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Research Article

Integrating OpenStreetMap and Lanelet2 Data Formats for an Ontological Framework Supporting Safe Autonomous Driving

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ABSTRACT

This paper introduces a structured architecture for integrating OpenStreetMap (OSM) data with ontology-based representations to advance the development and validation of automated driving systems. OSM contributes static geospatial information, while the Lanelet2 format offers detailed lane-level and topological road structure data. The fusion of these data sources enables the creation of high-fidelity simulation environments for evaluating vehicle behavior under realistic conditions. The ontology component facilitates semantic representation of roadway features and traffic regulations, thereby enabling the representation of complex and context-rich driving situations. By combining spatial and semantic layers, the proposed framework supports accurate simulation, traffic flow analysis, route planning, and autonomous decision-making processes. This integration enhances the scalability, precision, and robustness of autonomous driving applications, contributing to improved safety and reliability in real-world driving environments.

1. Introduction

Roadway accidents remain one of the leading causes of fatalities worldwide, often resulting from risky driving behaviors such as excessive speed, alcohol impairment, driver exhaustion, and distractions like smartphone usage. Autonomous vehicles (AVs) are designed to tackle these problems by leveraging sophisticated tools, including GPS, sensors, computer vision, and digital mapping, to interpret surroundings, make navigation decisions, and select efficient travel paths. By minimizing the role of human error, AVs hold promise for significantly enhancing road safety, optimizing traffic conditions, reducing fuel use, and improving accessibility for a wide range of road users [1]. Maps serve a crucial function in the functioning of autonomous vehicle systems, particularly in scenarios involving high-level automation. High-Definition (HAD) maps [2] provide accurate and fine-grained environmental data, which are essential for predicting object behavior, planning routes, and generating appropriate driving responses. These maps deliver detailed spatial information that helps the system interpret and respond to nearby elements such as other vehicles and pedestrians. In route optimization, they supply comprehensive road layout data, allowing autonomous vehicles to identify the most efficient travel routes. Additionally, HAD maps assist in crafting and executing complex driving maneuvers, contributing to safe, smooth, and intelligent operation of autonomous systems.

Lanelet2 [3] is an advanced mapping framework tailored to the demands of autonomous driving, offering detailed map components and supporting the simulation of intricate traffic scenarios. Its modular and adaptable design enables the representation of detailed lane information, traffic regulations, as well as dynamic roadway components. Such detail is crucial for current autonomous vehicle platforms, as it aids in precise positioning, route planning, and well-informed decisions in real-time scenarios. The decision-making process in self-driving vehicles involves more than identifying the physical layout of the road. Beyond mapping static road features, these systems must assess how to navigate safely and effectively among nearby drivers and travelers.

In order to enhance the functions of Lanelet2, an ontology-based framework can be utilized to establish connections between entities and conceptual elements, promoting semantic interpretation and knowledge integration [4]. This organized method enhances environmental awareness, enables complex logical inference, and improves the system's ability to engage with mapping data effectively. Through the inclusion of semantic context and intelligent, context-sensitive processing, Lanelet2 becomes part of a more flexible, insightful, and high-performing autonomous driving system

This research introduces an architecture which combines Lanelet2 mapping and OpenStreetMap (OSM) data with ontology-based platform approaches to support the development of self-driving technologies. Through the application of context-aware analysis and semantic reasoning, the system seeks to enhance localization accuracy, estimate vehicle actions, and manage critical decision-making tasks. This combination enables autonomous platforms to more effectively understand and adapt to changing traffic conditions, resulting in safer and more intelligent driving behavior. Furthermore, integrating a simulated environment allows for streamlined evaluation and refinement of autonomous control policies.

2. Methodology

The suggested architecture adopts a three-phase approach, consisting of data processing, simulated testing, and ontology-based integration, to build a detailed and realistic platform for representing actual driving conditions, as illustrated in Figure 1.

