



HAL
open science

Generic ontology and framework for critical scenario description and generation. Applied to evaluation and validation of Automated Vehicle

Maria Ruchiga, Rémi Saint, Guillaume Saint Pierre, Dominique Gruyer

► To cite this version:

Maria Ruchiga, Rémi Saint, Guillaume Saint Pierre, Dominique Gruyer. Generic ontology and framework for critical scenario description and generation. Applied to evaluation and validation of Automated Vehicle. 26th IEEE International Conference on Intelligent Transportation Systems ITSC 2023, IEEE, Sep 2023, Bilbao, Spain. hal-04430186

HAL Id: hal-04430186

<https://hal.science/hal-04430186>

Submitted on 31 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Generic ontology and framework for critical scenario description and generation. Applied to evaluation and validation of Automated Vehicle

Maria Ruchiga^{1,2}, Rémi Saint², Guillaume Saint Pierre¹, Dominique Gruyer²

Abstract—The safety of new autonomous vehicles must be evaluated before introducing them into mixed traffic. But before this can be done, safety-critical scenarios must be identified and tested. Using expert knowledge and field data we identify ten safety critical scenarios to simulate and therefore evaluate the autonomous vehicle performance compared to conventional, human-driven vehicles performance. This selection was made balancing the criticality and frequency of a given situation. To describe these scenarios, we create an ontology that considers the difference between autonomous vehicles and human drivers and provides an exhaustive description of the vehicle surrounding. In this paper, we propose a generic framework and ontology usable for safety-critical scenarios description and generation.

I. INTRODUCTION

Assessing the safety impact of autonomous vehicles (AVs) is a challenge, and many efforts have been made to develop and improve functionalities of autonomous driving in conventional driving situations. Large-scale tests around the world have proved the technology is efficient and ready, but still there is little knowledge about the potential impact on road safety of full autonomous driving deployment. A way to assess the safety is by scenario-based testing. There are two approaches for selecting scenarios: knowledge-based or data-based. Using both approaches, the selection can be made, and the impact of AV deployment can be evaluated through simulation. To do so the scenarios must be previously described, which can be done using ontologies. These are comprehensive description tools encompassing the elements of the scenario and their relationship. Ontologies have indeed been used to describe driving scenarios [1]–[10]. There is now a growing need for an ontology that describes all elements for safety-critical scenarios in mixed traffic i.e. when human-driven and autonomous vehicles drive together. This work proposes a selection of ten safety-critical scenarios for the AV in mixed traffic and an ontology adapted for their description and generation.

This paper is organized into two parts. In the first part, expert knowledge and real data analyses are used to select safety-critical scenarios in mixed traffic. In the second part, we propose an ontology used to describe them.

¹ ITS Research Team, Centre for Studies on Risks, Environment, Mobility and Urban Planning, 1 Avenue du Colonel Roche, F-31400, Toulouse, France maria.ruchiga@cerema.fr, guillaume.saintpierre@cerema.fr

² PICS-L, COSYS dept, Univ Gustave Eiffel, 25 allée des Maronniers, F-78000, Versailles, France remi.saint@univ-eiffel.fr, dominique.gruyer@univ-eiffel.fr

II. SCENARIO

A scenario can be described as a succession of several scenes, a time frame in which all actors have a constant state and movement. Every action or event that causes a change marks the transition from one scene to the next. An initial scene can generate several scenarios depending on the events and actions that occur. The beginning and the end can be chosen according to the objective.

A. Relevant scenarios for AV's

Selecting relevant scenarios is challenging for car makers, especially when dealing with AVs. Two approaches are commonly used, the knowledge-based approach and the data-based approach. As AVs behavior in emergency conditions is unpredictable, expert knowledge is mobilized to infer the critical scenarios depending on the chosen point of view. As an example, in the SURCA project (Safety of Road Users and Automated Driving), critical interaction scenarios between a future AV and a conventional vehicle (CV) have been identified by ITS experts according to the following criteria:

- 1) Is the scenario challenging for the AV, i.e., will, a priori, the situation be complex for the AV to manage?
- 2) Is this scenario frequently encountered during "normal" driving?
- 3) Does this scenario often generate an incident situation i. e. situation in which there is a near or real collision?
- 4) Does this scenario require decisive human intervention to avoid the accident?

This process led to selecting the subsequent interactions families: Intersections, cut-ins, roundabouts, insertions, and lane changes. This process involved real French accident statistics to evaluate frequency of situations for humans, and used the expert knowledge to take into account the technical difficulty from the AV point of view. Another way to due the selection is to examine the actual accidents that occurred with an AV. This will allow to refine the previous families of interaction situations.

