A Data Format Integration of Open-Street-Map and Lanelet2 Toward the Ontology Framework for Safety Automated driving systems

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Abstract

This study proposes a framework that integrates OpenStreetMap (OSM) data with ontology-based systems to enhance automated driving. OSM provides static geographical data, while the Lanelet2 mapping framework incorporates lane-level road information and topological relationships. This combination enables advanced testing of vehicle behavior in realistic environments. Ontology-based integration offers semantic representations of road elements and traffic rules, supporting the modeling of complex driving scenarios. By structuring spatial and semantic data, this approach ensures accurate simulation and testing, facilitating applications such as traffic analysis, route optimization, and automated driving decision-making. The framework enhances scalability, precision, and safety in autonomous vehicle development, enabling more effective testing and validation. This integration supports comprehensive, context-aware simulations that improve vehicle response to real-world driving conditions.

Keywords: OSM map, Lanelet2, Ontology, Coincar simulator, Automated driving.

1. Introduction

Road traffic crashes are a major cause of death, driven by dangerous behaviors like speeding, drunk driving, driver fatigue, and distractions such as mobile phone use. Autonomous vehicles (AVs) aim to address these issues by utilizing advanced technologies like computer vision, GPS, sensors, and mapping systems to navigate, detect environments, and determine optimal routes. By reducing human error, AVs offer potential benefits such as fewer accidents, improved traffic flow, lower fuel consumption, and enhanced mobility for all road users [1]. Maps are critical for autonomous vehicle systems, especially in highly automated driving, where High-Definition (HAD) maps [2] provide detailed, precise environmental data. These maps facilitate object prediction, routing, and the generation of driving behavior by offering high-resolution information essential for understanding and interacting with surrounding entities like vehicles and pedestrians. They are integral to route planning by providing complete road network information to determine efficient paths. Furthermore, HAD maps support the design and implementation of advanced driving strategies and maneuvers, ensuring autonomous vehicles operate safely, efficiently, and effectively.

Lanelet2 [3] is a sophisticated mapping framework designed to support autonomous vehicles by providing advanced map elements and enabling the modeling of complex driving scenarios. It offers a flexible and extensible structure, allowing for the representation of lane-level information, traffic rules, and dynamic road elements. This level of detail is crucial for the evolving needs of automated driving systems, as it enables precise localization, path planning, and decision-making in dynamic environments. Decision-making in autonomous vehicles extends beyond just mapping physical elements of the road. In addition to representing static road features, autonomous vehicles must make informed decisions about how to safely and efficiently interact with other road users.

To further enhance the functionality of Lanelet2, an ontology framework can be employed to define relationships between concepts and entities, facilitating knowledge sharing and semantic representation [4]. This structured approach improves the understanding of surroundings, supports advanced reasoning, and enables more effective interaction with map data. By integrating semantic knowledge and context-aware reasoning, Lanelet2 contributes to a more adaptive, intelligent, and effective driving system.

This study proposes a framework that integrates Lanelet2 and OpenStreetMap (OSM) data with ontology-based systems to enhance automated driving systems. By leveraging semantic reasoning and context-aware insights, the framework aims to improve navigation precision, predict vehicle behavior, and support complex decision-making. This integration enables autonomous systems to better interpret and respond to dynamic driving environments, promoting safer, smarter, and more adaptive vehicle operations. The use of simulator facilitates efficient testing and optimization of automated driving strategies.

2. Methodology

The proposed framework follows a three-step process that involves data handling, simulation, and ontology integration to create a comprehensive and realistic environment for modeling real-world driving scenarios as shown in Fig. 1.

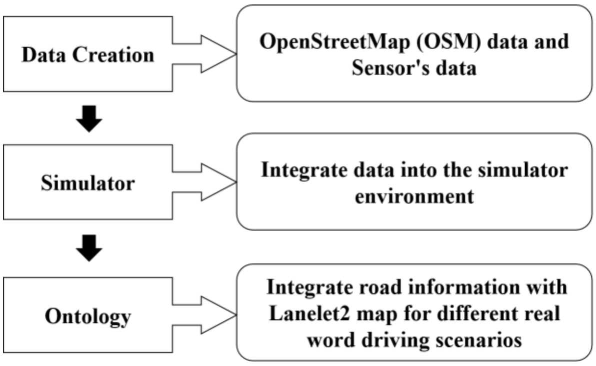


Fig. 1. Flowchart of Lanelet2 with Ontology Integration.