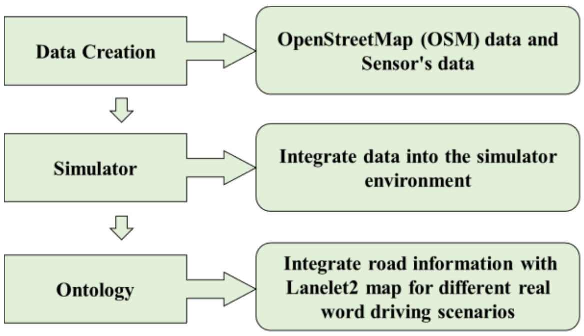


Figure 1. Architecture of Lanelet2 with Ontology Integration.

2.1. *Data Creation*

The foundational geographic framework is derived primarily from OpenStreetMap (OSM), which offers detailed static map components such as road configurations, junctions, lane delineations, and notable landmarks. These elements are vital for establishing the physical layout of the driving environment. To simulate dynamic aspects, real-world sensor data is integrated from sources such as cameras, LIDAR, and radar. These inputs capture essential details about traffic conditions, obstacles, pedestrian movement, and other mobile elements that influence how vehicles behave. All necessary data, including both OSM and sensor-derived information, will be provided by Aisan Technology Co., Ltd., ensuring the simulation environment is built on reliable, precise, and high-quality data.

2.2. *Coincar Simulation Platform*

The Coincar simulation patform offers a managed digital environment designed for simulating lifelike driving conditions, enabling the evaluation of atomated vehicle platforms in scenarios involving intricate interactions with diverse traffic participants [5]. Through this platform, the influence of Lanelet2's mapping accuracy and ontology-based decision-making can be systematically examined in terms of vehicle performance, safety, and operational efficiency. This simulation-driven validation process is essential for enhancing and fine-tuning autonomous driving strategies, supporting the advancement of more intelligent, responsive, and reliable vehicle systems.

2.3. *Integration of Lanelet2 with Ontology*

The construction of a Lanelet2 map begins by specifying geographic points, which are then linked to create linestrings that define the edges of roadways. These linestrings can enclose areas to represent specific zones, such as sidewalks, parking spaces, or pedestrian regions. Drivable lanes, referred to as Lanelets, are created by pairing two parallel linestrings that serve as the left and right borders, reflecting the directionality of traffic flow. To model traffic regulations, regulatory elements, like speed limits, traffic lights, and stop signs, are associated with relevant map features. This structured mapping approach enables a realistic and rule-aware virtual representation of real-world driving environments.

Lanelet2 maps are organized into three fundamental layers. The physical layer establishes the core geometry, using points and linestrings to depict tangible features such as road edges. Building upon this foundation, the relational layer structures these geometric elements into more complex constructs, including lanes, zones, and traffic regulations [6]. The topological layer defines how various map elements are connected and spatially related, supporting route planning and interaction among components. When combined, all three layers form a detailed and navigable road network tailored for autonomous driving, ensuring accurate and dependable pathfinding for self-driving systems [7]. Figure 2 shows the structural layout of Lanelet2, where lanelets are denoted using uppercase letters, areas are marked with lowercase letters, and linestrings are identified by numbers.

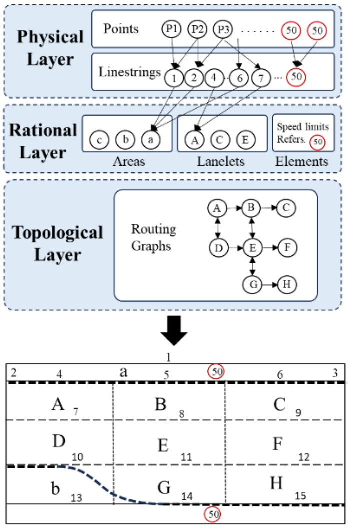


Figure 2. The architecture of Lanelet2 map designed for autonomous vehicle platforms.