In California, every AV accident must be informed to the DMV (department of motor vehicles). Thus there is a public database [16] containing every AV accident in California, which is widely used by researchers working on AV accidents. This section presents a review of five articles that did statistical analysis and investigations on AV accidents. Five use the DMV database: Favaro et al. [11], Liu et al. [17], Xu et al. [12], Sinha et al. [13], Song et al. [14]. Though those

TABLE I: Comparing road types for accidents involving an AV studied in the analyzed papers

Road Type	Intersection	Cross-shaped	X-shaped	T-shaped	Multiple Branches	Y-shaped	Other	Non Intersection	Urban	Expressway	Parking lot	Highway	Total
Favarò et al. [11]	100%	56%	-	12%	-	-	31%	0%	-	-	-	-	16
Xu et al.[12]	71%	41%	12%	11%	7%	-	-	29%	21%	4%	3%	1%	76
Sinha et al.[13]	63%	37%	-	10%	3%	7%	6%	37%	-	-	-	-	259
Song et al.[14]	73%	-	-	-	-	-	-	26%	-	-	2%	-	168
Schwall et al.[15]	68%	-	-	-	-	-	-	32%	-	-	-	-	42
Chosen Scenarios	A, B, C, D, E, F, G, and H	A, B, C, F, and G		H	E			I and J					

TABLE II: Comparing signalization in reported AV accidents

Traffic Sign							Other	Signalized Percentage Total	Not Signalized or Not Informed
Favarò et al. [11]	31%	25%	6%	6%	6%	6%	-	50%	50%
Sinha et al. [13]	-	-	-	-	-	-	49%	49%	51%
Song et al. [14]	51%	-	-	4%	13%	1%	-	69%	31%
Schwall et al. [15]	-	-	-	-	-	-	-	40%	60%
Chosen Scenario	A, F, and G	F	G and F	B	H	A, D, E, and F		A, B, D, E, F, G, and H	C, I and J

TABLE III: Comparing vehicle movements in reported AV accidents

Vehicle type	Vehicle Movement	Straight	Turn Left	Turn Right	Stopped	Stopping	Changing Lanes	Passing Vehicle	Parking	Merging	Other
AV	Favarò et al.[11]	19%	0%	6%	69%	0%	0%	6%	0%	0%	0%
	Xu et al. [12]	25%	7%	7%	40%	11%	8%	-	1%	1%	-
	Song et al. [14]	31%	7%	5%	41%	10%	5%	1%	-	1%	-
	Schwall et al. [15]	61%	9%	-	18%	7%	5%	-	-	-	-
CV	Favarò et al.[11]	88%	0%	12%	0%	0%	0%	0%	0%	0%	0%
	Xu et al. [12]	46%	7%	7%	1%	1%	6%	14%	-	-	18%
	Song et al. [14]	55%	6%	9%	4%	10%	5%	-	3%	8%	-
	Schwall et al. [15]	55%	20%	-	0%	2%	18%	-	-	-	5%

TABLE IV: Comparing types of reported AV accidents

Collision type							Other	Total
	Rear-end	Sideswipe	Broad Side	Hit Object	In Front	Pedestrian		
Favarò et al. [11]	81%	19%	-	-	-	-	-	16
Xu et al. [12]	56%	29%	3%	6%	0%	6%	-	76
Sinha et al. [13]	74%	18%	5%	0%	0%	1%	0%	141
Song et al. [14]	67%	22%	7%	2%	-	1%	2%	168
Schwall et al. [15]	34%	21%	32%	0%	2%	6%	4%	47
Scenario	A, B, C, D, E, and F	E, I, and J	E, G, and H			D	F	

articles explore different time slots in the database, some accidents overlap between articles. The sixth, Schwall et al. [15], analyzed two types of data: real accidents involving Waymo taxis in the Phoenix area and simulated accidents. The simulation used situations where the Waymo driver manually disengaged the autonomous system and analyzed what would have happened if the driver had not.

In order to select the most interesting scenarios from the point of view of road safety, We created four tables to classify all the accidents studied in these five articles, using four criteria: road type (table I), signalization (table II), vehicle movement (for both AV and CV, table III), and collision type (table IV).

As shown in table I, most accidents occurs in intersections. Table II shows there are approximately the same amount of accidents in signalized intersections as in non-signalized

ones. As shown in table III, the most usual movement at the time of the collision for both CV and AV is the straight one. AVs are much more likely to experience a collision while stopped or stopping than CVs.

When looking at the collision types, table IV indicates that rear-end collisions are the most frequent ones for AVs, which is consistent with the predominance of the stopping maneuver and the intersections among the characteristics of the observed accidents. Sideswipes are the second most significant type of collision. They could happen due to a car changing lanes too soon or too late. According to [12] the movements of turning and overtaking from the CV in respect to the AV are more likely to cause side swipes than rear-end collisions. In [17] lane changes count for 19% of accidents. We can estimate that lane changes and overtakes made by AVs and CVs in non-intersection-related areas can

cause accidents.

