), located from top to bottom, the lateral/longitudinal profiles obtained by incorporating the longitudinal criteria (fast, medium and slow).



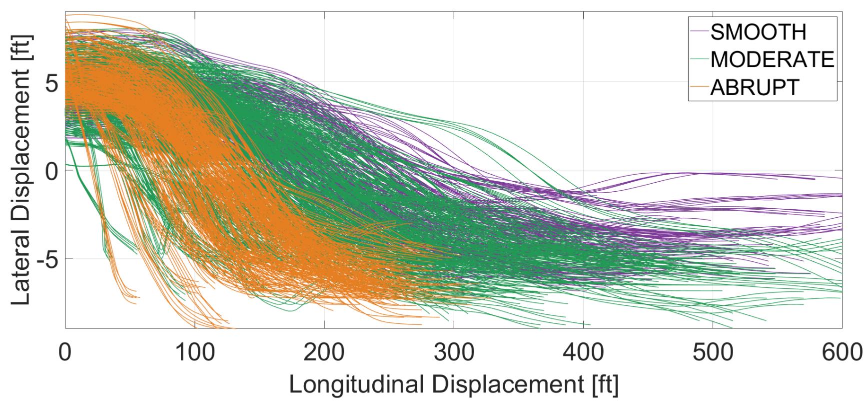


Figure 4.8: Profiles obtained for the lane change left maneuvers in lane 4 considering a single movement behavior. (a) Longitudinal movement behavior. (b) Lateral movement behavior.

Notably, not all traffic lanes show the nine profiles that consider the behavior in both axes of movement; extreme profiles such as "abrupt-fast" and "smooth-slow", among others, are generally absent. In our opinion, this is related to vehicle movement's dynamic and kinematic restrictions. For example, aggressive behavior in one of the directions of the movement is generally accompanied by conservative or almost conservative behavior in the other direction of the movement, and vice versa. Understanding "abrupt" and "fast", as the most aggressive profiles in lateral and longitudinal movement, respectively, and "smooth" and "slow", as the most conservative profiles in lateral and longitudinal movement, respectively.

Finally, in Table 4.1 we show the total number of maneuvers according to the driving profiles obtained, expressed in percentage amounts, for the maneuvers of lane change left and those of lane change right, the latter denoted in parentheses. As can be seen in the lane change maneuvers to the left, it is notable that around half of the drivers (49.74%) are grouped according to the criterion of lateral traffic with a moderate profile, while according to the longitudinal circulation criterion, this distribution is more equitable between the three profiles (33.03%, 29.52%, and 37.45%). For its part, in lane change maneuvers to the right, a similar trend can be seen according to the lateral circulation criterion, although to a lesser extent, reaching up to (43.38 %) the percentage of moderate drivers. The differentiation according to the criterion of longitudinal movement follows the trend of lane change maneuvers to the left, with approximately equal proportions of profiles. In summary, similar trends are observed in both types of maneuvers.

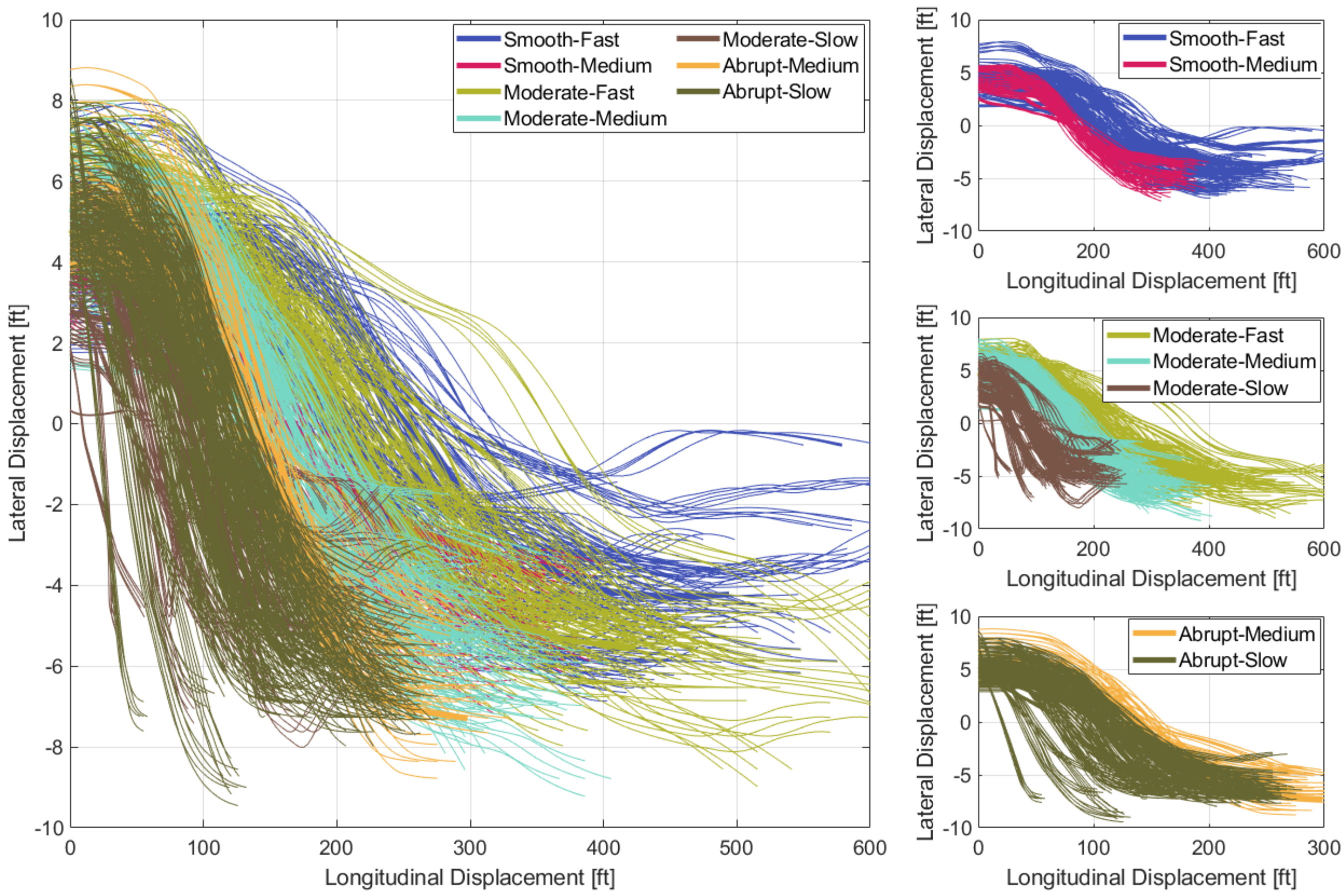


Figure 4.9: Profiles obtained for the lane change left maneuvers in lane 4 considering both movement behaviors.

Table 4.1: Percentage amounts of lane change left and (lane change right) maneuvers according to profiles obtained.

PROFILES	ABRUPT	MODERATE	SMOOTH	LONGITUDINAL TOTALS
FAST	16.58%	13.21%	3.24%	**33.03%**
	(12.79%)	(14.61%)	(6.39%)	**(33.79%)**
MEDIUM	5.66%	17.93%	5.93%	**29.52%**
	(8.68%)	(13.70%)	(7.76%)	**(30.14%)**
SLOW	4.04%	18.60%	14.80%	**37.45%**
	(6.85%)	(15.07%)	(14.16%)	**(36.07%)**
LATERAL TOTALS	**26.29%**	**49.74%**	**23.97%**	**100.00%**
	(28.31%)	**(43.38%)**	**(28.31%)**	**(100.00%)**

4.5 Driving profile modeling

This section describes the process for obtaining the analytical expressions that describe the different driving profiles for lane change maneuvers. Once the different driving profiles have been obtained through the clustering process of the trajectory data of the lane change maneuvers, the next step is to describe the process of obtaining the analytical expressions that describe each of these profiles.

In this sense, the behavior of the main parameters that describe it is analyzed, as well as the trends observed in the variation of these parameters when analyzing different driving profiles, as well as the study of behavior for different traffic lanes.

4.5.1 Results

Based on the criteria for obtaining profiles used in the previous section, which considers the behavior of both movements (lateral and longitudinal), a logistic regression model was designed to determine the mathematical expression that describes each of these profiles. As described previously, the B, Q, and M parameters for each driving profile were adjusted during the logistic fitting process. During this process, the left and right lane change maneuvers and, simultaneously, the behavior followed in each lane, were analyzed.

The logistic coefficients of the curves that describe the profiles of lane change maneuvers considering: (i) the longitudinal grouping criterion, are shown in Table 4.2, (ii) the lateral grouping criteria, are shown in Table 4.3 and (iii) both grouping criteria, are shown in Table 4.4. The expected behavior for parameter B, associated with the growth/decrease rate of the logistic function, is analyzed for the different traffic lanes and types of maneuvers, depending on whether they are turning to the right or left. We can observe a generally increasing trend of the parameter in the lane change maneuvers to the left, which become more complex to execute, to the extent that we are joining higher speed lanes, coming from lower speed lanes, for example, which, by requiring greater longitudinal/lateral displacement, makes it more likely to perform lane change maneuvers with a less steep slope. The opposite occurs in lane change maneuvers to the right, where the decreasing trend can be explained by the fact that drivers with a fast and/or abrupt profile can more easily access slower lanes from faster lanes, performing maneuvers with a steeper slope, which minimizes the time in which they execute the crossing between lanes. To reduce the effect of traffic speed in different lanes, an intra-lane analysis is performed. In it we can observe an increasing tendency when moving from a fast profile to a slow profile according to the longitudinal criterion and a decreasing tendency when moving from an abrupt profile to a smooth one according to the lateral criterion, which is consistent with the fact that for higher values of speed and longitudinal displacement, the maneuvers tend to be carried out with a less pronounced slope and in the opposite case with higher values of speed and lateral displacement, the maneuvers are carried out with a steeper slope. This general trend can be evidenced in the column of profile parameters: "PR. PAR.", of Tables 4.2 and 4.3. An atypical behavior is shown in lane change maneuvers to the right when considering the lateral criterion (Table 4.3), specifically in lanes 2, 4, and 5 (LCR2, LCR4, and LCR5), which we assume may be related to particular characteristics associated with the traffic densities in these lanes.