2.1. *Data creation*

OpenStreetMap (OSM) Data serves as the primary source of geographical information, providing crucial static map elements such as road networks, intersections, lane markings, and landmarks. This information is essential for defining the structure of the driving environment. Real-world sensor data, such as inputs from cameras, LIDAR, and radar, is incorporated to add dynamic elements to the simulation. This data enriches the environment with critical information on traffic flow, road obstacles, pedestrians, and other moving entities that influence vehicle behavior. The data required for this step, including OSM data and sensor data, will be supplied by Aisan Technology Co., Ltd., ensuring accuracy, consistency, and high-quality input for the simulation process.

2.2. *Coincar simulator*

Coincar simulator provides a controlled, virtual platform to simulate realistic driving scenarios and assess the performance of autonomous systems in handling complex interactions with other road users [5]. By using Coincar simulator, the impact of Lanelet2's mapping precision and ontology-driven decision-making on vehicle behavior, safety, and efficiency can be analyzed. This simulation-based validation process plays a crucial role in refining and optimizing autonomous vehicle decision-making, ultimately contributing to the development of a more adaptive, intelligent, and effective driving system.

2.3. *Lanelet2-Ontology integration*

The Lanelet2 map creation process starts with defining geographic points, which are connected to form linestrings outlining road boundaries. Enclosed linestrings create areas to represent regions like pedestrian zones or parking lots. Lanelets, which define drivable paths, are formed using two parallel linestrings as left and right boundaries to represent directional traffic flow. Finally, regulatory elements are added to link traffic rules, such as speed limits and stop signs, to the map components, enabling an accurate representation of real-world driving environments.

Lanelet2 maps are divided into three key layers. The physical layer defines the basic geometry with points and linestrings to represent physical features like road boundaries. The relational layer builds on this by grouping these elements into higher-level structures, such as lanes, areas, and road rules [6]. The topological layer establishes connectivity and spatial relationships between these elements, allowing for route planning and interaction between different components. Together, these layers create a comprehensive and navigable road network for autonomous vehicles, enabling precise and reliable navigation [7]. Fig. 2 illustrates the architecture of Lanelet2, where lanelets are represented by capital letters, areas by lowercase letters, and linestrings by numbers.

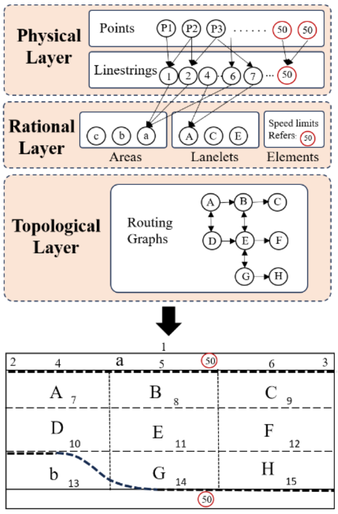


Fig. 2. Lanelet2 map architecture for automated driving systems.

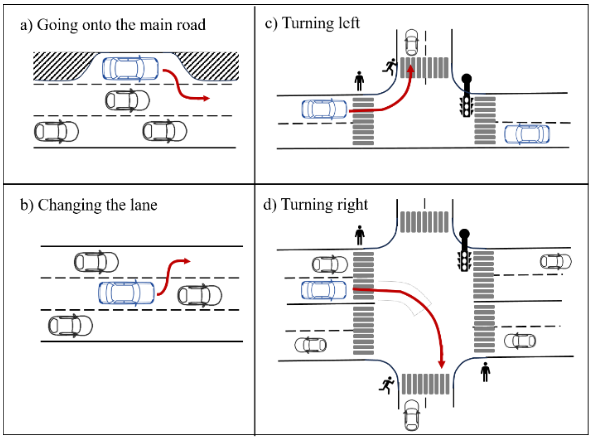


Fig. 3. Examples of real-world driving scenarios.