Rear-end collisions represent roughly 60% of AV accidents (minimum 34% [15], maximum 81% [11]). They are, on average, three times more frequent than sideswipes and over ten times more than any other accident type. In [12], after a bootstrap regression, the correlation coefficient between the AV turning and having a rear-end type of accident is significantly positive. As turning is a maneuver done in intersections, we can presume that those accidents largely transpire in intersection-related areas, which are the most common road type for accidents involving AVs. [17] cites as a typical scenario, the AV stopping for a traffic signal or before making a right turn representing 37% of accidents. [13] indicate that 55% of accidents were rear-ending at intersections, and more than half of those accidents were at signalized ones. Another possible cause for rear-end accidents in intersections is another vehicle or pedestrian encroaching into the front vehicle lane. In [17], this account for at least 10% of the accidents. Four accidents at intersections analyzed in [15] happened while the AV was waiting for crossing traffic to clear. We can estimate that accidents occurring in intersection areas are likely rear-ends in which the front vehicle brakes due to either signalization, stopping for tuning, or another vehicle encroaching into the lane.

Broadside is the third most common type of accident. Those accidents most likely occur in intersections as the vehicles need to be in a relative angular position. Both vehicles are probably proceeding straight in different directions, as those are the most common motions in table III. However, it may also happen that one of the vehicles is turning and gets hit. The cause of a broadside can be the non respect of traffic rules.

B. Scenario choice

Choosing scenarios suitable to assess the safety impact of autonomous vehicles is a challenge. They should be representative of safety critical situations encountered for AVs involved in mixed traffic (i.e. including CVs) taking into account both frequency and severity. In the previous section, the global picture of accidents involving AVs has been described to complete the more common knowledge based approach as in the SURCA project. This section describes the set of scenarios we propose to use as a basis for safety impact assessment evaluation of AVs using simulations.

Let us note first that, contrary to the SURCA project selected scenarios, we did not include the roundabout situation as the real challenging situation for the AV occurs before entering the roundabout itself. Therefore this configuration can be considered similar to intersections. Furthermore, as roundabouts are rare in the USA there is no accident data involving AVs in roundabouts.

Interaction between vehicles, pedestrians and cyclists were included as they have a higher fatality rate. A diverse representation of traffic signs and intersection shapes was included to cover most situations represented in tables II and I. According to [18], in conventional traffic, road departs, and loss control are the most frequent fatal accidents. They will

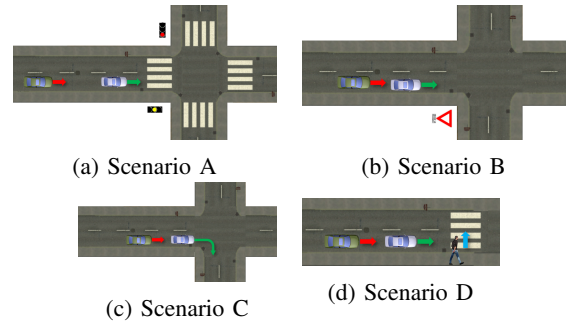


Fig. 1: Following Scenarios

not be considered as it is estimated that the AV will do better than CVs in this type of situation.

The selected scenarios were classified into three categories: Following, Cross Paths, and Lane change (cf. Figures 1, 2 and 3).

a) Following: This category involves an AV stopping whilst being followed by a CV near an intersection. This situation is the most frequent in the DMV database. However, it is not usually dangerous for the people involved. Three reasons for the deceleration were identified: the presence of a signalization (scenarios A and B), before making a turn (scenario C) and another vehicle or pedestrian potentially encroaching into the lane (scenario D). For the last one, the lead vehicle/Av stops due to a pedestrian on the sidewalk intending to cross the road on a crosswalk. Traffic signs in scenario A (traffic light) and B (yield sign) were chosen according to their frequency on II. All the scenarios have the same possible accident outcome: the rear end. Scenario D has a second one; the lead vehicle hitting the pedestrian. Those scenarios are illustrated in Fig 1.

b) Cross Paths: In this category, a CV, not respecting road rules, crosses the path of an AV (Scenario E, F, G, and H). According to [18], this is the second most frequent accident type between CVs and, concerning fatality, the most frequent involving at least two vehicles. Different road configurations were selected according to table I. Scenario E takes place in a five-branch intersection; two branches are at a 45° angle. One contains two vehicles proceeding straight, and the other includes one third vehicle making a 135° angle turn. Since the third vehicle is harder to spot in this configuration, the lead vehicle's decision can either cause a rear end with the vehicle following it or a sideswipe/broadside with the one turning. Scenario F and G take place in a cross-shaped intersection. In scenario F two vehicles are approaching a green light while a cyclist in the neighboring branch does not stop at the red light giving two possible accident outcomes: the lead vehicle collides with the cyclist, or the two vehicles collide - resulting in a rear end. In scenario G the two vehicles arrive from opposite branches of the cross-shaped intersection. One of the branches is signalized with a green light giving this vehicle priority. The vehicle from this branch is proceeding straight, and the other is making a left turn. This scenario was