For its part, the parameter Q associated with the value Y_0 of the logistic function reflects a less predictable behavior, although part of the explanation for its behavior can be associated with the type of maneuver, whether it is a lane change to the right or the left when considering whether we are going from a faster lane to a slower lane or from a slower lane to a faster lane, respectively. In a general sense, higher values of this parameter are associated with a greater delay in the initial moment of the execution of the maneuver, that is, at the point of no return in its execution. When changing lanes to the left, it can be seen that the highest values of this parameter are found in the center lanes, as evidenced in the lane parameter rows: "L. PAR." in Tables 4.2 and 4.3, which reflects an environment where one is trying to access lanes with a high traffic density and with higher traffic speeds than in the origin lane, which induces a delay in the start of the maneuver. For its part, in the lane changes to the right, the behavior of this parameter is analyzed from the lane parameter rows: "L. PAR." as follows: from Tables 4.2 and 4.3, the phenomenon that is observed is that the extreme lanes are the ones with the highest value of this parameter. In the case of Lane 1, an attempt

Table 4.2: Logistic coefficients obtained for the lane change left and lane change right maneuvers considering the longitudinal grouping criterion, represented as Fast (FAST), Medium (MED.) and Slow (SLOW).

PR.	**LCL2 (LCR1)**	**LCL3 (LCR2)**	**LCL4 (LCR3)**	**LCL5 (LCR4)**	**LCL6 (LCR5)**	**PR. PAR.**
			PARAMETER B			
FAST	0.0202 (0.0229)	0.0223 (0.0216)	0.0203 (0.0181)	0.0208 (0.0180)	0.0256 (0.0316)	0.0218 (0.0224)
MED.	0.0259 (0.0270)	0.0294 (0.0266)	0.0295 (0.0259)	0.0301 (0.0257)	0.0349 (0.0328)	0.0299 (0.0276)
SLOW	0.0356 (0.0405)	0.0419 (0.0358)	0.0466 (0.0356)	0.0431 (0.0317)	0.0508 (0.0466)	0.0436 (0.0380)
L. PAR.	0.0272 (0.0301)	0.0312 (0.0280)	0.0321 (0.0265)	0.0313 (0.0251)	0.0371 (0.0370)	
			PARAMETER Q			
FAST	0.4030 (1.3770)	0.9484 (0.9488)	0.8365 (0.8546)	1.4810 (0.9917)	0.9360 (0.7030)	0.9210 (0.9750)
MED.	0.4741 (1.1820)	0.8000 (0.6233)	1.1500 (0.7768)	1.3610 (0.5053)	1.0750 (1.0280)	0.9720 (0.8231)
SLOW	0.7009 (0.9236)	1.0100 (0.8378)	0.6496 (0.6275)	0.9145 (0.8190)	0.5309 (1.1190)	0.7612 (0.8654)
L. PAR.	0.5260 (1.1609)	0.9195 (0.8033)	0.8787 (0.7530)	1.2522 (0.7720)	0.8473 (0.9500)	
			PARAMETER M			
FAST	265.90 (235.20)	219.50 (233.10)	237.80 (236.50)	209.90 (245.20)	161.90 (155.30)	219.00 (221.06)
MED.	201.00 (180.80)	161.90 (165.00)	156.80 (168.10)	146.80 (196.90)	112.10 (110.90)	155.72 (164.34)
SLOW	141.90 (113.20)	111.90 (109.80)	104.70 (117.50)	97.45 (140.60)	89.45 (77.00)	108.88 (111.62)
L. PAR.	202.93 (176.40)	164.10 (169.30)	166.43 (174.03)	151.38 (194.23)	121.15 (114.40)	

Table 4.3: Logistic coefficients obtained for the lane change left and lane change right maneuvers considering the lateral grouping criterion, represented as Abrupt (ABR.), Moderate (MOD.) and Smooth (SMO.).

PR.	**LCL2 (LCR1)**	**LCL3 (LCR2)**	**LCL4 (LCR3)**	**LCL5 (LCR4)**	**LCL6 (LCR5)**	**PR. PAR.**
			PARAMETER B			
ABR.	0.0303 (0.0337)	0.0395 (0.0210)	0.0400 (0.0278)	0.0404 (0.0180)	0.0287 (0.0317)	0.0358 (0.0264)
MOD.	0.0251 (0.0281)	0.0313 (0.0292)	0.0293 (0.0255)	0.0299 (0.0245)	0.0346 (0.0350)	0.0300 (0.0284)
SMO.	0.0229 (0.0230)	0.0241 (0.0341)	0.0235 (0.0215)	0.0225 (0.0312)	0.0502 (0.0429)	0.0286 (0.0305)
L. PAR.	0.0261 (0.0283)	0.0316 (0.0281)	0.0309 (0.0249)	0.0309 (0.0246)	0.0378 (0.0365)	
			PARAMETER Q			
ABR.	0.3730 (1.1960)	1.2480 (1.0690)	0.9442 (0.4930)	0.8756 (0.7262)	0.6847 (0.9750)	0.8251 (0.8918)
MOD.	0.4416 (1.4120)	0.9582 (0.9812)	1.0090 (0.7859)	1.2330 (0.9071)	0.8873 (0.8507)	0.9058 (0.9874)
SMO.	0.3099 (1.0340)	0.7042 (0.6251)	0.8452 (0.7203)	1.3650 (0.8405)	0.5779 (1.2840)	0.7604 (0.9008)
L. PAR.	0.3748 (1.2140)	0.9701 (0.8918)	0.9328 (0.6664)	1.1579 (0.8246)	0.7166 (1.0366)	
			PARAMETER M			
ABR.	171.70 (133.90)	106.40 (197.50)	113.70 (150.30)	107.20 (240.00)	153.60 (147.80)	130.52 (173.90)
MOD.	214.20 (181.80)	151.40 (156.70)	154.60 (174.30)	142.10 (186.10)	121.00 (117.20)	156.66 (163.22)
SMO.	261.20 (231.80)	221.40 (116.50)	220.60 (213.00)	214.10 (152.90)	90.17 (75.73)	201.49 (157.99)
L. PAR.	215.70 (182.50)	159.73 (156.90)	162.97 (179.20)	154.47 (193.00)	121.59 (113.58)	

Table 4.4: Logistic coefficients obtained for the lane change left maneuvers and the (lane change right maneuvers) considering both grouping criteria. The lateral grouping criterion is represented as Abrupt (ABR.), Moderate (MOD.), and Smooth (SMO.), and the longitudinal grouping criterion is represented as Fast (FAST), Medium (MED.), and Slow (SLOW).

PARAMETER		**B**			**Q**			**M**		
LANE	**PROFILE**	**FAST**	**MED.**	**SLOW**	**FAST**	**MED.**	**SLOW**	**FAST**	**MED.**	**SLOW**
LCL2 (LCR1)	**ABR.**	- (-)	0.0257 (0.0308)	0.0355 (0.0380)	- (-)	0.3104 (1.3440)	0.6143 (0.7782)	- (-)	211.4000 (169.80009	132.9000 (112.0000)
	MOD.	0.0174 (0.0240)	0.0265 (0.0254)	0.0364 (0.0450)	0.5924 (2.2290)	0.4552 (1.1710)	0.7951 (1.2130)	264.4000 (214.3000)	200.4000 (177.8000)	151.0000 (113.8000)
	SMO.	0.0227 (0.0223)	0.0234 (0.0250)	- (-)	0.2849 (1.0810)	0.6541 (0.9010)	- (-)	266.9000 (246.1000)	216.1000 (203.1000)	- (-)
LCL3 (LCR2)	**ABR.**	- (0.0201)	0.0271 (0.0246)	0.0410 (-)	- (0.8972)	1.3740 (0.5210)	0.6353 (-)	- (234.6000)	134.8000 (173.4000)	120.0000 (-)
	MOD.	0.0226 (0.0253)	0.0293 (0.0309)	0.0435 (0.0342)	0.8111 (1.3650)	0.8431 (0.6486)	1.3640 (0.9284)	221.8000 (220.6000)	157.2000 (170.5000)	108.0000 (120.3000)
	SMO.	0.0223 (-)	0.0329 (0.0260)	- (0.0410)	0.7331 (-)	0.5555 (0.7147)	- (0.5877)	232.5000 (-)	182.4000 (149.8000)	- (99.8000)
LCL4 (LCR3)	**ABR.**	- (0.0205)	0.0324 (0.0242)	0.0427 (0.0331)	- (0.7003)	1.1390 (0.5446)	0.9205 (0.7456)	- (214.3000)	140.3000 (174.2000)	105.4000 (111.2000)
	MOD.	0.0183 (0.0170)	0.0300 (0.0270)	0.0535 (0.0436)	1.0890 (0.9473)	1.1930 (0.8516)	1.0430 (0.5222)	226.4000 (235.8000)	156.5000 (170.5000)	83.1800 (117.3000)
	SMO.	0.0229 (0.0197)	0.0263 (0.0276)	- (0.0287)	0.7580 (0.7436)	1.0860 (0.7250)	- (0.8981)	238.9000 (241.0000)	174.1000 (170.4000)	- (130.3000)
LCL5 (LCR4)	**ABR.**	- (0.0161)	0.0349 (0.0224)	0.0426 (-)	- (0.9450)	0.8476 (0.4763)	1.0030 (-)	157.4000 (259.2000)	143.1000 (204.5000)	94.1000 (-)
	MOD.	0.0215 (0.0208)	0.0283 (0.0266)	0.0440 (0.0315)	1.5080 (1.0530)	1.1890 (0.4932)	1.0930 (0.6645)	215.8000 (231.3000)	151.2000 (197.5000)	93.0200 (142.8000)
	SMO.	0.0207 (-)	0.0338 (0.0287)	- (0.0325)	1.0060 (-)	2.4150 (0.9723)	- (0.7767)	238.6000 (-)	157.4000 (170.5000)	- (144.9000)
LCL6 (LCR5)	**ABR.**	0.0264 (0.0317)	0.0326 (-)	- (-)	1.3010 (0.9750)	0.5415 (-)	- (-)	144.3000 (147.8000)	138.4000 (-)	- (-)
	MOD.	0.0249 (0.0312)	0.0345 (0.0332)	0.0487 (0.0454)	0.8772 (0.7168)	0.8419 (0.9063)	0.4502 (1.8680)	170.2000 (146.1000)	118.9000 (113.8000)	97.0100 (76.0600)
	SMO.	- (-)	0.0447 (0.0320)	0.0529 (0.0458)	- (-)	0.5681 (1.6360)	1.1040 (1.2120)	- (-)	114.5000 (100.7000)	71.7500 (71.1900)

is made to access the central lanes where the traffic density is higher and therefore the execution of the maneuver tends to be delayed. The same is observed in Lane 5 when trying to access the entrance/exit lanes of the highway, where the main tendency is to find a flow of vehicles entering and making the lane change maneuver difficult.