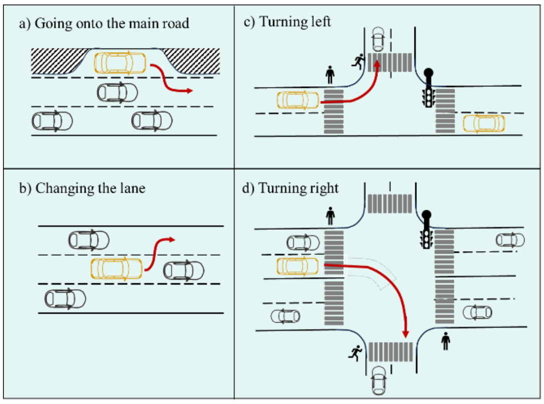


Figure 3. Examples of real-world traffic flow patterns.

The integration of Lanelet2 with ontology-based frameworks strengthens autonomous driving capabilities by linking Lanelet2 components, such as lanelets, zones, and regulatory elements, to their corresponding ontology categories and attributes.This method facilitates a richer representation of spatial relationships and logical dependencies between road elements, supporting advanced functionalities like traffic regulation compliance, optimized route planning, and predictive behavior modeling. Figure 3 illustrates representative examples of real-world traffic flow patterns.

This figure presents four common traffic situations encountered by self-driving systems. Scenario (a) depicts a vehicle merging onto a main road, which requires the vehicle to assess traffic gaps and perform a safe merge. Scenario (b) depicts a lane change during congestion, where the system must estimate distances to surrounding vehicles, manage spacing, and execute a smooth lateral transition. In scenario (c), the vehicle approaches an intersection to make a left turn, necessitating recognition of traffic signals, surrounding vehicles, and pedestrians. Scenario (d) presents a right turn at a busy intersection, where accurate timing and calculated actions are critical for safe navigation.

3. Experimental design and discussion

3.1. Creating Maps with Vector-Map-Builders

Figure 4 presents a road network map created using the Vector-Map-Builder tool. This map depicts intricate geometric details, such as curves, intersections, and lane structures, making it highly compatible for visualization, modification, and refinement within the Java OpenStreetMap (JOSM) platform [8]. The map includes a comprehensive set of elements, comprising 55,998 points, 3,082 linestrings (representing roadways and pathways), 714 polygons (bounded regions), 806 lanelets (separate driving paths), and 91 traffic regulation components, including road signs and related rules.

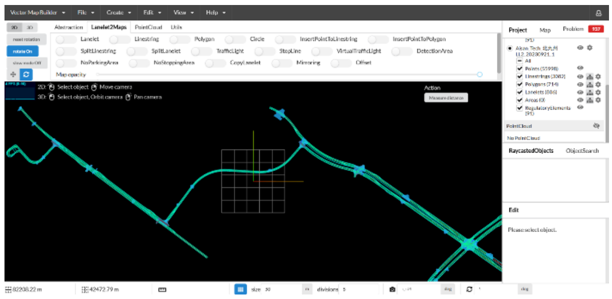


Figure 4. Road network map generated and visualized through Vector-Map-Builder.

3.2. Coincar-Based Visualization of Vehicle Behavior

The Coincar simulation patform uses Rviz, a Robot Operating System (ROS) [9] integrated platform for 3D visual representation, to support the creation and validation of collaborative navigation algorithms for self-driving vehicles. Rviz, a commonly adopted tool in the robotics community, facilitates the visual representation and error analysis of robotic behavior. It also allows the extension of its capabilities through custom plugins, enabling the visualization of selected ROS messages for improved interpretability and analysis. A key functionality of the Coincar simulation patform is its ability to visualize color-coded trajectories, where each vehicle's planned path is depicted using color-coding to reflect its timing over the course of motion. When overlapping trajectories are color-matched, it highlights likely collision points, making it easier to visually assess and refine vehicle interaction logic in the simulation. For environment visualization, custom modules will be developed to display the Lanelet mapping structures, object positions, and intended vehicle movement through trajectories. A color-coded format will be applied to these trajectories to indicate actual time and enhance interpretability. adopting a strategy resembling the one introduced in described in [10]. Figure 5 demonstrates the visualization of the Lanelet road network and color-coded vehicle paths in the Coincar environment.