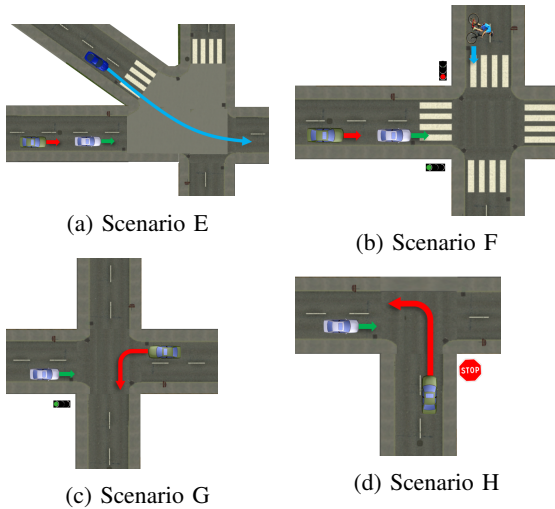


Fig. 2: Cross Paths Scenarios

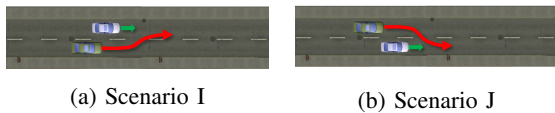


Fig. 3: Lane Change Scenarios

included as it was the most severe collision simulated in [15]. In scenario H, the two vehicles are approaching a T-shaped intersection. One is proceeding straight; the other is making a left turn, disregarding a stop sign. Those two scenarios can end on a broad side. F, H and G represent the most common maneuvers in which accidents between two vehicles occur at intersections [18]. The scenarios are illustrated in Fig 2.

c) Lane Change: The last category encompasses lane changes and passing other vehicles. This category contains two scenarios in which two vehicles travel on an urban road when the following vehicle changes lanes to the left in I and to the right in J. This class was observed as an important class in the SURCA project; the possible accident outcome is a sideswipe, which is the second most frequent accident type. The scenarios are illustrated in Fig 3.

The scenarios chosen are sufficient to cover all interaction between different road users, types of maneuvers, road types and signalization that appear in the most critical or frequent accidents described in the literature.

III. ONTOLOGY

To simulate those scenarios, they need to be described in detail. To do so we created an ontology, which is a representation of the area of interest using a taxonomy relations and rules.

Our ontology needs to have elements that describe a human and an AV driving styles. Furthermore the presence of obstacles on the road, its condition, weather, and lighting conditions are all parameters that can influence the safety of the scenario and must be fully described. With the advance of autonomous cars, it is estimated that the problems caused

by the selected scenarios will be solved and new ones will emerge. For our ontology to stand the test of time it needs to take into account every possible element found in a driving scenario.

A. Ontologies for AV's simulation

Ontologies have been used in the field of automated vehicles for different purposes such as: situation assessment [1], [3], [5]–[7], [10], technologies evaluation [6], [7], and scene creation [8]–[10].

Several different aspects must be taken into account when modeling a safety-critical scenario. There must be a complete description of the environment, the dynamic elements' motion and state, and the road and any possible obstacle on it.

Bagshik et al.[8], Chen and Kloul [9], and Zhao et al.[7] have all the three elements cited above described in their ontology. Their final product is a combination of multiple ontologies. A five-layer process (road-level, traffic infrastructure, temporary manipulation of the first two levels, objects, and environment) was used in [8]. In [9] and in [7] the layers are represented by three ontologies: highway, weather, and vehicle for former and map, control, and car for the latter. The main purpose of [8] and [9] is scenario modeling in highways; therefore they are not adapted to be used in urban roads. As the larger portion of our scenarios takes place on intersections and urban roads, those ontologies can not describe them.

Huang et al.[10], and Xiong et al.,[6] ontologies are used for real-time driving scenarios. They are vehicle centered. This approach is not ideal for a safety-critical scenario evaluation where all the vehicles involved have a priori the same value: a vehicle-centered approach would not correctly evaluate an accident that does not involve the AV directly, for example if the AV's behavior causes another vehicle to lose control.

Armand et al. ([3]) create an ontology using properties to model the interaction of road users. Although the road user interaction is thorough, the ontology lacks a road description. In [1] the authors propose to use an ontology to relax traffic regulation to facilitate traffic flow, and Mohammad et al. [5] propose an ontology for risk assessment using video. This ontology is used to evaluate if the distance between the automated vehicle and other road users is safe depending on their motion. Due to their objectives, those ontologies have a limited description of the road and dynamic elements' motion.

None of the ontologies above have a description of the human driver, whereas a driver's experience, distraction level, impairment or emotion are all known to have substantial impacts on a CV's behavior, and are often one of the accidents causes. In [4] the driver is modeled using an ontology, but there is no description of the road.

In this paper, we propose an ontology that combines the description of the scenery, environment, and the dynamic elements' condition and behavior (for both humans and AVs), which are needed to have a successful mixed traffic

scenario model. A comparison between the ontologies can be found in table V. Our ontology is divided into three classes: Scenery, Dynamic elements, and Environment. Those classes are divided as well, as seen on Fig 4.