Integrating Lanelet2 with ontology-based systems enhances automated driving by mapping Lanelet2 elements like lanelets, areas, and regulatory elements to ontology classes and properties. This approach allows for more effective modeling of relationships and dependencies between road elements, enabling complex tasks such as traffic rule enforcement, route optimization, and behavior prediction. Fig. 3 shows examples of simple and complex real-world driving scenarios.

The figure illustrates four driving scenarios for autonomous systems. Scenario (a) involves merging into traffic, requiring gap detection and safe merging. Scenario (b) depicts lane changes in a traffic jam, requiring distance adjustments and smooth maneuvers. Scenario (c) shows intersection entry, where the system must recognize pedestrians, vehicles, and traffic lights. Scenario (d) highlights a complex intersection, requiring advanced decision-making to determine the optimal timing and action.

3. Experiment and discussion

Fig. 4 illustrates a map created using Vector-Map-Builder. The map represents a road network with detailed geometry, including curves and intersections, offering a high-resolution depiction suitable for analysis and editing within the Java OpenStreetMap (JOSM) editor [8]. The map contains detailed elements, including 55,998 points, 3,082 linestrings (roads or paths), 714 polygons (enclosed areas), 806 lanelets (individual lanes), and 91 regulatory elements (e.g., traffic signs).

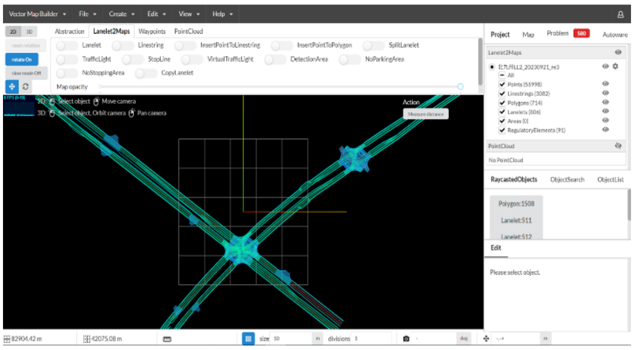


Fig. 4. Visualization of OSM map created using Vector-Map-Builder.

Coincar Simulator utilizes Rviz, a 3D visualization tool provided by the Robot Operating System (ROS) [9], to enhance development and evaluation processes for cooperative motion planning in autonomous vehicles. Widely used in the robotics community, Rviz enables visualization and debugging of various aspects of robot operation. It also supports extensions through custom plugins to visualize specific ROS messages, facilitating more tailored and effective visualization. A notable feature of Coincar simulator is its visualization capability, which includes the use of color-coded trajectories. In this system, each vehicle's planned future trajectory is displayed with a color gradient representing time progression. Overlapping trajectory segments of the same color indicate potential future collisions, providing an intuitive means to assess and debug vehicle interactions within the simulation environment. To represent the environment, plugins will be created to visualize the Lanelet map, object states, and desired motion using trajectories. These trajectories will utilize a color-coded scheme to represent absolute time, following a method similar to that outlined in [10]. Fig. 5 illustrates the visualization of the Lanelet map and color-coded trajectories in the Coincar simulator.

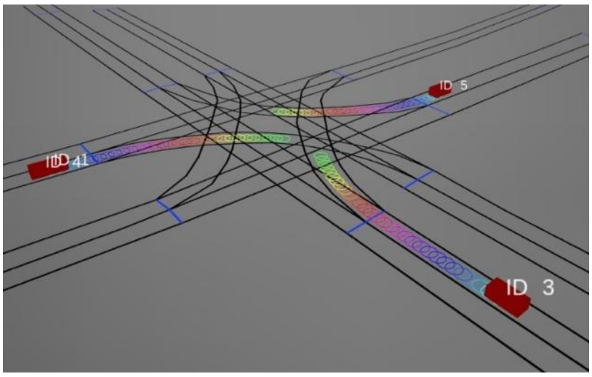


Fig. 5. Lanelet map and color-coded trajectories in Coincar simulator.

