Towards Developing an Ontology for Safety of Navigation Sensors in Autonomous Vehicles

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Keywords: Autonomous Vehicles, Ontologies, Sensor Uncertainty, Uncertainty Assessment, Autonomous Navigation.

Abstract: Understanding and handling uncertainties associated with navigation sensors in autonomous vehicles (AVs) is vital to enhancing their safety and reliability. Given the unpredictable nature of real-world driving environments, accurate interpretation and management of such uncertainties can significantly improve navigation decision-making in AVs. This paper proposes a novel semantic model (ontology) for navigation sensors and their interactions in AVs, focusing specifically on sensor uncertainties. At the heart of this new ontology is understanding the sources of sensor uncertainties within specific environments. The ultimate goal of the proposed ontology is to standardize knowledge of AV navigation systems for the purpose of alleviating safety concerns that stand in the way of widespread AV adoption. The proposed ontology was evaluated with scenarios to demonstrate its functionality.

1 INTRODUCTION

Autonomous vehicles (AVs), equipped with advanced navigation sensors, stand as a pivotal development towards mitigating the widespread casualties and injuries resulting from human driving errors. AVs' perception sensors, algorithms, and electronics constantly monitor driving space and execute navigation tasks such as planning paths, maneuvering, and detecting objects. Human behaviors contribute to around 90% of fatal car accidents, positioning automation as a revolutionary safety solution (National Highway Traffic Safety Administration, 2022). However, to achieve a high level of safety, AVs should be deliberately engineered to favor safety over convenience and speed. Otherwise, their superior perception would only prevent about a third of these accidents (Mueller et al., 2020).

AV navigation systems face vulnerabilities stemming from the inherent limitations of their sensors and algorithms. For instance, camera-based object detection techniques are compromised in rainy conditions, while the accuracy of global navigation satellite systems (GNSSs) degrades due to physical obstructions like buildings and tunnels. These limitations result in uncertainties and failures in navigation tasks, raising legitimate concerns about the safety of passengers, properties, and other road users. Consequently, the development of AV navigation that is reliable and trustworthy remains a challenge, particularly for intricate navigation tasks.

Addressing this challenge has prompted intensified efforts in researching, developing, and validating automated driving systems. A typical reliability metric for AVs is distance traveled without accidents or failures. Experiencing adequate failure and accident rates requires AVs to drive hundreds of millions of miles successfully, taking hundreds of years for a fleet of 100 vehicles driving at a speed of 25 miles per hour (Kalra and Paddock, 2016). Moreover, such tests are unlikely to expose AVs to the full spectrum of driving conditions.

To overcome the problem of high-mileage travel testing, advanced or complementary assessment techniques are required. An example of such techniques is scenario-based that prioritizes safety (Riedmaier et al., 2020). Such scenarios can be generated using knowledge-based (e.g., Chen and Kloul, 2018) or data-driven (e.g., Krajewski et al., 2018; Zhou and del Re, 2017) approaches. In the former, ontologies are widely used for organizing and preserving expert knowledge, while the latter leverages machine-learning and data fusion methods for pattern recognition and scenario classification. However, the cur-

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Alharbi, M. and Karimi, H.
Towards Developing an Ontology for Safety of Navigation Sensors in Autonomous Vehicles.
DOI: 10.5220/0012207300003598
In *Proceedings of the 15th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2023) - Volume 2: KEOD*, pages 231-239
ISBN: 978-989-758-671-2; ISSN: 2184-3228

rent literature on scenario-based techniques is centered around safety aspects related to driving maneuvers (e.g., Zhou and del Re, 2017), road conditions (e.g., Chen and Kloul, 2018), intersections (e.g., Jesenski et al., 2019), and difficult weather conditions (e.g., Gyllenhammar et al., 2020), with little or no attention paid to navigation sensor safety aspects.

To fill this research gap, we propose a semantic model (ontology) for AVs to understand and handle uncertainties associated with navigation sensors. The fundamental idea underlying our ontology involves identifying and recognizing sources of sensor limitation within a specific space.

The paper is structured as follows. Section 2 summarizes relevant AV ontologies. Section 3 introduces the proposed ontology. Section 4 examines three scenarios to demonstrate the efficacy of the proposed ontology in enhancing the safety and reliability of AVs. Finally, Section 5 concludes the paper with the key findings and potential future research directions.