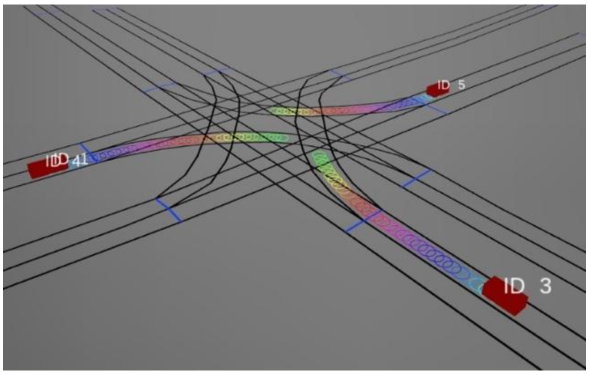


Figure 5. Demonstration of the Lanelet road network and color-coded vehicle paths in the Coincar environment.

3.3. *Localization and Safe Navigation in Intersection Scenarios*

To enhance the simulation environment for autonomous driving analysis, custom 3D models were created using Autodesk 3D Maya software, as shown in Figure 6. These models, including a pedestrian and a traffic light, were designed with realistic proportions to reflect actual road elements. Once modeled, they were exported and integrated into the Coincar simulator, which supports ROS-based visualization. Figure 7 illustrates the integration of these 3D assets within the simulation environment alongside a high-precision road network map provided by Aisan Technology, based on OpenStreetMap (OSM) data. This integration allows for detailed evaluation of vehicle behavior in response to static elements such as traffic lights and pedestrians. The combined use of semantic maps and realistic 3D objects supports complex navigation tasks, enabling the system to simulate perception, interaction, and decision-making processes with higher fidelity, particularly at intersections and areas requiring compliance with traffic regulations.

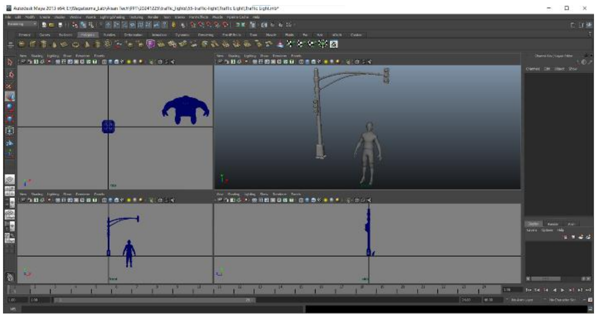


Figure 6. Modeling 3D traffic elements in Autodesk 3D Maya.

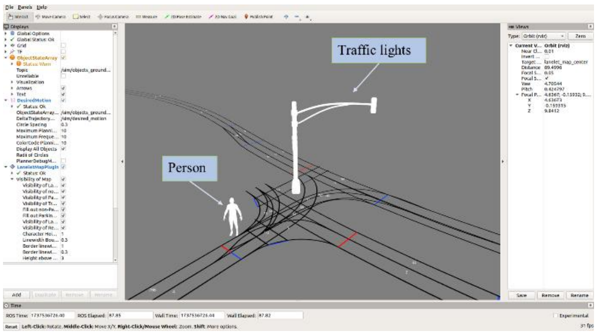


Figure 7. Visualization of imported 3D objects and Aisan Tech OSM map in Coincar simulator.