Finally, the parameter M, associated with the displacement on the abscissa axis, reflects a decreasing behavior as we move from faster lanes to slower lanes, as can be seen in the lane parameter rows: "L.PAR." of Tables 4.2 and 4.3. This behavior is because, in the faster lanes, maneuvers are generally executed with a greater longitudinal and lateral displacement than in the slower lanes. For its part, a decrease in the parameter is generally observed when we go from the fastest/abrupt profiles to the slowest/softest profiles, respectively, as reflected in the profile parameter columns: "PR.PAR". A particular case is shown in the lane change maneuvers to the left when considering the lateral criterion, where an increasing trend of this profile is evident. This can be seen in Table 4.3, in the profile parameter columns: "PR.PAR". Only in lane 6 is the expected trend met (LCL6). In Table 4.4 the description of the parameters B, Q, and M is summarized but this time analyzing joint lane change profiles that consider both grouping criteria. Note that in some cases the "-" symbol indicates the non-existence of that joint profile.

Some of the maneuvers grouped into these obtained profiles, for example, lane change maneuvers to the left of lane 4 characterized by a smooth-fast profile, are shown in Figure 4.10. The modeling reference curves used in this work are also highlighted, associated with the different profiles: the logistic curve that models the mean trajectory of the line, the logistic curve that models the smooth

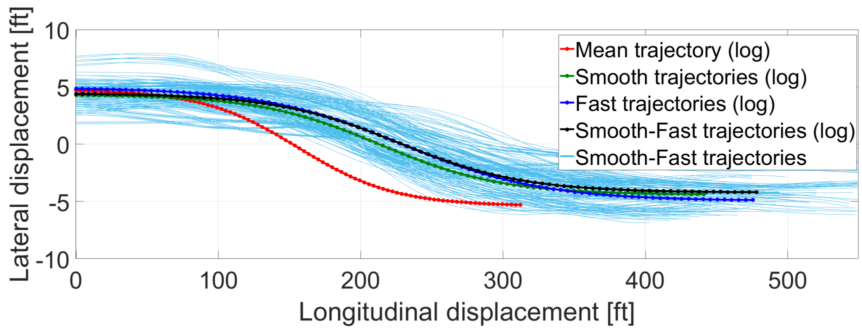


Figure 4.10: Maneuvers characterized as Smooth-Fast in LCL4. (log): the logistic curve that models these trajectories.

trajectories, the logistic curve that models the fast trajectories, and the logistic curve that models the smooth-fast trajectories. As we can see, the trajectories characterized by a smooth-fast profile are not properly represented by the logistic curve that models the average trajectory of the lane, which shows the importance of considering different driving profiles within the same lane. Instead, a better approximation of the curves that model the different profiles mentioned above is seen.

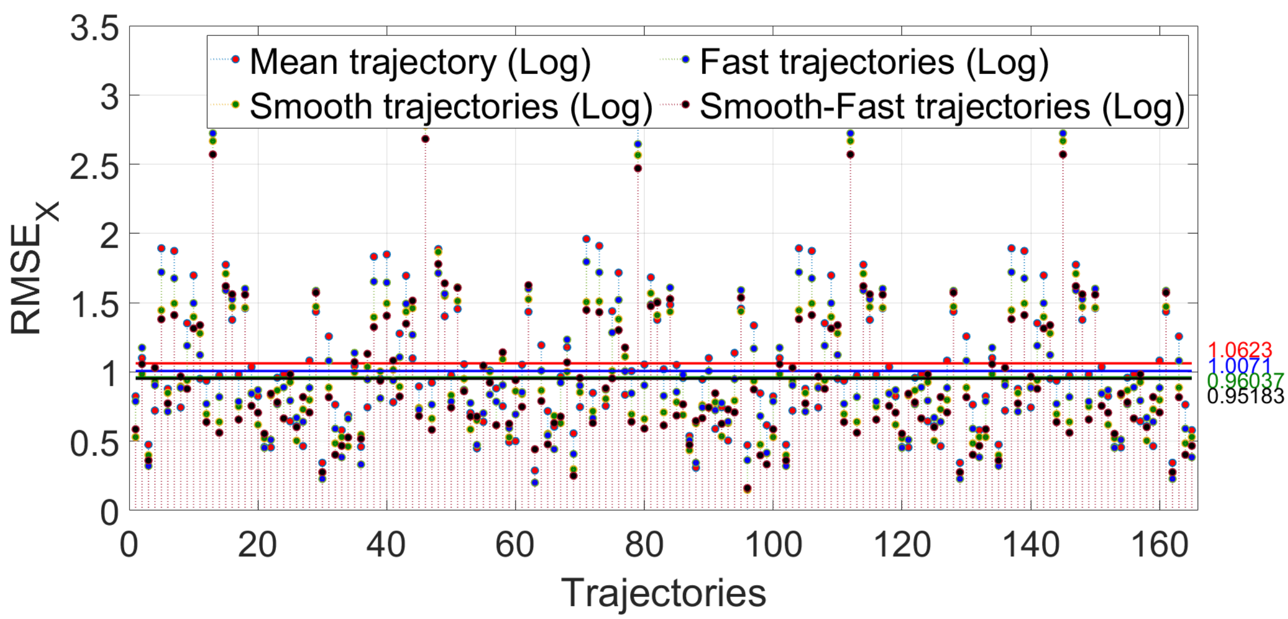


Figure 4.11: Lateral error obtained from the modeling of lane change maneuvers to the left in Lane 4 characterized as Smooth-Fast profile. The errors are expressed in feet, the horizontal line being the average error obtained when evaluating the total number of maneuvers. (Log): the logistic curve that models these trajectories.

The RMSE metric metric is used in this work to mathematically evaluate the result of the logistic modeling of these trajectories. The behavior obtained for lane change maneuver to the left in lane 4, can be seen in Figures 4.11 and 4.12. We have divided the analysis of the results obtained according to the type of vehicle movement: the error in the estimation of the lateral coordinates of the vehicle can be seen in Figure 4.11 and the error in the estimation of the longitudinal coordinates of the vehicle can be seen in Figure 4.12.

As can be seen, the error obtained in the lateral movement is around 1 foot and with narrow mar-

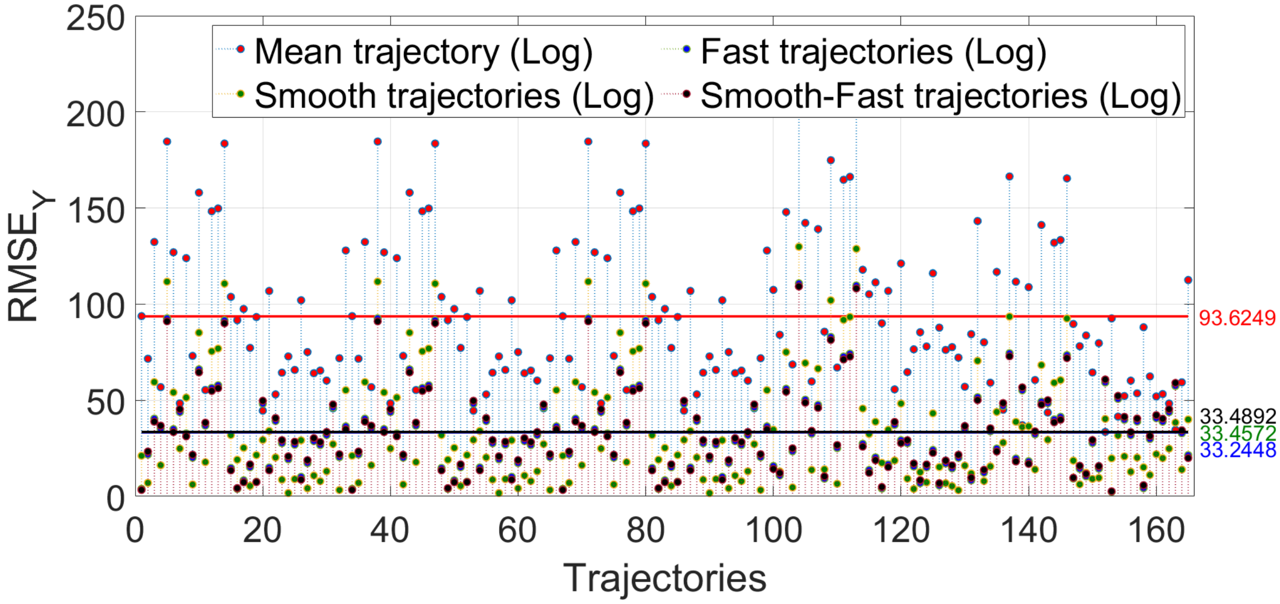


Figure 4.12: Longitudinal error obtained from the modeling of lane change maneuvers to the left in Lane 4 characterized as Smooth-Fast profile. The errors are expressed in feet, the horizontal line being the average error obtained when evaluating the total number of maneuvers. (Log): the logistic curve that models these trajectories.

gins of difference in all cases, with the logistic curve that models the smooth-fast profile trajectories being the one that obtains the best results, with a lower average RMSE at 0.96 feet. For its part, in the modeling of the longitudinal movement, a greater difference is seen in the results obtained when modeling with the different logistic curves (considering driving profiles), with the curve that models the mean trajectories (not considering driving profiles). The results when considering the logistic curves that employ a single criterion and both criteria are approximated the same, with an average RMSE lower than 34 feet in all cases. These figures show how the best results emerge from modeling the behavior of lane change maneuvers through the logistic curves that characterize each of the profiles obtained, over the use of more general curves such as the step curve or the linear curve.