2 RELATED WORKS

To date, several ontologies related to AVs have been proposed. Schlenoff et al. (2003) developed an ontology to represent objects in the AV surroundings for enhanced path planning. The ontology integrated rules for collision damage estimation with respect to each object, allowing the path planner to evaluate the rules and decide whether a specific object should be avoided. Regele (2008) introduced an ontology for common traffic features like intersections, multi-lane roads, opposing traffic lanes, and bi-directional lanes to support AV decision-making processes. Hülsen et al. (2011) proposed an extended traffic-oriented ontology that covers complex traffic situations involving roads with multiple lanes, vehicles, traffic lights, and signs. Zhao et al. (2015a, 2016, 2015b) developed an ontology centered on safety improvement, targeting intersections without traffic lights and narrow roads in urban areas. In collaborative navigation, an ontology was created to regulate communications between vehicles, pedestrians, and infrastructures in order to avoid collisions (Syzdykbayev et al., 2019). A situational-awareness ontology was introduced to guide the behaviors of AVs inside manufacturing plants (El Asmar et al., 2021). The ontology has the capacity to analyze current and predicted situations in a smart facility where interactions between agents are critical.

The proposed ontology is different than these aforementioned ontologies that are intended to enhance path planning, traffic modeling, and situational awareness in AVs in that its emphasis is on sensor uncertainty. The objectives of the proposed ontology are to provide a comprehensive model of AV navigation in order to assess the impact of varying environments on navigation sensors' performance, identify the limitations of navigation sensors in specific environments, and provide standardized knowledge for safe AV navigation.

3 AV NAVIGATION ONTOLOGY

3.1 Vision

An ontology that prioritizes the safety of AV navigation sensors can be articulated through an analogy highlighting humans' interaction with the environment to navigate. In humans, five sensors—nose, tongue, eyes, ears, and hands—collect data and convey it to the brain via neurons. The brain processes and encodes this information in perception areas, enabling the extraction of relevant features and aiding in performing various tasks such as object detection, identification, and proximity. The outcomes of certain tasks can trigger actions directed towards actuators, which control the movements of hand and foot extremities.

These outcomes may be susceptible to uncertainties that can arise from either an internal data-processing issue, such as cognitive impairment, or an external factor, such as a severe weather condition. Given its complexity, the human brain possesses the ability to account for these uncertainty sources by evaluating the quality of collected data and perceptions. It can analyze data to detect patterns, anomalies, faults, and events, and to determine appropriate responses. However, uncertainties occasionally originate from sensor limitations as the quality of sensors varies among people. Thus, people have to be aware of their own limitations and plan environments accordingly. For instance, people who have visual impairments may opt for accessible environments, featuring easily detectable and safe walking paths.

3.2 Design

To ensure the applicability and effectiveness of an ontology, its creation should adhere to well-established guidelines, like the six-step process proposed by (Noy and McGuinness, 2001). The initial step involves identifying the scope and domain of the ontology, which, in this case, pertains to sensor uncertainty related to navigation in AVs. The second step entails augmenting the domain knowledge by leveraging concepts from existing ontologies. The proposed ontology incorporates several concepts pertaining to road, time, and sensor, which are widely accepted in the AI community (El Asmar et al., 2021; Paull et al., 2012; Syzdykbayev et al., 2019; Zhao et al., 2015b). Section 3.3 provides further details about these concepts. The third step defines important concepts and terms to be incorporated into the ontology. This step also establishes term interactions. The fourth step organizes these concepts hierarchically based on shared properties. The fifth step details concept properties, including descriptive attributes and interrelation properties. Lastly, the sixth step sets restrictions on ontology properties.

The proposed ontology considers common navigation sensors in AVs: GNSSs, inertial measurement units (IMUs), cameras, light detection and ranging (lidar), and radio detection and ranging (radar). GNSSs utilize a constellation of navigation satellites orbiting the earth and are used for AV positioning. IMUs provide AVs with 6-DoF motion or state measurements, including orientation, velocity, and gravity. Cameras capture visual images that perceive color and texture information. Lidar and radar, as range sensors, measure distances to objects in a space using laser beams and radio waves, respectively.