3.4. *Intersections and detection areas in Lanelet maps*

Localization management typically depends on Cartesian coordinates, while actual locations are situated on the Earth's ellipsoidal geometry. To resolve this mismatch, the Universal Transverse Mercator (UTM) projection is utilized, facilitating precise alignment between geographic coordinates and map representation. An illustration of a right-turn movement at a road junction, through Rviz, is presented in Figure 8. This visualization will be incorporated into the constructed map to simulate and visualize the behavior of the self-driving system throughout the turning maneuver. For safe navigation of the intersection, the system needs to perform real-time decision-making, such as giving way to pedestrians at crossings and modulating vehicle speed to preserve proper spacing, and planning paths for smooth and effective turning maneuvers. Road regulations, including compliance with signals and yielding to other road users, are factored into the decision workflow. This structured map guarantees autonomous vehicles with safety manegements by preventing collisions, following traffic rules, and optimizing operational efficiency by reducing delays while strictly observing all safety measures.

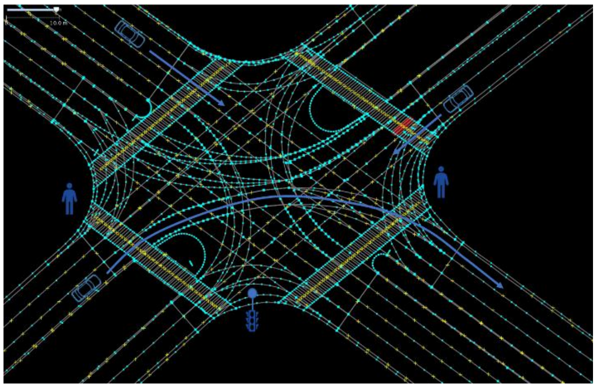
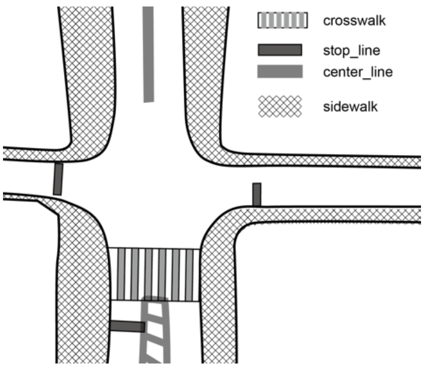


Figure 8. Navigation strategies with safety and efficacy for autonomous vehicles safety in multi-lane intersection.

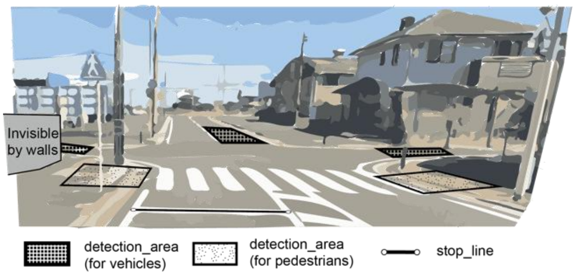
3.5. *Intersections and detection areas in Lanelet maps*

This research introduces a robust framework aimed at improving autonomous vehicle navigation, decision-making, and safety by integrating Lanelet2, OSM data, and ontology-driven systems. Through the use of semantic reasoning and context-sensitive insights, the framework supports accurate localization, efficient route optimization, and flexible driving behaviors. The layered structure of Lanelet2, when combined with ontology integration, allows for the detailed representation of intricate situations, including lane transitions, joining maneuvers, and navigating intersections.

In intersections, particularly those lacking traffic signals, accurate map representation is essential for ensuring the safety of self-driving vehicle. For instance, as illustrated in Figure 9, it is essential to precisely define the detection zone in relation to the stop line. The vehicle must be able to detect obstacles in its path and remain vigilant of any potential hazards that could lead to a collision. In the Lanelet [7], the "Detection Area" can be incorporated into the "Extra Regulatory Components " through an expansion of the Autoware [11] data format. Our focus was on the variation in automobile behavior, particularly in its decision-making process, influenced by the type of targets, including vehicles and pedestrians. We presented distinguishing detection zones based on these target types, which were categorized separately within the ontology.



(a) Map view



(b) Perspective view

Figure 9. Visualization of detection area and stop line in autonomous driving systems.

As illustrated in Figure 10 and Figure 11, the detection zone is specified within the Lanelet framework [7], allowing the automated driving system to focus on this area. Nevertheless, the safety strategy may vary depending on whether the detected target is a vehicle or a pedestrian, as shown in Figure 12.