Table 4.5: Lateral RMSE [ft] obtained by modeling lane change maneuvers. Driving profiles from up to down: smooth-slow (SS), smooth-medium (SM), smooth-fast (SF), moderate-slow (MS), moderate-medium (MM), moderate-fast (MF), abrupt-slow (AS), abrupt-medium (AM) and abrupt-fast (AF).(LA): Lane average. (PA): Profile average.

P/L	L1	L2	L3	L4	L5	L6	**PA**
SS	-	1.20	0.25	1.06	0.93	0.89	**0.87**
SM	1.31	0.94	0.78	0.71	0.99	0.89	**0.94**
SF	1.26	1.29	0.88	0.93	0.89	-	**1.05**
MS	0.66	0.81	1.11	1.11	0.95	0.86	**0.92**
MM	0.85	0.86	0.99	0.92	1.10	0.94	**0.94**
MF	0.92	0.83	0.93	1.12	0.87	0.87	**0.92**
AS	0.88	0.56	1.00	0.73	0.56	-	**0.75**
AM	1.18	1.02	0.84	1.31	0.88	0.93	**1.03**
AF	-	0.92	0.58	0.66	1.04	0.99	**0.84**
L.A	**1.01**	**0.93**	**0.81**	**0.95**	**0.91**	**0.91**	**0.92**

Table 4.6: Longitudinal RMSE [ft] obtained by modeling lane change maneuvers. Driving profiles from up to down: smooth-slow (SS), smooth-medium (SM), smooth-fast (SF), moderate-slow (MS), moderate-medium (MM), moderate-fast (MF), abrupt-slow (AS), abrupt-medium (AM) and abrupt-fast (AF).(LA): Lane average. (PA): Profile average.

P/L	L1	L2	L3	L4	L5	L6	**PA**
SS	-	30.64	3.26	27.28	19.81	17.90	**19.78**
SM	9.15	7.94	9.47	10.28	7.32	11.92	**9.35**
SF	27.20	31.38	25.70	33.49	36.79	-	**30.91**
MS	32.26	22.91	21.45	31.87	18.64	14.80	**23.65**
MM	20.33	15.40	16.33	18.06	12.51	11.67	**15.72**
MF	26.95	20.66	27.89	30.68	28.68	29.86	**27.45**
AS	33.50	27.22	24.03	25.05	25.49	-	**27.06**
AM	14.99	11.90	9.82	9.06	8.54	9.71	**10.67**
AF	-	43.32	4.59	29.38	17.41	21.63	**23.27**
L.A	**23.48**	**23.49**	**15.84**	**23.91**	**19.46**	**16.78**	**20.49**

The results obtained for different configurations of lane/profile of lane change maneuvers can be seen in Tables 4.5 y 4.6. As can be seen in the lateral error table, the dispersion of the average RMSE values by profile was generally low. No profile model was sufficiently in error concerning the others. This is even more noticeable in the middle profiles: (MS), (MM), and (MF). Regarding the average values by lane, a similar behavior is noted. In general, the errors were below 1 foot, which is considered a good result for this type of maneuver. Regarding the longitudinal errors, we see a more dispersed behavior, both between profiles and between lanes. The behavior of these values according to the traffic lane does not present an explainable pattern, except that the highest errors are obtained in the longitudinal lanes with the highest speeds. In this case, lane 4 presents atypical behavior, even being the one with the worst results. The behavior according to the driving profiles is equally dispersed, but it can be observed that the middle lanes (SM), (MM), and (AM) are the ones that present the best results. It is the maneuvers of these medium profiles that present less intraprofile dispersion. The medium profiles show lower RMSE values, specifically the smooth-medium and abrupt-medium, indicating that at medium longitudinal velocity, the extreme lateral profiles are well-distinguished maneuvers, behavior generally exhibited in all traffic lanes. The high dispersion of values for different driving profiles is notable, especially the smooth profiles, where the longitudinal component of the movement makes the greatest difference in the trajectories. In contrast, the values of RMSE according to the driving lanes are less dispersed. In general, the results of considering the logistic curves to model the lane change maneuvers are around 20 feet on average, for different configurations of lane/profile.

4.6 Trajectory prediction

This section describes the procedure used to predict the most probable trajectory for a particular driver, whose driving profile has been previously detected. This driver is then modeled using the logistic curve fitting that describes the profile to which he or she belongs, and classification models are again employed, this time to detect that particular driver within a set of lane-change maneuver execution instances randomly generated by a Monte Carlo experiment. Finally, the logistic curve that models that particular driver is established as the most probable trajectory.

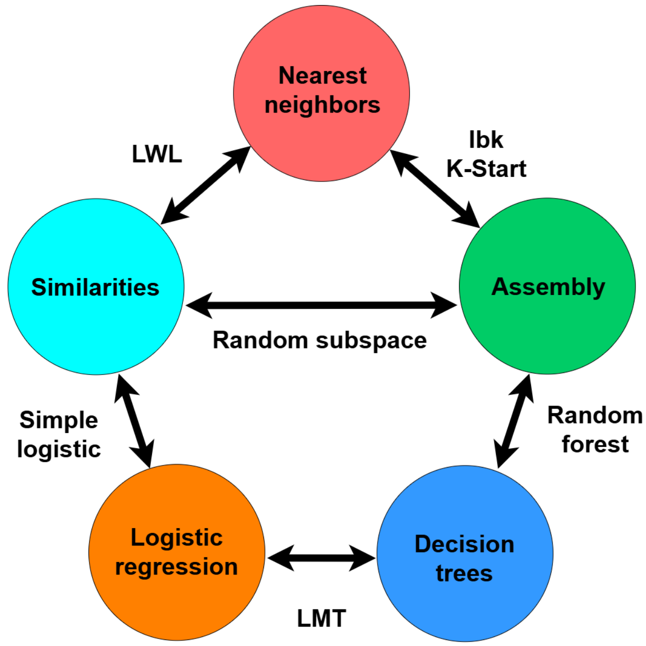


Figure 4.13: Relationship between the different classification models used in this study, according to their similarities and differences.

4.6.1 Driving profiles detection

The Auto Machine Learning design concept allows you to define as inputs the datasets, the evaluation metrics that you want to optimize, and the cost and execution time constraints of the algorithm. Internally, the algorithm (AutoWEKA in our case) performs a double optimization process: first, it selects the classification algorithms with the best results and then it optimizes the parameters of those selected algorithms. AutoWEKA uses the Secuential model-based algorithm classification (SMAC) metric [176] to select the algorithm with the highest performance on the given dataset. As an output of this process, it gives us a ranking with the models that deliver the best results, according to the metrics and restrictions previously defined by us. The metrics used in the analysis was the accuracy, a limit of 15 minutes was imposed as the maximum execution time of the AutoWEKA algorithm.

In the first instance, simulations were run with the AutoWEKA classifier for each of the analyzed datasets and the results of the 3 best-ranked classifiers for each dataset were extracted. Next, the results obtained were tabulated and the 7 classifiers that showed the best results globally for all the datasets were selected, that is, according to the total number of appearances of the classifier in positions 1, 2, and 3 of the rankings previously obtained according to AutoWEKA. Finally, an experiment was developed in Waikato environment for knowledge analysis (WEKA), where all the datasets used were cross-analyzed against each of the 7 previously selected classifiers, for each of the 3 defined dataset construction variants. The selected classifiers in this work, attending to the AutoWEKA results, were: Instance based learner (IBK), KStar, Logistic model tree (LMT), Simple Logistic, Random Forest, Random Subspace, and Locally weighted learning (LWL). A graphical representation of the relationship of these classifiers, reflecting their similarities and differences, is presented in Figure 4.13.

IBK is the name given to the implementation of the **K-NN** classifier in WEKA. To a large extent, the effectiveness of this classifier depends on a correct choice of the parameter K, which is obtained internally as a result of the hyperparameter optimization process used by AutoWEKA. **KStar** classifier is an instance-based learner that combines the simplicity of the K-NN algorithm with feature selection techniques. Unlike traditional K-NN, the KStar classifier also incorporates feature selection to determine which features are most relevant for the detection tasks. The feature selection stage reduces the data´s dimensionality and improves the efficiency and interpretability of the classifier. **LWL** classifier is a machine learning algorithm that assigns weights to the training instances based on their similarity to the new instance being classified. The classifier assigns higher weights to instances that are more similar to the new instance, indicating their greater influence on the classification.

A Random Forest classifier is an ensemble learning method that combines multiple decision trees to make predictions. An important parameter in this classifier is the importance of the features. In the training stage, each feature is analyzed and its importance is determined during the prediction of a correct classification. **Random Subspace** classifier is based on the concept of random feature sub-spaces, where each base classifier is trained on a randomly selected subset of the available features, this, reduces the risk of over-fitting and improves generalization by considering a diverse set of features.

Simple Logistic, also known as the logistic regression classifier, is a classification model that predicts the probability of an instance belonging to a particular class based on the analysis of the independent features. The Simple Logistic classifier assumes a linear relationship between the features and the log odds of the target variable. **LMT** classifier is a hybrid algorithm that combines the interpretability of decision trees while incorporating the probabilistic modeling capabilities of logistic regression. By constructing decision trees and using logistic regression to model the probabilities at each leaf node, the LMT classifier captures both the hierarchical structure of decision trees and the smooth probabilistic nature of logistic regression.

4.6.2 Results

The data structure used by the classifier considers an addressable header field with variables like the value of the vehicle ID, the lane ID, the profile ID, and the path ID. This last data is to consider the different maneuvers performed by the same vehicle, that is, by the same driver. Additionally, as a payload of the data structure, it will be made up of 200 trajectory data, which represent 100 position data to describe the longitudinal movement of the vehicle and 100 position data to describe the lateral movement of the vehicle. These trajectory data were modified to improve the results of detection and estimation tasks, defining the lateral data range being X:[-x_min, x_max], where x_min is greater than or equal to -12 feet and x_max is less than or equal to 12 feet, associated with the lateral dimension of the lane, and the longitudinal data range Y:[0,y_max], where y_max represents the maximum displacement of the vehicle in longitudinal movement. We propose the use of 3 variants of the dataset to analyze the driving profiles, analyzing variables of different categories. Variant 1 (V1) uses only the profile ID and the 200 trajectory data. The other 2 variants of datasets were also evaluated, to accentuate the predictive character of the trajectory data in association with other variables indicative of the intention of the driver and/or the traffic lane. These variables could be obtained in a real-case implementation of a data acquisition system, from modules on board the vehicle that monitor the driver's behavior, such as: monitoring the display of the side mirrors or monitoring the lines of the lane in which it is driving, with cameras installed in the front of the vehicle. Variant 2 (V2) incorporates the previous variant, an attribute related to the type of turn: "-1" to describe a turn to the left and "1" to describe a turn to the right, in addition to reducing the class labels to 9, related to the 9 types of profiles. Variant 3 (V3), incorporates the previous variant, a new attribute related to the traffic lane ID, with values defined in the range [1-6].