Uncertainty sources in AV navigation can be categorized into sensor, algorithm, and environment. Uncertainty in sensors is inherent to their characteristics. GNSS performance is considerably impacted by the surrounding conditions, such as obstacles that block line-of-sight or cause multipath problems, satellite availability and geometry, and the ionospheric scintillation phenomenon (Yu and Liu, 2021).

IMUs, comprising accelerometers, gyroscopes, and magnetometers, are susceptible to accumulated error, leading to drift due to rounding of fractions during calculations. While drifts can be resolved by augmenting IMUs using other sensors like GNSSs, in this work, each sensor is conceptualized and treated independently because each sensor has its own limitations, and data fusion is typically handled by navigation algorithms.

Camera challenges in AV navigation include lens distortion, calibration, and environmental conditions. Lens distortion, due to curved lenses, causes straight lines to appear curvilinear in images. Calibration is sensitive, and its accuracy is limited, even under controlled conditions (O'Mahony et al., 2018). Environmental conditions like poor illumination, fog, rain, snow, and sun glare can easily obscure important features in the environment. Furthermore, image quality is determined by several technical specifications, including lens *focal length*, *aperture*, and *resolution*.

In radar, the signal *frequency* and wavelength have an inverse correlation; the frequency increases with decreasing wavelength. Signal *resolution* and *angle* could also result in scattered and incomplete representations of objects (Bilik et al., 2019). Lidar's fundamental properties are field of view (*FoV*), *range*, and *resolution*. The vertical and horizontal angles where lights are transmitted determine the FoV. The term "Range" refers to the maximum detectable distance, while resolution denotes the point cloud density.

Navigation sensors often underperform in harsh conditions, leading to navigation-related uncertainty. Difficulties arise in extreme weather conditions (e.g., haze, rain, and snow), in the presence of obstacles, and on complex roads, where sensors may malfunction (e.g., radar interference with conductive materials and poor visibility by cameras). Therefore, understanding the tolerance and impact of such environments on AV navigation is critical for robust performance.

Algorithm performance also contributes to AV navigation uncertainties. Though *accuracy* is the primary performance metric for algorithms, even algorithms with a high accuracy, typically based on machine learning models, might not ensure optimal AV navigation in some real-world scenarios.

For a comprehensive understanding of sensor uncertainty in AV navigation, various competency questions can be used to evaluate the proposed ontology. Examples of such questions are as follows. What are common AV navigation characteristics? What are common components of AV navigation? What are typical tasks of AV navigation? Which properties of a sensor directly affect its performance? Which weather conditions and road features have an inverse effect on sensor performance? Which road features cause sensor uncertainty? What degree of uncertainty is associated with a navigation task under specific environmental conditions and sensor configurations? Which sensor is susceptible to a particular source of uncertainty?

3.3 Model

Drawing upon a thorough examination of existing AV ontologies and literature addressing uncertainty in AVs (e.g., Alharbi and Karimi, 2020, 2021; El Asmar et al., 2021; Paull et al., 2012; Syzdykbayev et al., 2019; Zhao et al., 2015a, 2016, 2015b) as well as a deep understanding of the functional principles of AVs, described by Pendleton et al. (2017), as our foundation, we devised the metadata or attribute structure and established the primary concepts and their relationships. The result is the ontology de-