B. Dynamic elements

The dynamic elements class contains all mobile objects, whether they are in motion or not. This class is divided into five sub classes: Moving Objects, Driver, Scenario Implication, Maneuver, and Trajectory.

a) *Moving Objects*: This class is divided into Motorized and Non-motorized. This division is due to Motorized objects mainly traveling on the road, which is not necessarily valid with non-motorized objects, which can travel on the sidewalk.

b) *Driver*: This class describes the drivers' characteristics, which are essential to model their environment perception and behavior being linked to the class maneuver. The class is divided into Autonomous and Human because they have different means of perception, and their behavior can differ (class characteristics for the human).

c) *Scenario Implication*: This class is used in the simulation process and splits all dynamics elements into two categories, actors and extras. The actors take actions during the scenario according to their characteristics and the environment, whereas the extras have their behavior/trajectory predetermined.

d) *Maneuver*: The values of this class can differ for every dynamic element and every scene in the scenario. They encompass every possible action a dynamic element can make and are divided into two subclasses : Longitudinal Maneuver and Lateral Maneuver. These subclasses can be combined to describe a complex maneuver, like changing lanes while accelerating. At any point in the scenario, every actor and every extra has a maneuver. Every maneuver change made by an actor implies a scene change.

e) *Trajectory*: This class describes the position of the dynamic elements on the road and the time that has passed since the beginning of the scenario.

C. Scenery

The class scenery contains all stationary elements of the scenario. This class is divided into three sub classes: Road, Traffic Signs, and Road Objects.

a) *Road*: This class describes the road structure. It is divided into five subclasses: Road Type, Road Part, Geometry, Surface, and Speed Limit. The Surface subclass Condition also is related to the Weather class (section III-D).

b) *Traffic Signs*: This class contains one- or two-dimensional signs that guide the vehicle on the road.

c) *Road Objects*: This class describes elements that are not a part of the road nor traffic sign. It is divided into three subclasses: On the Road Structure, a list of structures found on the road; On the Road Object, containing wheel tracks and random objects possibly found on the road; and Road Side, listing all the elements that can be found on the roadside except traffic signs.

D. Environment

The class environment contains weather and lighting conditions.

The outcome of the selected scenarios depends on their initial parameters defined in the dynamic element part of the ontology. Environment changes and road conditions can also be tested, creating variants of the original scenarios. With those elements, the boundary between a safe scenario and an unsafe one can be determined.

E. Application Example

In this section we will use the ontology to describe a simple scenario: two vehicles following each other approach a traffic light turning yellow. This scenario has multiples outcomes; thus, we will start by the fixed elements which are described in the class scenery. The instantiation of the ontology describing the initial state of the scenario is shown on Fig 5

As depicted in the figure road type is set to urban. The road consists of one lane defined in the class Road Part, its geometry, surface and speed limit definition are set on Fig 5. There are three traffic signs: a yellow traffic light and two continuous margin lines

In this scenario the class environment individuals are fixed weather is set to clear and lighting to day.

Regarding the dynamic elements, there are two moving objects: the lead vehicle V1 and the follower vehicle V2; both individuals of the class car, connected to the lane by the property *isOn* and connected to each other by the symmetric properties *isBehind* and *isInFront*. In this scenario we opted for an autonomous leader vehicle and a driven by a human (conventional) follower.

The autonomous vehicle is equipped with a GPS of 4m precision and a camera located in the front center of the vehicle (at the same level as the rear view mirror), with resolution of one micrometer and color RGB.

The conventional vehicle is driven by a human thus their characteristics are defined using the class Human, a middle age female experienced driver with no distractions or impairments and neutral emotion see on Fig5.

In this scenario we consider that both vehicles are actors.

The only aspects of our ontology changing over time are the individuals of classes Maneuver, Position, and Time. Their evolution is shown on Table VI

It describes the following scenario progression: As soon as the leading vehicle notes the light changing to yellow, it decelerates. The following vehicle, perceiving the color change and the lead vehicle deceleration also decelerates.

The LateralManeuver for both vehicles is fixed and set to straight.

IV. CONCLUSION

In this paper, we used expert knowledge and field data to identify the most safety-critical scenarios, taking into account their frequency and severity. We divided them into three categories: following, cross path, and lane changes.