The result obtained for the 3 dataset variants, by the 3 best-performing classifiers for each traffic lane, can be seen in Table 4.8. As can be seen, the results obtained for each of the 3 types of datasets

Table 4.7: Results obtained from the classification of lane change left and (lane change right maneuvers) of Lane 4 using dataset V1. The numbers in the top row and the most left column, represent the driving profiles, ranked according to whether they are lane change left maneuvers [class ID: 1-9] or lane change right maneuvers [class ID: 10-18], considering the following order:Smooth-Fast, Smooth-Medium, Smooth-Slow, Moderate-Fast, Moderate-Medium, Moderate-Slow, Abrupt-Fast, Abrupt-Medium, and Abrupt-Slow.

PREDICTED REAL	1 (10)	2 (11)	3 (12)	4 (13)	5 (14)	6 (15)	7 (16)	8 (17)	9 (18)
2	0	**52**	0	0	0	0	0	0	0
(11)	(0)	**(4)**	(0)	(0)	(0)	(0)	(0)	(0)	(0)
3	0	0	**0**	0	0	0	0	0	0
(12)	(0)	(0)	**(0)**	(0)	(0)	(0)	(0)	(0)	(0)
4	0	0	0	**112**	0	0	0	0	0
(13)	**(1)**	(0)	(0)	**(6)**	(0)	(0)	(0)	(0)	(0)
5	0	0	0	**2**	**138**	0	0	0	0
(14)	(0)	**(1)**	(0)	(0)	**(2)**	(0)	(0)	(0)	(0)
6	0	0	0	0	0	**136**	0	0	0
(15)	(0)	(0)	(0)	(0)	(0)	**(6)**	(0)	(0)	(0)
7	0	0	0	0	0	0	**0**	0	0
(16)	(0)	(0)	(0)	(0)	(0)	(0)	**(0)**	(0)	(0)
8	0	0	0	0	**2**	0	0	**50**	0
(17)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	**(5)**	(0)
9	0	0	0	0	0	0	0	0	**192**
(18)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	**(11)**

are similar, with the results where the dataset V1 is used standing out slightly. This indicates that, at least with the use of the total maneuver trajectory data, a substantial improvement is not evident with the incorporation of variables such as the type of maneuver and the lane ID, in combination with the definition of only 9 driving profiles (class ID 1-9). Likewise, it can be seen how the result of the application of the AutoWEKA algorithm selects a reduced group of 4 classification algorithms, within a total set of 39 algorithms, where the IBK algorithm stands out, followed by the KStar, LMT and Simple logistic Simple logistic (SL) algorithms, which demonstrates the high degree of generalization that these algorithms present before various datasets.

To consider a more predictive behavior of the classifiers, we consider the use of partial trajectory data. To stop the profile using only partial data of the trajectory, we take different windows with the first 10, 20, 30, and 40 data of the trajectory, which translates into analyzing the maneuver executed up to intervals of 4 seconds, 3 seconds, 2 seconds and 1 second, respectively, before lane crossing. In this way, the system will not only be evaluated in terms of its ability to detect the type of lane change profile but also how early it can detect it with acceptable accuracy results.

We consider employing the Accuracy metric to analyze the profile detection task. The results obtained from the experiment implemented in WEKA, for dataset V1, dataset V2, and dataset V3, can be displayed in Table 4.9, Table 4.10 and Table 4.11. We can observe, that there are no significant differences between the different types of datasets in terms of the performance of most of the classifiers, either using the total trajectory data or partial trajectory data.

We can observe, first of all, that as in the case in which the total trajectory data is used when we use partial trajectory data there are no significant differences for the different types of datasets in terms of the performance of most of the classifiers. Once again, it turns out to be the IBK algorithm that demonstrates the best performance for the vast majority of datasets analyzed, obtaining the best

Table 4.8: Summary table with the accuracy metrics obtained for the top 3 classifiers with the best performance according to the AutoWeka algorithm, during the classification of the total lane change maneuvers for the different dataset variants. Instance-based learner with K-nearest neighbors (Ibk), Simple logistic (SL), KStar (KS) and Logistic model trees (LMT).

Dataset V1						
Lane	1	2	3	4	5	6
1st	Ibk 100.00%	Ibk 94.49%	Ibk 97.92%	Ibk 97.15%	Ibk 97.50%	Ibk 97.06%
2nd	K-Star 100.00%	LMT 93.70%	LMT 95.88%	LMT 95.89%	LMT 94.38%	LMT 94.38%
3rd	LMT 99.52%	SL 93.17%	SL 95.20%	SL 94.69%	K-Star 93.30%	K-Star 93.30%
Dataset V2						
Lane	1	2	3	4	5	6
1st	Ibk 100.00%	Ibk 94.16%	Ibk 97.85%	Ibk 97.09%	Ibk 97.57%	Ibk 97.01%
2nd	K-Star 100.00%	K-Star 91.64%	K-Star 94.90%	K-Star 95.34%	K-Star 95.65%	SL 95.00%
3rd	LMT 99.84%	SL 90.71%	SL 93.39%	LMT 91.97%	LMT 91.94%	LMT 94.27%
Dataset V3						
Lane	1	2	3	4	5	6
1st	Ibk 100.00%	Ibk 94.56%	Ibk 97.73%	Ibk 97.80%	Ibk 97.79%	Ibk 97.01%
2nd	K-Star 100.00%	SL 92.97%	K-Star 94.90%	K-Star 95.28%	K-Star 95.65%	SL 95.00%
3rd	LMT 99.84%	K-Star 91.64%	SL 93.58%	LMT 93.50%	LMT 93.25%	LMT 94.27%

average values for the 3 types of datasets. The KStar algorithm demonstrated better performance in the smaller datasets, whose data samples include up to 3 and 4 seconds before the crossing, demonstrating a better early detection capacity of the algorithm. This aspect results in a better predictive nature of the same. As in the case of using the total trajectory data, the list of the best-ranked algorithms evaluated, also considering the datasets with partial trajectory data, places IBK, KStar and LMT in the first positions and it is relevant to highlight that The Random Forest algorithm displaces the Simple Logistic algorithm to 4th position in the ranking, thereby demonstrating better performance than the latter when using partial trajectory data. Finally, it can be seen that in a general sense, degradation occurs in the performance of the classifiers while they are evaluated with datasets that have less and less trajectory data, that is, the best results are with the complete dataset and the worst results are with the dataset that has data only up to 4 seconds before the crossing. Although this result would be expected a priori, it should be noted that such degradation is not so significant, in most cases it does not exceed 10-15% of the accuracy. This demonstrates that to a certain extent, the classifiers are robust enough to moderately maintain their performance when evaluated with an increasingly smaller number of trajectory data, which is a desired characteristic in environments of information loss during data exchange in vehicular communication networks through advanced cooperative driving assistance systems. As expected a priori, to the extent that datasets with a smaller number of data are used, the performance of the classifiers is affected when it comes to correctly detecting the profiles. This can be observed with the accuracy metric, this performance degradation is to a certain extent tolerable in terms of the magnitude of the error.

To conclude this section, we show a Summary Table 4.12 attending to the accuracy results

Table 4.9: Accuracy metric of classifiers for Dataset V1. From left to right, the selected classifiers are: Instance-based learner with K-nearest neighbors (Ibk), Simple logistic (SL), Random forest (RF), Random subspace (RS), KStar (KS), Locally weighted learning (LWL) and Logistic model trees (LMT).

Dataset	**Ibk**	**SL**	**RF**	**RS**	**KS**	**LWL**	**LMT**
Lane1	100.00	98.41	94.92	87.78	100.00	77.62	99.52
Lane1-1sec	100.00	96.67	96.03	89.68	100.00	47.94	98.41
Lane1-2sec	100.00	97.78	96.19	93.49	100.00	48.41	97.30
Lane1-3sec	100.00	96.83	94.29	90.63	100.00	47.78	95.87
Lane1-4sec	100.00	84.60	91.27	85.24	100.00	47.78	94.60
Lane2	94.49	93.17	88.98	82.94	91.44	39.45	93.70
Lane2-1sec	93.96	87.52	85.27	78.82	94.83	37.99	87.65
Lane2-2sec	93.97	86.19	85.94	78.22	94.56	41.11	87.93
Lane2-3sec	91.64	79.29	86.86	79.09	92.90	39.44	83.92
Lane2-4sec	90.32	68.26	82.68	75.17	92.37	37.32	81.80
Lane3	97.92	95.20	90.89	85.19	94.90	53.10	95.88
Lane3-1sec	97.20	85.19	88.96	82.50	96.49	46.90	89.80
Lane3-2sec	97.28	79.90	88.36	81.26	96.71	46.86	86.21
Lane3-3sec	95.24	74.00	87.11	78.69	95.54	46.03	84.77
Lane3-4sec	87.00	63.79	83.22	75.85	89.79	45.12	81.78
Lane4	97.15	94.69	90.61	86.31	94.40	46.15	95.89
Lane4-1sec	96.54	80.91	88.87	81.94	95.11	44.27	88.28
Lane4-2sec	96.60	77.80	88.58	81.17	95.66	46.05	86.12
Lane4-3sec	94.08	72.49	86.21	78.19	94.47	45.47	83.82
Lane4-4sec	87.93	64.40	83.04	73.85	89.87	43.95	76.21
Lane5	97.50	94.67	91.49	85.09	95.78	51.50	95.36
Lane5-1sec	96.98	82.91	89.61	83.01	96.53	42.66	85.87
Lane5-2sec	96.30	77.88	89.35	83.08	96.33	42.50	85.09
Lane5-3sec	95.71	71.80	88.70	82.04	96.36	42.40	85.96
Lane5-4sec	93.44	63.65	85.16	77.91	95.32	42.27	82.20
Lane6	97.06	92.06	89.89	83.45	93.30	39.37	94.38
Lane6-1sec	95.78	90.15	86.48	77.66	95.00	39.31	91.33
Lane6-2sec	95.67	82.30	87.05	79.15	94.59	35.96	87.77
Lane6-3sec	95.57	67.86	85.81	75.13	93.92	45.10	83.59
Lane6-4sec	93.40	61.09	79.67	71.57	89.74	37.72	80.70
Average	**95.62**	**82.05**	**88.38**	**81.47**	**95.20**	**44.92**	**88.72**

Table 4.10: Accuracy metric of classifiers for Dataset V2. From left to right, the selected classifiers are: Instance-based learner with K-nearest neighbors (Ibk), Simple logistic (SL), Random forest (RF), Random subspace (RS), KStar (KS), Locally weighted learning (LWL) and Logistic model trees (LMT).