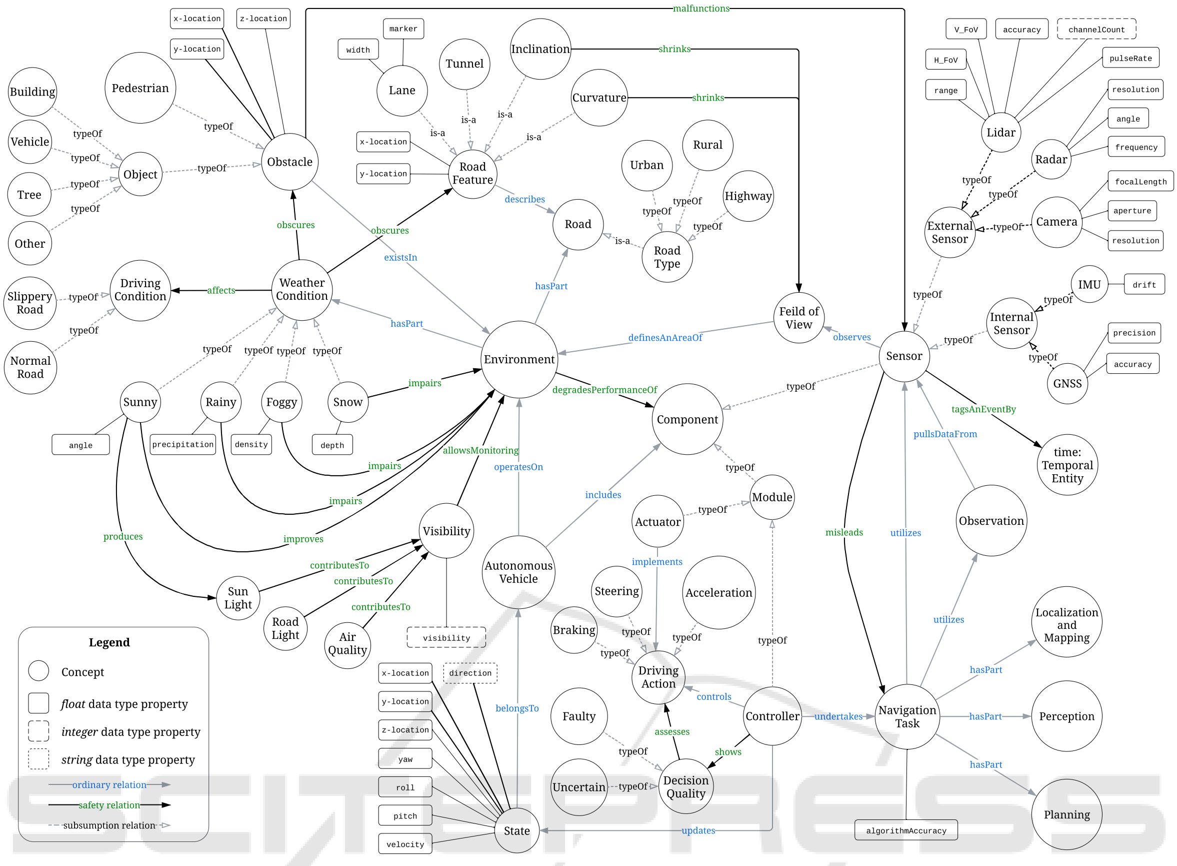

Figure 1: An ontology for safety of navigation sensors in autonomous vehicles.

picted in Figure 1. The core concept of this ontology is *Autonomous Vehicle*, which holds relationships with *Environment* and *Component* (i.e., *Sensor* and *Module*). Although our ontology borrows some concepts from existing ontologies, including *Lane*, *Road Type*, *Highway*, *Driving Condition*, *Sensor*, *Vehicle*, *Temporal Entity*, *Observation*, and *Road*, we employ these concepts in the proposed ontology in different ways to meet the goal of AV navigation safety.

3.3.1 Component

Component denotes the essential elements that make up a navigation system in AVs and can be classified into *Module* and *Sensor*. *Module* represents the AV components that are used to process sensor data in order to compute and execute the vehicle's *State* and *Driving Action* (i.e., *Acceleration*, *Steering*, or *Braking*). The typical structure of *Module* consists of two units: *Controller* and *Actuator*. The former *controls* driving actions and updates the vehicle's *State*, while the latter *implements* those actions. *State* is captured through data properties: *velocity*, *x-location*, *y-location*, *z-location*, *yaw*, *roll*, *pitch*, and *direction*.

Sensor represents devices engineered to detect and measure physical phenomena during navigation. In our ontology, *Sensor* is grouped, based on the information each sensor provides and its mode of operation, into: *External Sensor* (*Lidar*, *Radar*, and *Camera*) and *Internal Sensor* (*GNSS* and *IMU*). The former provides information about the shape, position, and movement of objects in the vehicle's environment, and the latter monitors various internal parameters, such as velocity and location.

Quality of *Sensor* is captured in data properties: *Resolution*, *Aperture*, and *FocalLength* for *Camera*; *ChannelCount*, *PulseRate*, *Accuracy*, *FoV*, and *Range* for *Lidar*; *Resolution*, *Frequency*, and *Angle* for *Radar*; *Accuracy* and *Precision* for *GNSS*; *Drift* for *IMU*. Another concept related to *Sensor* (via *pullsDataFrom*) is *Observation*. This concept represents the intermediate or initial measurements made by a sensor, which are *utilized* by *Navigation Task*. *Sensor* can only observe a specific *Field of View* that defines an area of *Environment*.