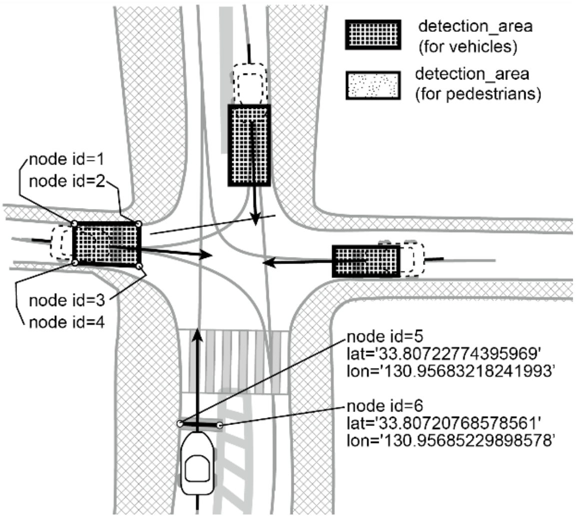


Figure 10. A mapped visualization of detection zones based on vehicle movement paths.


```xml
<node id=1 version='1' lat='33.80734177738309'
lon='130.95688633086124'>
  <tag k='ele' v='0'/>
</node>
<node id=2 version='1' lat='33.807319490552416'
lon='130.95690711797926'>
  <tag k='ele' v='0'/>
</node>
<node id=3 version='1' lat='33.807304446938424'
lon='130.95688566030907'>
  <tag k='ele' v='0'/>
</node>
<node id=4 version='1' lat='33.80732840528539'
lon='130.9568615204301'>
  <tag k='ele' v='0'/>
</node>
<node id=5 version='1' lat='33.80722774395969'
lon='130.95683218241993'>
  <tag k='ele' v='0'/>
</node>
<node id=6 version='1' lat='33.80720768578561'
lon='130.95685229898578'>
  <tag k='ele' v='0'/>
</node>
<way id=11 version='1'>
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  <nd ref=2 />
  <nd ref=3 />
  <nd ref=4 />
  <nd ref=1 />
  <tag k='type' v='detection_area' />
  <tag k='area' v='yes' />
</way>
<way id=12 version='1'>
  <nd ref=5 />
  <nd ref=6 />
  <tag k='type' v='stop_line' />
</way>
<relation id='13'>
  <tag k='type' v='regulatory_element'/>
  <tag k='subtype' v='detection_area'/>
  <member type='way' ref='11' role='refers'/>
  <member type='way' ref='12' role='ref_line'/>
</relation>
```


Figure 11. XML representation according to Lanelet format on detection areas depicted in Fig. 10.

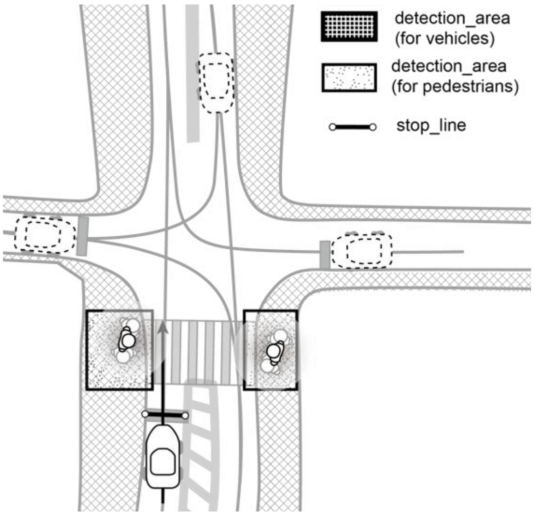

Figure 12. Detection zones for pedestrians, semantically differentiated to reflect unexpected movement patterns.

In Lanelet [7], vehicles move along a specific lane, with transitions between lane IDs as illustrated in Figure 13. To prevent collisions with other vehicles, the automated driving system calculates potential actions based on lane behavior. However, the risk level differs when the detected target is a pedestrian.