Dataset	**Ibk**	**SL**	**RF**	**RS**	**KS**	**LWL**	**LMT**
Lane1	100.00	98.25	95.24	89.21	100.00	77.62	99.84
Lane1-1sec	100.00	97.14	96.67	90.63	100.00	47.94	98.25
Lane1-2sec	100.00	97.46	96.35	93.33	100.00	48.41	97.30
Lane1-3sec	100.00	95.71	93.17	91.27	100.00	47.78	96.03
Lane1-4sec	100.00	83.02	91.27	86.03	100.00	47.78	94.92
Lane2	94.16	90.71	89.71	81.95	91.64	46.88	89.45
Lane2-1sec	94.10	75.10	85.20	76.75	94.96	38.65	85.13
Lane2-2sec	94.10	70.45	85.00	76.43	94.56	39.58	84.08
Lane2-3sec	91.97	61.02	84.60	76.02	92.90	38.45	80.67
Lane2-4sec	90.38	58.42	84.46	75.49	92.23	36.72	82.80
Lane3	97.85	93.39	91.23	84.69	94.90	53.29	92.82
Lane3-1sec	97.05	77.20	89.27	82.85	96.48	38.78	88.14
Lane3-2sec	97.13	71.39	89.08	80.92	96.71	38.96	86.85
Lane3-3sec	95.16	64.97	87.45	80.39	95.61	39.12	84.43
Lane3-4sec	86.58	57.49	84.09	76.23	89.42	38.89	83.03
Lane4	97.09	90.94	90.55	85.31	95.34	43.24	91.97
Lane4-1sec	96.44	70.13	89.16	83.72	94.82	41.00	86.05
Lane4-2sec	96.44	67.54	88.58	81.42	95.44	44.85	85.95
Lane4-3sec	93.82	62.56	86.57	79.26	94.43	44.27	85.70
Lane4-4sec	87.86	57.83	82.85	73.85	89.81	42.10	81.81
Lane5	97.57	89.45	91.75	86.49	95.65	48.02	91.94
Lane5-1sec	96.95	74.08	89.93	83.08	96.36	41.20	84.73
Lane5-2sec	96.27	72.62	89.51	83.17	96.14	39.99	83.85
Lane5-3sec	95.68	65.24	88.18	80.84	96.07	40.06	84.87
Lane5-4sec	93.24	60.66	85.22	76.45	95.16	39.64	82.94
Lane6	97.01	95.00	90.45	82.45	93.50	40.45	94.27
Lane6-1sec	95.78	86.48	87.46	78.28	95.31	38.59	90.15
Lane6-2sec	95.62	78.43	87.36	78.85	95.05	35.65	86.43
Lane6-3sec	95.31	67.18	85.20	75.94	94.27	45.30	83.80
Lane6-4sec	93.60	62.13	80.55	70.55	89.80	38.59	79.45
Average	**95.57**	**76.40**	**88.54**	**81.40**	**95.22**	**43.39**	**87.92**

Table 4.11: Accuracy metric of classifiers for Dataset V3. From left to right, the selected classifiers are: Instance-based learner with K-nearest neighbors (Ibk), Simple logistic (SL), Random forest (RF), Random subspace (RS), KStar (KS), Locally weighted learning (LWL) and Logistic model trees (LMT).

Dataset	**Ibk**	**SL**	**RF**	**RS**	**KS**	**LWL**	**LMT**
Lane1	100.00	98.25	95.08	90.00	100.00	77.62	99.84
Lane1-1sec	100.00	97.14	96.98	91.11	100.00	47.94	98.25
Lane1-2sec	100.00	97.46	96.03	90.95	100.00	48.41	97.30
Lane1-3sec	100.00	95.71	94.13	91.43	100.00	47.78	96.03
Lane1-4sec	100.00	83.02	91.27	86.67	100.00	47.78	94.92
Lane2	94.56	92.97	89.71	82.34	91.64	46.68	91.51
Lane2-1sec	93.96	77.03	84.73	78.62	94.96	38.52	86.33
Lane2-2sec	94.03	71.52	84.74	76.89	94.56	39.38	86.20
Lane2-3sec	92.10	62.43	84.40	75.77	92.90	37.72	84.13
Lane2-4sec	90.64	58.69	84.73	76.09	92.56	36.32	83.34
Lane3	97.73	93.58	90.85	85.03	94.90	53.29	92.82
Lane3-1sec	96.75	77.32	89.99	82.69	96.48	38.66	88.21
Lane3-2sec	96.45	71.09	88.89	81.22	96.71	38.78	86.51
Lane3-3sec	94.78	65.76	86.89	80.16	95.65	39.04	85.45
Lane3-4sec	86.32	58.05	83.75	75.13	89.30	38.51	83.98
Lane4	97.80	91.72	90.74	84.63	95.28	43.24	93.50
Lane4-1sec	96.93	70.39	89.68	83.27	94.98	40.97	86.08
Lane4-2sec	96.76	68.03	88.96	81.65	95.44	44.56	86.08
Lane4-3sec	94.30	63.85	86.86	79.29	94.43	43.50	85.53
Lane4-4sec	87.86	57.31	82.72	74.47	89.74	41.26	80.29
Lane5	97.79	92.01	91.43	86.10	95.65	48.02	93.25
Lane5-1sec	97.21	77.91	89.90	82.59	96.36	41.20	85.25
Lane5-2sec	96.65	74.05	89.51	81.74	96.14	39.86	85.12
Lane5-3sec	95.88	66.80	88.73	80.78	96.07	40.06	85.00
Lane5-4sec	93.27	61.99	85.35	76.03	95.13	39.64	83.21
Lane6	97.01	95.00	90.40	82.82	93.50	40.29	94.27
Lane6-1sec	95.78	86.48	87.57	78.44	95.31	38.38	90.15
Lane6-2sec	95.62	78.43	87.21	79.83	95.00	35.70	86.43
Lane6-3sec	95.31	67.18	85.55	74.62	94.27	45.04	83.70
Lane6-4sec	93.60	62.13	80.19	70.95	89.95	38.33	79.66
Average	**95.64**	**77.11**	**88.57**	**81.38**	**95.23**	**43.22**	**88.41**

Table 4.12: Summary table with the metrics obtained from the classification of the total lane change maneuvers for different historical data windows, the classifier, and the type of dataset selected for driving profile detection.

Classifier IBK					
Dataset V1	**Full**	**1sec**	**2sec**	**3sec**	**4sec**
Lane1	100.00%	100.00%	100.00%	100.00%	100.00%
Lane2	94.49%	93.96%	93.97%	91.64%	90.32%
Lane3	97.92%	97.20%	97.28%	95.24%	87.00%
Lane4	97.15%	96.54%	96.60%	94.08%	87.93%
Lane5	97.50%	96.98%	96.30%	95.71%	93.44%
Lane6	97.06%	95.78%	95.67%	95.57%	93.40%
Average	**97.35%**	**96.74%**	**96.64%**	**95.37%**	**92.02%**

obtained by the classifier and the type of dataset with the best global results obtained. These are selected to implement the system in charge of the vehicle trajectory prediction task. The data and the classification model, together with the logistic model that describes the different lane change profiles, will be used during the prediction stage of the most probable trajectory followed by the vehicle during the execution of the lane change maneuver, for different prediction windows before the crossover. As we can see, in a general sense, except in the case of Lane 1, the accuracy results show a decreasing trend to the extent that a smaller amount of data is used to evaluate the profile detection model, something that is completely expected. Despite this, the average accuracy data shown in the last column reflects that although this trend is maintained, the degradation of the performance of the profile detector drops just over 5%, to the value of 92.02%, which is a good result if we consider that this data corresponds to the case where there are only the first ten data points of the beginning of the trajectory, that is, four seconds before the lane crossing.

4.6.3 Driver detection

The probabilistic variation of the logistic parameters that describe a particular driver, aims to model with a certain degree of approximation the possible variations that the drivers present in different executions of a particular type of maneuver. To the extent that the standard deviation of these parameters increases, we can assume that in these cases it is a driver who is not well known at first. As the system gets to know the driver better and learns more about the specific environment in which he operates, through a holistic analysis of the main elements of road safety, as well as the two-way interactions between them, the prediction of the trajectory that the driver will follow for a particular instance of execution of the maneuver will be more precise.

To develop this analysis on a particular driver, a set of trajectory data would be required, grouped within the same driving profile, which describes the variations observed in different executions of the lane change maneuver by this driver, in different situations and/or times. Although these variations show differences in the execution of the maneuver, it is expected that these differences will not be so pronounced as to characterize the driver within another driving profile. In the absence of this diversity of data on the same driver in the database used in this study, we describe below the methodology used to carry out this analysis. We take as a reference the group of drivers characterized within a given driving profile. To describe the drivers of this driving profile, we assume a synthetic driver X, who performs a lane change trajectory represented by the [X,Y] coordinates associated with the mean values of the set of trajectories belonging to this driving profile and subsequently modeled by a set of parameters of the logistic function that describes this profile. This trajectory could ultimately be considered the most probable trajectory for this driving profile.