3.3.2 Environment

Environment describes the surroundings in which an AV operates. This concept includes *Road* and *Weather Condition* that could affect the vehicle's ability to navigate and function safely. *Road* has *Road Type* that specifies the design and function of a road, such as *Highway*, *Rural*, and *Urban*. *Road* can be described by *Road Feature* that serves its purpose, depending on the type and location of the road. For the purpose of our ontology, we consider only features of roads which may cause sensors to fail such as *Tunnel*, *Lane* (i.e., *marker* and *width*), *Inclination*, and *Curvature*. Of the road features, *Inclination* and *Curvature* might *shrink* the *Field of View* of *Sensor*. *Weather Condition*, categorized into *Sunny*, *Rainy*, *Foggy*, and *Snow*, could adversely affect sensor performance. These conditions are quantified using *angle*, *precipitation*, *density*, and *depth*, respectively. Sever weather conditions could *impair Environment* and *affects Driving Condition*, resulting in *Normal* or *Slippery* roads, and may also *obscure Obstacles*. Two common types of *Obstacle* are *Pedestrian* and *Object*, such as *Building*, *Vehicle*, *Tree*, among *Other* objects. If obstacles, such as debris, interfere with AVs' sensors, it could potentially impact the vehicle's ability to accurately perceive its environment and make safe driving decisions. *Sensor* also cannot observe objects with reflective or transparent materials. As a result, *Obstacle* can *malfunction Sensor*.

Another environment-related concept is *Visibility*, which expresses how well an object can be seen in *Environment*, typically expressed in terms of distance at, or clarity with, which the object can be seen. Visibility can be affected by a variety of contributors, including Sun Light, Road Light, and Air Quality. Good visibility is important for a variety of reasons, including safety and navigation since it allows for monitoring Environment. Considering the complexity and dynamicity of Environment factors, Environment is very likely to degrade the performance of AV Component.

3.3.3 Navigation Tasks

The concept of *Navigation Task* consists of subclasses that include *Localization and Mapping* (LM), *Perception*, and *Planning* (linked to *Navigation Task* through *hasPart*). The taxonomy of *Navigation Task* is depicted in Figure 2. LM enables AVs to pinpoint their location within the space. *Perception* has several subtasks: *Brake Assistance* (BA) inspects the area around AVs and helps them stop ahead of impending crash with an obstacle; *Collision Avoidance* (CA) analyzes AV trajectories to maneuver obstacles; *Lane-Keeping Assistance* (LKA) actively aids AVs to maintain themselves in the center of the lane; *Parking Assistance* (PA) locates vacant parking spots, which then parks the vehicle comfortably; *Detection* includes tasks such as *Object Detection* (OD), *Object Classification* (OC), *Object Tracking* (OT), *Blind-Spot Detection* (BSD), *Automatic Distance Control* (ADC), all connected using *subTaskOf*. BSD monitors zones at the sides of the vehicle, which navigation sensors cannot sense, requiring dedicated sensors. ADC detects the vehicle ahead and ensures that a safe distance is maintained. *Planning* represents *Route* or RP (i.e., an itinerary between two places), *Trajectory* or TP (i.e., a local path with respect to vehicle and space constraints), and *Behavior* or BP (i.e., driving decisions such as lane changes). The *taskOf* relationship links the descendant concepts with *Perception* and *Planning*. Each navigation task is executed by a set of algorithms that are designed to be resilient to sensor failures or malfunctions so that certain risks can be mitigated. These algorithms can encounter unknown circumstances, including sensors with manufacturing defects, wear and tear, or software bugs, which can affect their performance. Thus, *Sensor* can *mislead* the algorithms as they could be error sources. The quality of a navigation task in the ontology is expressed through the *algorithmAccuracy* data property (principally in percent).

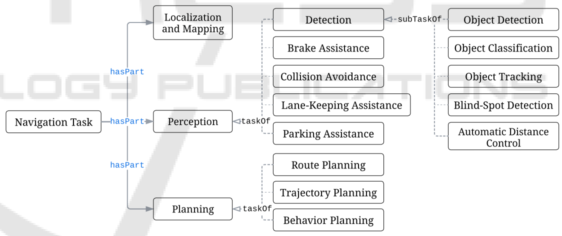

Figure 2: Taxonomy of navigation tasks.