Localization management relies on Cartesian coordinates, while real-world locations exist on the Earth's curved surface. To bridge this discrepancy, the Universal Transverse Mercator (UTM) projection is employed, enabling accurate alignment between real-world locations and their corresponding map representations. An example of a right-turn scenario for autonomous systems at an intersection, represented using Rviz, is illustrated in Fig. 6. This representation will be applied to the created map to visualize and simulate the autonomous system's behavior during the turn. To navigate this intersection safely, the system must make dynamic decisions, including yielding to pedestrians at crosswalks, adjusting vehicle speed to maintain safe distances, and planning trajectories to execute turns efficiently. Traffic rules, such as adherence to signals and yielding requirements, are integrated into the decision-making process. This structured map ensures that the autonomous system prioritizes safety by avoiding collisions, complies with traffic laws, and operates efficiently by minimizing delays while adhering to all safety protocols

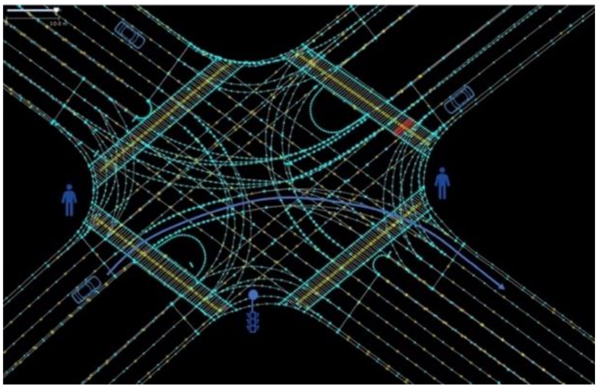
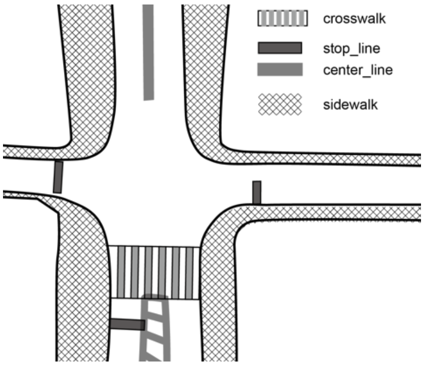


Fig. 6. Safe and efficient navigation strategies for autonomous vehicles in multi-lane intersection.

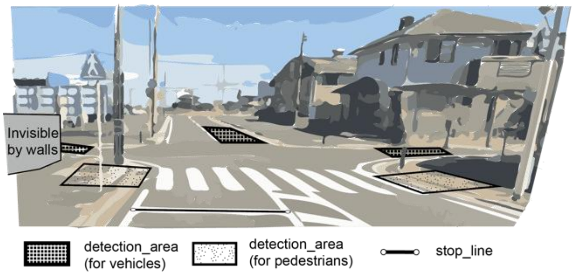
4. Experimental design and discussion

This study presents a comprehensive framework for enhancing autonomous vehicle navigation, decision-making, and safety through the integration of Lanelet2, OSM data, and ontology-based systems. By leveraging semantic reasoning and context-aware insights, the framework facilitates precise localization, route planning, and adaptive driving behavior. Lanelet2's multi-layered architecture, combined with ontology integration, enables the modeling of complex scenarios, such as lane changes, merging, and intersection navigation.

In the intersection especially without any traffic signal, the map representation is highly important for automated driving to ensure its safety. For example, as shown in Fig. 7, the detection area must be defined clearly with respect to the stop line. The vehicle can sense surrounding obstacles in the pathway to travel, and it requires to pay attention to targets that may cause a potential accident. In the Lanelet [7], it can be embedded as “Detection Area” in the “Extra Regulatory Elements” by the extension of Autoware [11] data format. We focused on the difference in vehicle behaviors including its decision-making process, depending on types of targets such as vehicles and pedestrians, and proposed the differentiation of detection areas depending on types of targets, which were differently categorized in the ontology.



(a) Map view



(b) Perspective view

Fig. 7. Detection area and stop line are represented by the set of points of interest.