Since our logistic modeling curve directly relates lateral and longitudinal coordinates, we cannot synthetically generate a Y coordinate vector, for example, that fits an X coordinate vector, using the set of logistic parameters that describe the driving profile. This is because we do not know the implicit functions that describe the lateral and longitudinal movements of the vehicle, which allow us to generate realistic Y and X coordinate vectors for that driving profile. For this reason, we need to convert the logistic function from the Cartesian domain Y(X) to the temporal domain Y(t), where we can synthetically generate a time data vector, with samples temporally separated every 100 milliseconds, which is the frequency with which the position data was taken from the database used. With this domain conversion from Y(x) to Y(t), we obtain a new set of parameters B and Q for the resulting logistic equation. These time domain parameters will be identified from now on as Bt and Qt, to differentiate them from the initial parameters in the spatial domain: B and Q. The parameter M of the spatial domain remains unchanged, since it is more related to the longitudinal movement and the speed with which the driver normally executes the turn, which is less likely to show significant changes for the same driver.

For the random generation of synthetic trajectories Y(t), corresponding to the different executions of the maneuver by the same driver, we developed a Monte Carlo simulation experiment. To do this, we randomly generated 1000 realizations using a set of parameters Bt and Qt, normally distributed, with means Bt and Qt of the driver's profile and standard deviations of 1%, 2% and 5% around the mean, respectively. These parameters related to the slope and the moment of initiation of the turn, describe the differences in the executions of the maneuver by the driver. During these realizations, we kept the parameter M fixed, as well as the rest of the parameters described in the Equation 4.1. Using the Y-coordinate data vector of these synthetic curves Y(t) and the set of spatial domain parameters B, Q and M that describe the driving profile, we obtain the X-coordinate data vector by using the inverse function of Y(t). In this way, we obtain a set of synthetic trajectories in the spatial domain Y(X), which represent the different instances of the lane change maneuver performed by the same driver. To evaluate the proposed method, we analyze the RMSE values obtained as a result of predicting the movement of each of these synthetic trajectories Y(X), using the logistic model that describes the trajectory of driver X defined previously. In other words, how precise can we be in predicting the movement that a driver, whose driving profile we previously know, will follow during different instances of the lane change maneuver performed by him.

4.6.4 Results

This section shows the results obtained to predict the trajectory of a particular driver after having previously identified his most probable driving profile and considering different degrees of randomness in the logistic parameters that describe the movement during the execution of a lane change maneuver. Following the style of previous sections, we show the results of a driver with a smooth-fast driving profile performing a lane change left maneuver in lane 4 (LCL4).

The process of generating the synthetic trajectories Y(t) was validated as follows. Standard deviation values of the coefficients of 1%, 2% and 5% were simulated, to ensure that the artificially generated trajectories would continue to be classified within the same driving profile to which the trajectory that gave rise to them belongs, that is, that the different realizations of the same driver continue to be characterized with the same driving profile of said driver. The RMSE results obtained by using a value of 1% standard deviation of the coefficients Bt and Qt for the synthetic trajectories of driver X who makes a lane change to the left in lane 4 with a smooth-fast profile, can be observed

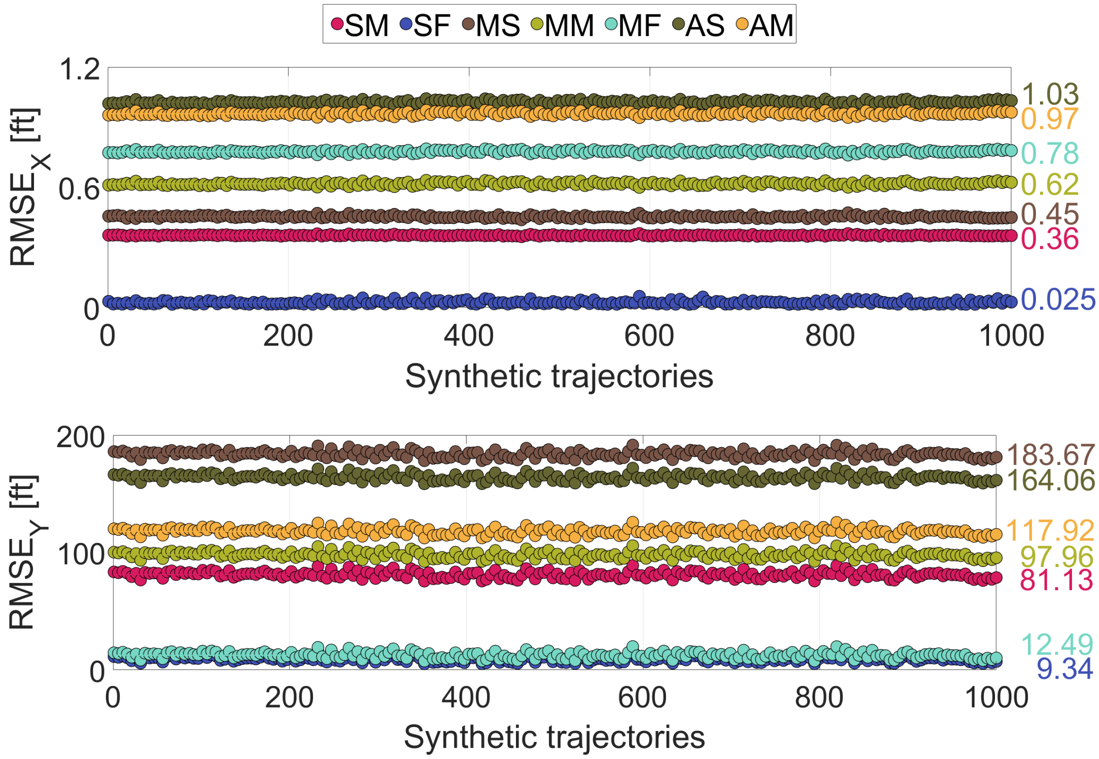


Figure 4.14: RMSE obtained by modeling 1000 instances of LCL4 maneuver execution by a driver X, previously identified with a smooth-fast driving profile and employing 1% of the standard deviation of B and Q coefficients. Smooth-medium (SM), smooth-fast (SF), moderate-slow (MS), moderate-medium (MM), moderate-fast (MF), abrupt-slow (AS), and abrupt-medium (AM). (a) Lateral RMSE. (b) Longitudinal RMSE.

in Figure 4.14. As we can see, on average a lateral error obtained is less than 0.025 feet and a longitudinal error is less than 9.35 feet for 1000 executions of the maneuver by the driver previously identifying with one of the profiles considered in this work. The total RMSE value obtained is less than 10 feet on average. Additionally, the errors obtained when modeling the synthetic smooth-fast trajectories are shown using the logistic curves that characterize the different driving profiles of lane 4. Tables 4.13 and 4.14 show the errors incurred in modeling different lane configurations and driver profiles. As can be seen, the average values according to the lane and driving profile reflect a reduced degree of dispersion, between approximately 8 and 12 feet. On average, the total RMSE obtained by modeling different instances of a driver's maneuver execution is approximately 10 feet, for different lane/profile configurations. The average error per lane maintains the trend of the previous subsection, obtaining the highest values in high-speed lanes, reinforcing the importance of longitudinal movement in the overall result of the movement.

To validate the process of generating these synthetic data, we trained and tested the classifiers again, this time with the data generated by the Monte Carlo experiment. The results obtained reflected that the synthetic realizations of a driver continue to be detected with the same profile to which he belongs. To illustrate these results, the detection metrics obtained for different classifiers and standard deviations of the Bt and Qt coefficients are shown in Table 4.15. Similar to the results obtained in the detection of the driving profile, IBK is among the classifiers that obtain the best results in detecting the driver for the different instances of maneuver execution by him, with an average value greater than 99.9%. For this reason, we selected the IBK classifier to implement the driver detection model. Table 4.16 shows the results of using this classifier with different historical data

Table 4.13: Lateral RMSE [ft] obtained by modeling 1000 instances of maneuver execution by a driver X, for different configurations of driving profiles, road lanes, and standard deviation of B and Q coefficients. Driving profiles from up to down: smooth-slow (SS), smooth-medium (SM), smooth-fast (SF), moderate-slow (MS), moderate-medium (MM), moderate-fast (MF), abrupt-slow (AS), abrupt-medium (AM) and abrupt-fats (AF). (PA): Profile average. (LA): Lane average.

P/L	L1	L2	L3	L4	L5	L6	**PA**
SS	-	0.09	0.21	0.07	0.11	0.08	**0.11**
SM	0.07	0.07	0.07	0.06	0.13	0.08	**0.08**
SF	0.04	0.05	0.06	0.03	0.06	-	**0.05**
MS	0.06	0.08	0.08	0.07	0.09	0.11	**0.08**
MM	0.07	0.15	0.10	0.08	0.10	0.10	**0.10**
MF	0.08	0.14	0.08	0.08	0.20	0.07	**0.11**
AS	0.19	0.07	0.11	0.07	0.11	-	**0.11**
AM	0.08	0.09	0.9	0.11	0.7	0.12	**0.09**
AF	-	0.08	0.10	0.09	0.09	0.12	**0.09**
LA	**0.08**	**0.09**	**0.10**	**0.07**	**0.11**	**0.10**	**0.09**

Table 4.14: Longitudinal RMSE [ft] obtained by modeling 1000 instances of maneuver execution by a driver X, for different configurations of driving profiles, road lanes, and standard deviation of B and Q coefficients. Driving profiles from up to down: smooth-slow (SS), smooth-medium (SM), smooth-fast (SF), moderate-slow (MS), moderate-medium (MM), moderate-fast (MF), abrupt-slow (AS), abrupt-medium (AM) and abrupt-fats (AF). (PA): Profile average. (LA): Lane average.

P/L	L1	L2	L3	L4	L5	L6	**PA**
SS	-	3.29	14.89	16.29	6.74	6.12	**9.47**
SM	21.23	13.98	12.12	11.20	5.44	9.10	**11.86**
SF	11.31	10.71	10.94	9.35	10.60	-	**10.58**
MS	3.35	9.36	7.49	6.16	6.68	11.89	**7.49**
MM	4.69	12.89	8.47	10.28	9.40	5.09	**8.47**
MF	14.62	10.58	11.90	11.15	10.73	5.26	**10.71**
AS	13.39	17.25	8.18	8.78	7.96	-	**11.11**
AM	4.78	20.16	8.96	7.96	3.64	13.65	**9.85**
AF	-	11.43	10.65	15.35	10.49	5.34	**10.65**
LA	**10.48**	**12.18**	**10.40**	**10.72**	**7.96**	**8.06**	**9.97**

Table 4.15: Accuracy metric of classifiers for Dataset V1. The selected classifiers are: Instance-based learner with K-nearest neighbors (Ibk), KStar (KS), Random forest (RF), Random subspace (RS), Locally weighted learning (LWL), Simple logistic (SL) and Logistic model trees (LMT). (Std): standard deviation of 1%, 2% and 5%.