3.3.4 Decision Quality

Decision Quality provides knowledge about the extent to which a decision is likely to produce a desired *Driving Action*. *Decision Quality* is a measure of the effectiveness and appropriateness of a decision, taking into account the available sensors, their constraints, and the objectives of the situation in which AVs operate. Sub-concepts like *Faulty* and *Uncertain* further describe *Decision Quality*. *Faulty* quality indicates incorrect decisions due to issues with the sensors involved in processing that decision, whereas *Uncertain* quality implies noise-induced disruptions. Navigation decisions are typically made by *Controller*, which is related to *Decision Quality* via the *shows* relationship.

Table 1: Ontology rules.

		Impacted Navigation Tasks (*F: failure, U: uncertainty*)												
			Perception									**Planning**		
			Detection											
Rule #	**Condition**	**LM**	OD	OC	OT	BSD	ADC	CA	LKA	BA	PA	RP	TP	BP
1	AV is deployed without *GNSS*.	*F*										*F*		
2	AV drives in *Tunnel*.	*U*										*U*		
3	AV is deployed without *IMU*.	*U*			*U*			*U*		*U*	*U*		*U*	*U*
4	AV is deployed without *Radar*.		*U*		*U*	*U*	*U*	*U*		*U*	*U*		*U*	*U*
5	AV is deployed without *Lidar*.		*U*	*U*	*U*	*U*	*U*	*U*	*U*	*U*			*U*	*U*
6	AV is deployed without *Camera*.	*U*	*U*	*F*	*U*	*U*		*U*	*U*	*U*	*U*		*U*	*U*
7	AV drives on *Road* without lane markers.	*U*							*U*				*U*	*U*
8	AV drives on a *Slippery* road or on extreme weather conditions such as *Snow*, *Foggy*, or *Rainy*.	*U*	*U*	*U*	*U*			*U*	*U*	*U*	*U*	*U*	*U*	*U*
9	AV drives in an environment with low *Visibility*.	*U*	*U*	*U*	*U*			*U*	*U*	*U*	*U*	*U*	*U*	*U*
10	AV navigates while facing sun glare.	*U*	*U*	*U*	*U*			*U*	*U*	*U*	*U*	*U*	*U*	*U*

3.4 Constraints

Constraints indicate the conditions under which a property (i.e., object or data properties) or a relation holds true for a given ontological element. These constraints include cardinality restrictions, which specify the number of times a property can be utilized, and value restrictions, which specify the types of values that a property can take, so that the relationships between entities in the ontology are consistent and logical. Beyond these domain-related constraints, we designed various property constraints in our ontology to ensure its integrity and accuracy by limiting the permissible ways that the properties can be used. As can be seen in Figure 1, the ontology treats all data properties as either *integer*, *float*, or *string*, all defined by the XML Schema (Biron et al., 2004)). Alongside data types, we define the following constraints.

Constraint 1 (*Autonomous Vehicle*)**.** Each *Autonomous Vehicle* must include some navigation *Component* to ensure the presence of automated driving features.

Constraint 2 (*Component*)**.** Each *Component* must be classified as either *Sensor*, for collecting data, or *Module*, for processing data and control.

Constraint 3 (*Module*)**.** Each *Module* must possess a designated role of either *Actuator*, for physically controlling AVs, or *Controller*, for data processing and decision-making.

Constraint 4 (*Controller*)**.** Each *Controller* must be capable of handling one or multiple *Navigation Task* simultaneously.

Constraint 5 (*Environment*)**.** Each *Road* must inherently exhibit descriptive *Feature*.

Constraint 6 (*Sensor*)**.** Each *Sensor* must be evaluated separately with no interactions with other sensors since each sensor is of a different type with its own specifications.

Constraint 7 (*Environment*)**.** *Weather Condition* must be uniquely associated with each *Environment*.

Constraint 8 (*Algorithm*)**.** Accuracy of each algorithm must fall within an acceptable range, which is defined as 80 to 100 percent.