As shown in Fig. 8 and Fig. 9, the detection area is described in Lanelet [7], and the automated driving system can pay attention to the area. However, the safety strategy might be different in cases of vehicles and pedestrians (Fig. 10).

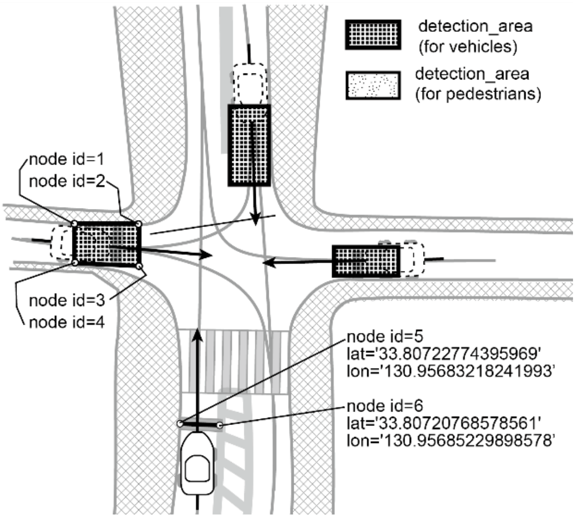


Fig. 8. A map view with detection areas considering pathways of vehicles.

```
<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'>
  <nd ref=1 />
  <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>
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Fig. 9. Lanelet XML representation of detection areas in Fig. 8.

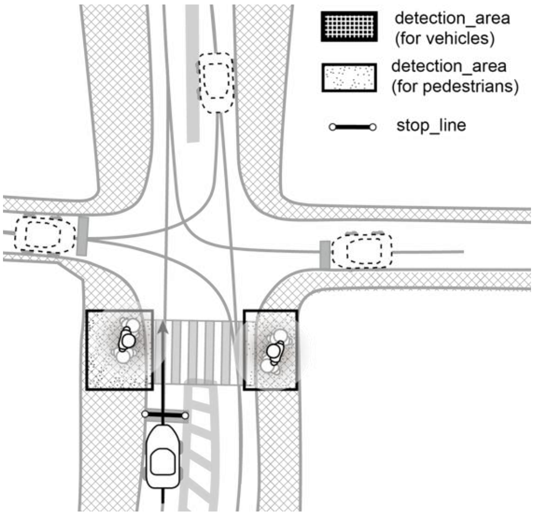

Fig. 10. Semantically differentiated detection area for pedestrians due to unexpected behaviors.

In Lanelet [7], individual vehicles travel on the lane as the transition of a lane ID to other lane ID (Fig. 11). For avoidance of collisions with other vehicles, the behavior of the automated driving will be calculated on potential actions of behaviors on the lanes. On the other hand, the risk level is different if it is a pedestrian.

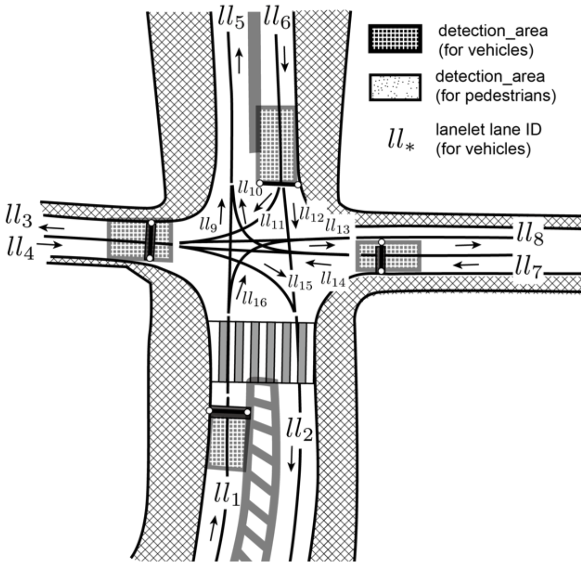

Fig. 11. Lanelet map with Lane IDs for vehicles.

By newly defining of the lane ID and detection areas specifically for pedestrians, the collision avoidance procedure, or strategy can clearly differentiate with respect to vehicle interactions (Fig. 12).

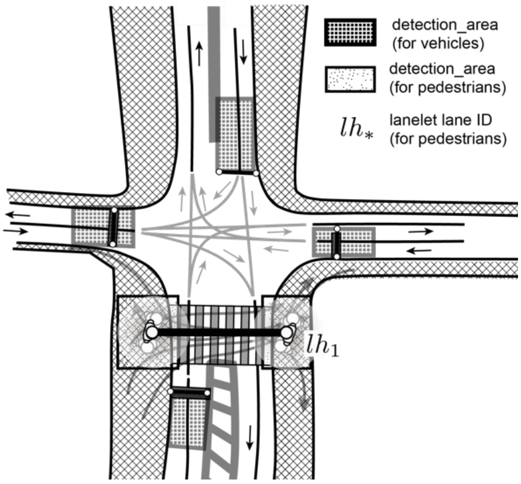

Fig. 12. An extended lane ID to cover potential pedestrian behaviors around the crosswalk.

Future work could integrate Lanelet representation with the ontology-based logical reasoning with different safety strategy behaviors depending on targets to interact. In this sense, the computer simulation is possible in a dynamic environment considering not only vehicle but also vulnerable road users such as pedestrians, wheel chairs, bicycles and so on, which requires different safety strategy to minimize potential risk. For the evaluation of automated driving systems to test overall performance, the real-world driving scenarios can be generated dynamically from the refined map data and ontology-based logical reasoning if they are successfully integrated.