Dataset	**Ibk**	**KS**	**RF**	**RS**	**LWL**	**SL**	**LMT**
Std01	100.0	100.0	100.0	100.0	99.95	98.85	99.54
Std02	100.0	100.0	100.0	99.99	99.67	99.29	99.95
Std05	99.98	99.98	99.97	99.95	98.16	99.12	99.39
Average	**99.99**	**99.99**	**99.99**	**99.98**	**96.26**	**99.09**	**99.63**

Table 4.16: Summary table with the accuracy obtained from the classification of the total lane change maneuvers for different historical data windows, the classifier and the type of dataset selected for the driver detection.

Classifier Ibk					
Dataset V1	**Full**	**1sec**	**2sec**	**3sec**	**4sec**
Lane1	100.00	99.99	99.98	99.97	99.97
Lane2	99.98	99.96	99.96	99.95	99.96
Lane3	99.98	99.91	99.79	99.60	99.65
Lane4	100.00	99.96	99.97	99.97	99.95
Lane5	100.00	99.95	99.97	99.98	99.98
Lane6	100.00	99.99	99.99	99.99	99.99
Average	**99.99**	**99.96**	**99.94**	**99.91**	**99.91**

windows. Performance exceeding 99.9% can be observed in all cases. The performance degradation, considering early detection 4 seconds before the intersection, is only 0.08%, demonstrating the high degree of inference about the data and the degree of generalization of the classifier.

In Table 4.17 we establish a comparison of our work with similar studies consulted in the literature. This analysis focused mainly on three aspects: the early detection of the maneuver type/profile, the trajectory models' prediction horizon, and the error in trajectory estimation. Aspects related to the complexity of the proposed models and the level of granularity in maneuver modeling are also considered. Regarding the level of granularity in the modeling of the maneuver, most of the consulted works only focus on detecting the type of maneuver executed, only in [37] do we see that the profile with which the maneuver was executed is considered. In our work, both lateral and longitudinal profiles are considered. It can be seen how most of the works analyze highly complex models, using deep learning to detect types/profiles of maneuvers or trajectory prediction. In contrast, [35] uses least squares estimators to fit cubic spline curves and in our work, IBK is used for profile detection and logistic curve fitting for trajectory estimation. In this work, the authors report an early detection time of around 3 seconds, however, they do not report the accuracy values with which the system performs the detection. We can observe how our models exceed the prediction horizon established by other works, sometimes doubling or tripling their values. Regarding trajectory estimation error, the authors in [35] report a lower mean absolute error (MAE) value than our system, but in this case, our work models the trajectories with a higher level of granularity, which makes it a more personalized model, specific to each driving profile, while we achieve these profiles with a longer prediction horizon, almost double that reported in [35]. In [31] the authors obtain a lower value of RMSE than ours, but at the expense of using more complex models and modeling the trajectories only at the maneuver level. Similarly, In the early detection, our models obtain better results. For a second advance detection, only [37] approaches the accuracy value of our system. In the results 2 seconds prior, we see that a system proposed in this work improves the performance of previous studies, which also occurs for 3 seconds prior, by a greater difference, and, finally, for the early detection instant 4 seconds prior, we see that the other works do not even consider it. Overall, our systems maintain acceptable performance results as the lead time before detection increases, and a balance between accuracy and RMSE metric with a long time for early detection and a prediction horizon is achieved, which is significant and desired for improving the decision-making process in ADAS.

Table 4.17: Comparative analysis of the proposed work with similar studies consulted in the literature. (PH): Prediction Horizon. (MC): Model Complexity. (GL): Granularity Level. (M): Maneuver. (P) Profile. (BP): Bidirectional Profile.

SOTA	Early detection accuracy [%]				PH	Trajectory Estimation		MC	GL
	4 Sec.	3 Sec.	2 Sec.	1 Sec.	[Sec.]	RMSE [Ft.]	MAE [Ft.]		
[30]	-	77.00	79.00	93.00	up to 3	-	-	Very high	M
[31]	-	-	94.00	-	up to 3	6.0	-	Very high	M
[35]	-	-	-	-	up to 5	-	7	Low	M
[36]	-	-	83.48	93.57	up to 4	12.0	-	Very high	M
[37]	-	60.00	95.00	98.98	up to 5	15.0	-	Very high	P
[38]	-	84.40	86.90	-	-	-	-	Very high	M
Our work	99.91	99.91	99.94	99.96	up to 9	10.0	9	Low	BP

4.7 General considerations of the chapter

The proposed system for predicting the most probable trajectory during the execution of a lane change maneuver on the highway, which considers the driving profiles previously detected, acts as follows: first, the most probable driving profile is detected. Based on the initial trajectory data of the maneuver in progress and once the profile has been determined, the logistic curve that models the detected driving profile is selected and is assumed to be the most probable trajectory to be followed by the vehicle, assuming that the driver that it is executed is described with greater probability by the previously detected driving profile. Additionally, a Monte Carlo statistical analysis is developed to describe the variation in a particular driver's behavior during different lane change maneuvers. Using logistic curve fitting, we can model, within certain tolerances, this driver's behavior during these maneuvers.

These logistic curves are mathematically described by a set of parameters, which can be sent through the vehicular communications network, as additional information to the vehicle movement data. This would allow for more robust and reliable information in the event of packet loss in the network and data with a more predictive nature of the evolution of the vehicle's movement, which translates into a benefit for the design of C-ADAS and, in a general sense, for road safety in ITS.

The exchange of hyperparameters obtained for each driving profile through the communications network allows the prediction capacity to be available in neighboring vehicles, which makes the system cooperative. The amount of information that needs to be exchanged over the network is minimal since the information processing associated with the learning process of the artificial intelligence models can be developed in the vehicle itself. Likewise, the ability to make decisions will be conditioned by the ability to simulate the most probable behavior and trajectory, then this road safety information will be exchanged in the vehicular network. Some works study the efficient methods of RSA information exchange, the most realistic channel models, and the wireless technology that should be used according to the scenario. To this end, our architecture conceives that this exchange is independent of the communication technology, whether the processing and analysis are developed locally or centrally, under the concept of IoV.

5 Conclusions

One of the main contributions of this work is the proposal of a C-ADAS design architecture that involves the main elements related to road safety, from a holistic and systemic perspective. It contributes from a theoretical perspective, to how to approach the design process of a C-ADAS. It reinforces the premise that a C-ADAS must take into consideration the three fundamental elements described: driver, vehicle, and environment, and must be designed on an abstraction layer higher than the interaction plane of these elements, that support the principal module of the C-ADAS system. The main challenges must be focused on understanding the current challenges present in each of the three areas of interaction described throughout this work. From the point of view of vehicle-environment interaction, we can highlight the standardized incorporation of sensing and communication devices in new vehicles, the reduction in the cost of sensor technologies, and the development of the necessary infrastructure to support vehicular communications. Concerning the vehicle-driver interaction, work should be done on increasing the degree of customization of the ADAS system, considering the particularities with which each driver acts on the vehicle's driving elements, as well as how it reacts individually to the notices and alerts issued by the system. Work must also be done on the design of a flexible HMI interface that adapts continuously to the behavior of the driver in various situations that arise on the road, capable of switching between the driver assistance function or taking control of the vehicle before a situation of danger given that the driver is not able to resolve favorably. One of the areas where greater action is required is the driver-environment interaction, the detection of the driver's intention remains a latent challenge in the design of ADAS systems. To do this, the study of explicit and implicit characteristics of the driver's behavior must be promoted through the use of devices attached to the interior of the vehicle, which must act in a minimally invasive way so as not to distract or general annoyance to the driver, while being able to capture the greatest amount of relevant information from it.

Another relevant contribution is the design of bidirectional driving profile models that describe driver behavior during lane change maneuvers on highways, through the analysis of real trajectory data. We discuss the importance of speed, logistical modeling, and the analysis of driving profiles, explaining how these factors and models affect the lateral and longitudinal vehicle's movement in lane change situations. About the logistical modeling of the driving profiles, it was demonstrated that in most of the cases analyzed, considering both grouping criteria to obtain the profiles: the lateral criterion and the longitudinal criterion of movement, provides better results than considering only one of these criteria separately. The results demonstrate that both the logistic modeling for the description of lane change driving profiles on highways and the IBK classification model for detecting these profiles, achieve a good description of the physical phenomenon addressed in this study. In driving profile detection, the results showed that considering less data to classify maneuvers slightly degraded the accuracy metrics. In our case, this degradation was just 0.8%. The average accuracy for considering all trajectory data was of the order of 99.99% and considering trajectory data up to 4 seconds before the crossing the accuracy dropped to 99.91%. In terms of the prediction error of this most likely trajectory of the identified driver, our model obtained values between 8 and 12 feet for the different lane/driving profile configurations, which reported an average of less than 10 feet. This model proposes a system capable of recognizing a driver whose driving profile has been previously identified, to model that driver's behavior under certain uncertainty limits and estimate the most likely trajectory with which the driver would execute the maneuver.

As future work and a natural continuation of this research work on the design of C-ADAS, we consider moving on to the implementation stage of the C-ADAS design architecture proposed in this doctoral thesis, to create a customized cooperative assistance system that incorporates these driving profile modeling parameters into the exchange of road safety information between vehicles and other road users, proposing collaborative strategies that minimize the effects of data and information loss on the vehicular communication network. Furthermore, we consider that the necessary future work is the design of a C-ADAS oriented to a higher level of cooperative systems, where cooperation goes beyond the exchange of information. We refer to the risk estimation and decision-making process as a consensual act between different road users. In this approach, the C-ADAS of each vehicle includes as an additional input in its decision-making, the result of the decision of C-ADAS implemented in neighbor vehicles. The concept of IoV, a cloud-based service, and emerging technologies like 5G-Advanced can play a crucial role in the sensing and exchange of the information associated with the three main interactions described in the proposed architecture of C-ADAS: driver-vehicle, driver-environment, and vehicle-environment, managing the integration of many data sources, sometimes very different from each other.

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