3.5 Ontology Rules

Rules represent statements that establish connections between concepts and properties and facilitate drawing inferences and imposing restrictions on the knowledge contained in the ontology. In particular, rules are designed to explicitly model situations where factors could impact the quality of decisions made by navigation algorithms in AVs. Appropriate rules ensure that the ontology remains consistent, coherent, and accurate, preventing errors or inconsistencies. A total of ten rules have been established in the proposed ontology. Table 1 summarizes these rules and what *Navigation Task* is affected by each rule.

Rule 1. *GNSS* malfunctioning considers all decisions, made by *Controller* (LM or RP), *Faulty*.

Rule 2. Passing through a tunnel makes all decisions, made by *Controller* (LM or RP), *Faulty* due to *GNSS* signal blockage.

Rule 3. *IMU* malfunctioning considers all decisions, made by *Controller* (LM, OT, CA, BA, PA, TP, or BP), *Uncertain*.

Rule 4. *Radar* malfunctioning considers all decisions, made by *Controller* (OD, OT, BSD, ADC, CA, BA, PA, TP, or BP), *Uncertain*.

Rule 5. *Lidar* malfunctioning considers all decisions, made by *Controller* (OD, OC, OT, BSD, ADC, CA, BA, PA, TP, or BP), *Uncertain*.

Rule 6. *Camera* malfunctioning considers all decisions, made by *Controller* (LM, OD, OT, BSD, LKA, CA, BA, PA, TP, or BP), *Uncertain*.

Rule 7. Navigating on a road without lane markers considers all decisions, made by *Controller* (LM, LKA, TP, or BP), *Uncertain*.

Table 2: Evaluation scenarios descriptions and results.

<table>
<tr><th>Scenario #</th><th>Weather Condition</th><th>Visibility</th><th>Road</th><th>Sensor</th><th>Impacted Sensor</th><th>Navigation Task</th><th>Ontology Inference</th></tr>
<tr><td rowspan="2">1</td><td rowspan="2">Normal</td><td rowspan="2">Clear</td><td>Urban</td><td>GNSS</td><td>GNSS</td><td>LM</td><td>Uncertain</td></tr>
<tr><td>Heavy traffic</td><td>Camera</td><td>IMU, Lidar</td><td>OD</td><td>Uncertain</td></tr>
<tr><td rowspan="2">2</td><td rowspan="2">Heavy rain</td><td rowspan="2">Poor</td><td rowspan="2">Highway</td><td rowspan="4">GNSS
IMU
Camera
Lidar
Radar</td><td rowspan="2">Camera</td><td>LM</td><td>Uncertain</td></tr>
<tr><td>OD</td><td>Uncertain</td></tr>
<tr><td rowspan="2">3</td><td rowspan="2">Not applicable</td><td rowspan="2">Clear</td><td rowspan="2">Tunnel</td><td rowspan="2">GNSS</td><td>LM</td><td>Uncertain</td></tr>
<tr><td>OD</td><td>Certain</td></tr>
</table>

Rule 8. Traveling on a slippery road or under adverse weather conditions, such as snow, fog, or rain considers all decisions, made by *Controller* (LM, OD, OC, OT, LKA, CA, BA, PA, RP, TP, or BP), *Uncertain*.

Rule 9. Low-visibility conditions consider all decisions, made by *Controller* (LM, OD, OC, OT, LKA, CA, BA, PA, RP, TP, or BP), *Uncertain*.

Rule 10. During sunrise or sunset, an AV traveling towards east or west and relying on visual sensors may face glare conditions that impair their performance. Such conditions consider all decisions, made by *Controller* (LM, OD, OC, OT, LKA, CA, BA, PA, TP, or BP), *Uncertain*.

3.6 Ontology Development

The proposed ontology was implemented in Protégé, a well-established open-source platform for creating ontologies (Musen, 2015). To ensure flexibility and standardization, the ontology was encoded in the Web Ontology Language (OWL) format since it is a W3C recommendation and is based on the Resource Description Framework (RDF) and RDF Schema (RDFS), facilitating its sharing and integration. Protégé along with OWL offers a comprehensive range of tools for defining classes, properties, and their relationships, and for articulating rules and constraints. To detect inconsistencies and enable inference on the ontology, we employed Pellet model reasoner supported by Protégé (Sirin et al., 2007). Protégé also provides DL (description logic) queries for retrieving ontology information. The ontology constraints were encoded as class expressions. To specify complex logical expressions and inference rules for reasoning over the ontology, the Semantic Web Rule Language (SWRL) was adopted, which facilitated automated inference and performance of complex reasoning tasks by Pellet, enhancing the ontology's effectiveness and usefulness.