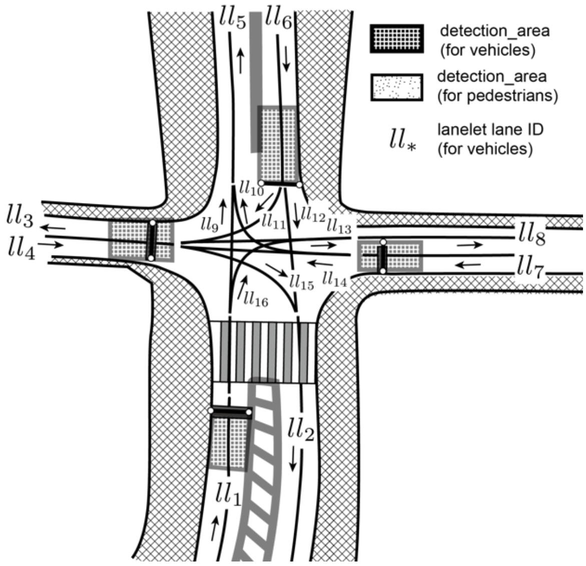

Figure 13. Lanelet map with Lane IDs for vehicles.

By redefining pedestrian-specific Lanelet IDs and detection areas, as depicted in Figure 14, the system distinguishes collision avoidance strategies from those applied to vehicles.

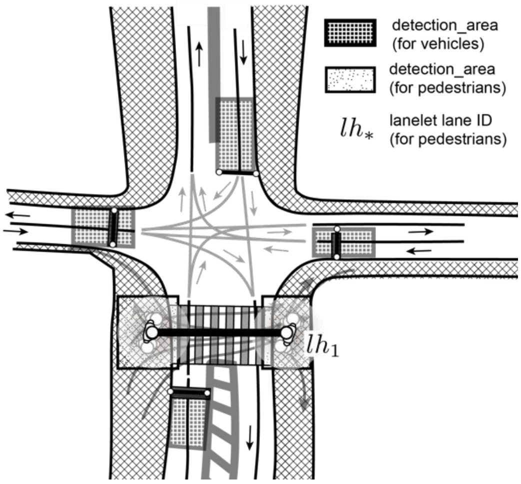

Figure 14. Modeling Potential Pedestrian Behaviors Around the Crosswalk Using Extended Lanelet IDs.

4. Conclusion

This study introduces a robust framework aimed at enhancing the navigation, decision-making, and operational safety of autonomous vehicles by combining Lanelet2, OpenStreetMap (OSM) data, and ontology-based systems. By utilizing semantic inference and context-sensitive analysis, the approach enables accurate localization, efficient route planning, and flexible driving behavior. The layered structure of Lanelet2, when integrated with ontological models, supports the detailed representation of intricate situations, including lane transitions, joining maneuvers, and navigating intersections. Additionally, the Coincar simulator provides a platform for thorough testing and optimization of autonomous driving strategies, ensuring the system's performance is evaluated across diverse conditions. This framework lays a strong foundation for the development of smarter, safer, and more context-aware autonomous systems, capable of operating efficiently in dynamic real-world environments.

Future work could investigate the integration of Lanelet representations with ontology-based logical reasoning to create customized safety strategies that adjust to various interaction scenarios. This would enable the simulation of dynamic environments, accounting not only for vehicles but also transportation disadvantaged, such as pedestrians, cyclists, individuals using wheelchairs, and so on, each requiring specific safety protocols to minimize potential risks. Furthermore, to assess the overall performance of autonomous driving systems, refined map data combined with integrated logical reasoning enables the dynamic generation of realistic driving scenarios, enhancing the testing and optimization of system behavior in diverse, real-world conditions.

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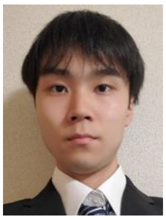

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