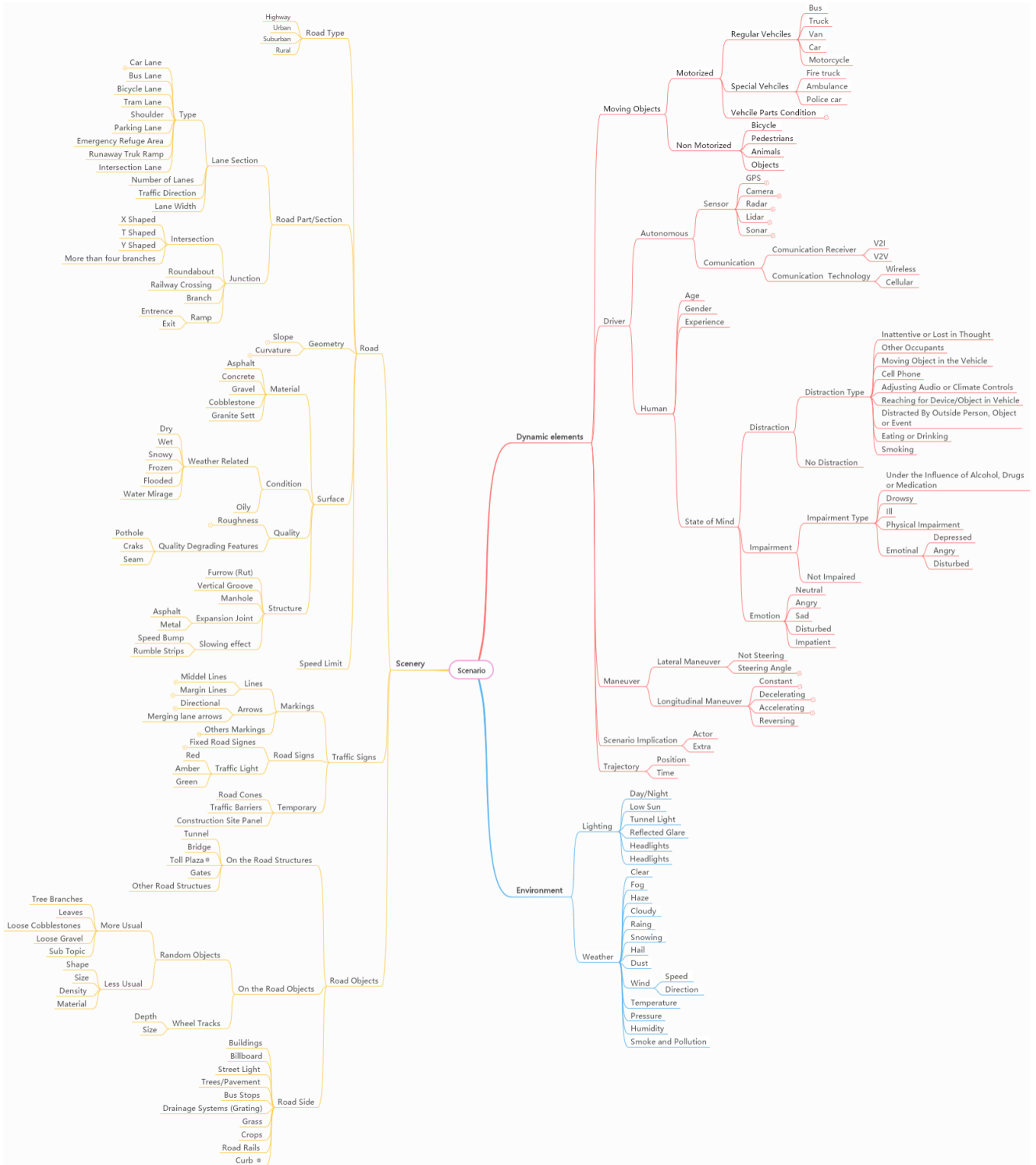


Fig. 4: Ontology

TABLE V: Comparison between the ontologies found in the literature’s elements and the elements presented in the ontology we propose using the ten highest subclasses of our ontology as division

Reference	Dynamic Elements					Scenery			Environment	
	Moving Objects	Scenario Implication	Driver	Maneuver	Trajectory	Road	Traffic Signs	Road Objects	Lighting	Weather
Morignot and Nashashibi[1]	yes	no	yes	yes	no	yes	yes	no	no	no
Armand et al.[3]	yes	no	no	yes	yes	yes	no	no	no	no
Fernandez and Ito[4]	yes	no	yes	no	yes	no	no	no	no	no
Mohammad et al.[5]	yes	no	no	no	yes	yes	yes	no	yes	yes
Xiong et al.[6]	yes	no	yes	no	yes	yes	yes	yes	no	no
Zhao et al. [7]	yes	no	yes	yes	yes	yes	yes	yes	no	no
Bagshik et al[8]	yes	no	no	yes	no	yes	yes	yes	yes	yes
Chen and Kloul[9]	no	no	no	yes	yes	yes	yes	yes	yes	no
Huang et al.[10]	yes	no	no	yes	yes	yes	yes	yes	no	no
Urbietta et al.[2]	yes	no	no	yes	yes	yes	yes	yes	yes	yes
Our proposition	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