The final version of the ontology consists of 71 classes, 140 object properties, and 39 data properties. The selected classes effectively capture the essential features and relationships in the ontology domain. The properties define the relationships between the classes and articulate the constraints and rules that govern the ontology. In addition to the classes and properties, we also included 635 axioms in the ontology to formally represent the relationships and constraints between the classes and properties. These axioms specify the logical rules that must be followed to maintain consistency and coherence within the ontology, thereby enabling a more complete and nuanced representation of the knowledge in the ontology domain. To further enhance the reasoning capabilities of the ontology, we also encoded 10 SWRL rules. The following link can be used to gain access to the ontology: https://github.com/MHarbi/Safety-AV-Nav-Ontology.

4 EVALUATION

The ontology was evaluated to assess its effectiveness in addressing AV navigation safety. This evaluation involved the execution of ontology queries within Protégé 5.6.1, installed on a MacBook Pro running macOS 12.6.9. Model reasoning was conducted using Pellet 2.2.0. To evaluate the ontology's effectiveness, three scenarios were devised, as described in literature (Degbelo, 2017; Obrst et al., 2007). These scenarios were designed to investigate specific aspects related to AV navigation safety. Specifically, the competency questions guiding this evaluation as follows. What are the implemented navigation tasks? What is the level of uncertainty for each navigation task? What is the identifiable source(s) of uncertainty? Which sensor is impacted by these sources? Table 2 provides descriptions for the scenarios and results. In each scenario, the AV used only LM and OD, which were identified by the ontology successfully, to make navigation-related decisions.

In the first scenario, an AV is navigating through heavy urban traffic under normal weather conditions with clear visibility. Within this context, the AV's cameras and GNSS operate optimally but the IMU and lidar do not. The ontology model reasoning infers *Uncertain* decisions for both navigation tasks (LM and OD). These uncertainties are primarily attributed to the lack of sensors like IMU and lidar, which play an important role in enhancing the vehicle's perception, particularly in intricate traffic scenarios.

The second scenario takes a place on a highway under heavy rain. Despite having a full array of sensors, the ontology still marked both navigation task decisions as *Uncertain*. This is because the adverse weather condition severely impedes visibility and, consequently, the performance of cameras. In particular, low-visibility conditions would impair the cameras' efficacy in identifying nearby vehicles and obstacles as well as localizing the AV.

The third scenario is a tunnel environment where camera visibility and weather conditions are not factors of concern. Here, the ontology rated OD as certain but LM as *Uncertain*. Upon entering the tunnel, the AV's GNSS experiences signal degradation or total loss due to the surrounding infrastructure. This compromises the utility of GNSS as a solo sensor for position estimation. In contrast, the IMU consistently delivers precise information on the vehicle's state, irrespective of GNSS signal availability. Additionally, cameras remain functional in the tunnel environment under adequate artificial illumination, allowing for object and environmental feature detection. Meanwhile, the lidar sensor can supply maps of the tunnel environment. In this scenario, despite the temporary loss of GNSS signals inside the tunnel, the sensor fusion algorithms can overcome potential navigational task failures. Upon exiting, the AV reestablishes GNSS signal and adjusts its global path planning accordingly.

The evaluation of the ontology reveals insights into its capacity to assess the quality and reliability of navigation tasks under diverse and challenging circumstances. By comprehending these circumstances, AVs can adapt proper strategies to avoid potential pitfalls and optimise sensor resources to navigate safely through diverse and dynamic environments.

5 CONCLUSIONS AND FUTURE WORKS

In this paper, we propose an ontology for AV navigation sensor uncertainty. Utilizing the knowledge represented in this ontology, uncertainties from different sources affecting sensor performance can be assessed and handled for safe operation. We evaluated the proposed ontology with three AV driving scenarios where typically navigation sensors are potentially challenged and prone to uncertainties. Our evaluation results indicate that the proposed ontology can detect the uncertainty sources, the impacted sensors and the navigation tasks to handle safety of AV navigation.

While the results of these initial validations of the proposed ontology are promising, the ontology, like any new ontology in any domain, needs to be tested with a wide variety of scenarios, examined by the AV community, and updated based on the received feedback.

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