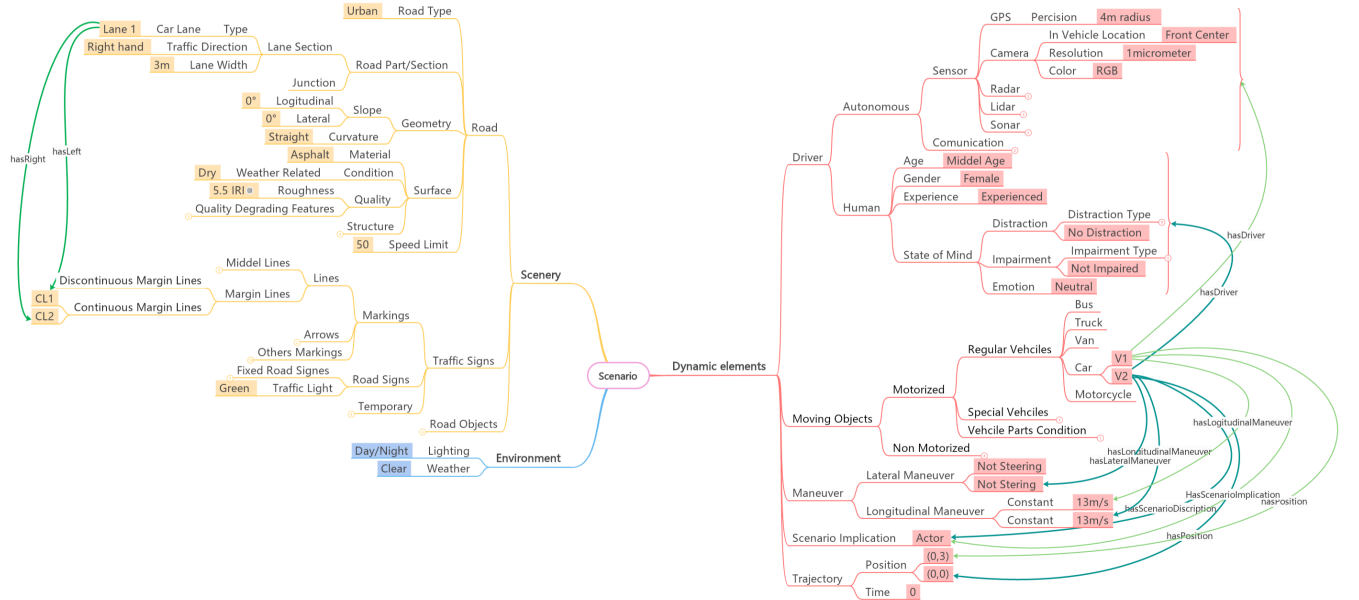


Fig. 5: Scenario’s description using the ontology

TABLE VI: The evolution of parameters Longitudinal Maneuver, Position and Time during the example scenario

Scene	Scene 0	Scene 1	Scene 2	Scenario End
Event/Action	Scenario beginning	TrafficLight = yellow	V1 LongitudinalManeuver = Decelerates	Collision
Time	0s	1.9s	3.1s	3.9s
V1 LongitudinalManeuver	Constant (13m/s)	Decelerating ($-2m/s^2$)	Decelerating ($-2m/s^2$)	Constant (0m/s)
V1 Position	(0, 5)	(0, 30)	(0, 44)	(0, 52)
V2 LongitudinalManeuver	Constant (13m/s)	Constant (13m/s)	Decelerating ($-3m/s^2$)	Constant (0m/s)
V2 Position	(0, 0)	(0, 25)	(0, 40)	(0, 50)

To describe these scenarios, we propose an ontology that distinguishes between automated and human-driven vehicles, an essential consideration as some accidents may happen due to a lack of understanding of the autonomous driver. We divided this ontology into three main classes. The first one, Dynamic elements, represents all the road users, their state, and their movement. The second, Scenery, describes the road and all the real-estate elements we may encounter. The last class, Environment, describes the weather and lighting. By including the distinction between AV and CV, our ontology provides a better representation of these two vehicular behav-

iors. Future works include creating a parameter generation algorithm based on real distributions, selecting a model for the human driver and simulating the scenarios.

ACKNOWLEDGMENT

This research was executed with the collaboration of both the SURCA project (Safety of Road Users and Automated Driving) and the PRISMA project (Research and Investment Platform for the Safety and Security of Autonomous Mobility).

REFERENCES

- [1] P. Morignot and F. Nashashibi, "An Ontology-based Approach to Relax Traffic Regulation for Autonomous Vehicle Assistance," en, in *Artificial Intelligence and Applications / 794: Modelling, Identification and Control / 795: Parallel and Distributed Computing and Networks / 796: Software Engineering / 792: Web-based Education*, Innsbruck, Austria: ACTAPRESS, 2013, ISBN: 978-0-88986-943-1. DOI: 10.2316/P.2013.793-024.
- [2] I. Urbietta, M. Nieto, M. García, and O. Otaegui, "Design and Implementation of an Ontology for Semantic Labeling and Testing: Automotive Global Ontology (AGO)," en, *Applied Sciences*, vol. 11, no. 17, p. 7782, Aug. 2021, ISSN: 2076-3417. DOI: 10.3390/app11177782.
- [3] A. Armand, D. Filliat, and J. Ibanez-Guzman, "Ontology-based context awareness for driving assistance systems," en, in *2014 IEEE Intelligent Vehicles Symposium Proceedings*, MI, USA: IEEE, Jun. 2014, pp. 227–233, ISBN: 978-1-4799-3638-0. DOI: 10.1109/IVS.2014.6856509.
- [4] S. Fernandez and T. Ito, "Driver Behavior Model Based on Ontology for Intelligent Transportation Systems," en, in *2015 IEEE 8th International Conference on Service-Oriented Computing and Applications (SOCA)*, Rome, Italy: IEEE, Oct. 2015, pp. 227–231, ISBN: 978-1-4673-9469-7. DOI: 10.1109/SOCA.2015.44.
- [5] M. A. Mohammad, I. Kaloskampis, Y. Hicks, and R. Setchi, "Ontology-based Framework for Risk Assessment in Road Scenes Using Videos," en, *Procedia Computer Science*, vol. 60, pp. 1532–1541, 2015, ISSN: 18770509. DOI: 10.1016/j.procs.2015.08.300.
- [6] Z. Xiong, V. V. Dixit, and S. T. Waller, "The development of an Ontology for driving Context Modelling and reasoning," en, in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, Rio de Janeiro, Brazil: IEEE, Nov. 2016, pp. 13–18, ISBN: 978-1-5090-1889-5. DOI: 10.1109/ITSC.2016.7795524.
- [7] L. Zhao, R. Ichise, Z. Liu, S. Mita, and Y. Sasaki, "Ontology-Based Driving Decision Making: A Feasibility Study at Uncontrolled Intersections," en, *IEICE Transactions on Information and Systems*, vol. E100.D, no. 7, pp. 1425–1439, 2017, ISSN: 0916-8532, 1745-1361. DOI: 10.1587/transinf.2016EDP7337.
- [8] G. Bagschik, T. Menzel, and M. Maurer, "Ontology based Scene Creation for the Development of Automated Vehicles," en, *arXiv:1704.01006 [cs]*, Apr. 2018, arXiv: 1704.01006.
- [9] W. Chen and L. Kloul, "An Ontology-based Approach to Generate the Advanced Driver Assistance Use Cases of Highway Traffic," en, in *Proceedings of the 10th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management*, Seville, Spain: SCITEPRESS - Science and Technology Publications, 2018, pp. 75–83, ISBN: 978-989-758-330-8. DOI: 10.5220/0006931700750083.
- [10] L. Huang, H. Liang, B. Yu, B. Li, and H. Zhu, "Ontology-Based Driving Scene Modeling, Situation Assessment and Decision Making for Autonomous Vehicles," en, in *2019 4th Asia-Pacific Conference on Intelligent Robot Systems (ACIRS)*, Nagoya, Japan: IEEE, Jul. 2019, pp. 57–62, ISBN: 978-1-72812-229-8. DOI: 10.1109/ACIRS.2019.8935984.
- [11] F. M. Favarò, N. Nader, S. O. Eurich, M. Tripp, and N. Varadaraju, "Examining accident reports involving autonomous vehicles in california," *PLOS ONE*, vol. 12, no. 9, e0184952, 2017, ISSN: 1932-6203. DOI: 10/gbw9sr.
- [12] C. Xu, Z. Ding, C. Wang, and Z. Li, "Statistical analysis of the patterns and characteristics of connected and autonomous vehicle involved crashes," *Journal of Safety Research*, vol. 71, pp. 41–47, Dec. 1, 2019, ISSN: 0022-4375. DOI: 10.1016/j.jsr.2019.09.001.
- [13] A. Sinha, V. Vu, S. Chand, K. Wijayaratra, and V. Dixit, "A crash injury model involving autonomous vehicle: Investigating of crash and disengagement reports," *Sustainability*, vol. 13, no. 14, p. 7938, Jan. 2021, Number: 14 Publisher: Multidisciplinary Digital Publishing Institute, ISSN: 2071-1050. DOI: 10.3390/su13147938. (visited on 06/09/2022).
- [14] Y. Song, M. V. Chitturi, and D. A. Noyce, "Automated vehicle crash sequences: Patterns and potential uses in safety testing," *Accident Analysis & Prevention*, vol. 153, p. 106017, Apr. 2021, ISSN: 00014575. DOI: 10.1016/j.aap.2021.106017.
- [15] M. Schwall, T. Daniel, T. Victor, F. Favarò, and H. Hohnhold, "Waymo public road safety performance data," p. 15,
- [16] *California department of motor vehicle disengagement report*, <https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/disengagement-reports/>, Accessed: 2022-10-26.
- [17] Q. Liu, X. Wang, X. Wu, Y. Glaser, and L. He, "Crash comparison of autonomous and conventional vehicles using pre-crash scenario typology," *Accident Analysis & Prevention*, vol. 159, p. 106281, Sep. 2021, ISSN: 00014575. DOI: 10.1016/j.aap.2021.106281.
- [18] E. D. Swanson, F. Foderaro, M. Yanagisawa, W. G. Najm, P. Azeredo, and John A. Volpe National Transportation Systems Center (U.S.), "Statistics of Light-Vehicle Pre-Crash Scenarios Based on 2011–2015 National Crash Data," English, Tech. Rep. DOT HS 812 745, Aug. 2019.