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References

1. Bathla G, Bhadane K, Singh RK, Kumar R, Aluvalu R, Krishnamurthi R, Kumar A, Thakur RN, Basheer S. Autonomous vehicles and intelligent automation: Applications, challenges, and opportunities. Mobile Information Systems, pp. 7632892, 2022.
2. Zheng S, Wang J. High definition map-based vehicle localization for highly automated driving: Geometric analysis. In2017 International Conference on Localization and GNSS (ICL-GNSS),IEEE, (pp. 1-8), 2017.
3. Naumann A, Hertlein F, Grimm D, Zipfl M, Thoma S, Rettinger A, Halilaj L, Luettin J, Schmid S, Caesar H. Lanelet2 for nuscenes: Enabling spatial semantic relationships and diverse map-based anchor paths. InProceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, (pp. 3247-3256), 2023.
4. Zhao L, Ichise R, Yoshikawa T, Naito T, Kakinami T, Sasaki Y. Ontology-based decision making on uncontrolled intersections and narrow roads. In2015 IEEE intelligent vehicles symposium (IV), (pp. 83-88), 2015.
5. Naumann M, Poggenhans F, Lauer M, Stiller C. Coincar-sim: An open-source simulation framework for cooperatively interacting automobiles. In2018 IEEE Intelligent Vehicles Symposium (IV), (pp. 1-6). 2018.
6. Bender P, Ziegler J, Stiller C. Lanelets: Efficient map representation for autonomous driving. In2014 IEEE Intelligent Vehicles Symposium Proceedings, (pp. 420-425). 2014.
7. Poggenhans F, Pauls JH, Janosovits J, Orf S, Naumann M, Kuhnt F, Mayr M. Lanelet2: A high-definition map framework for the future of automated driving. In2018 21st international conference on intelligent transportation systems (ITSC), IEEE, (pp. 1672-1679), 2018.
8. Java OpenStreetMap Editor. Available online: https://josm.openstreetmap.de/ (accessed on 25 December 2024).
9. Quigley M, Conley K, Gerkey B, Faust J, Foote T, Leibs J, Wheeler R, Ng AY. ROS: an open-source Robot Operating System. InICRA workshop on open source software, (Vol. 3, No. 3.2, p. 5), 2009.
10. Kumar A, Wagatsuma H. A Kamm's Circle-Based Potential Risk Estimation Scheme in the Local Dynamic Map Computation Enhanced by Binary Decision Diagrams. Sensors. 22(19):7253, 2022.
11. Autoware Documentation. Available online: https://tier4.github.io/autoware.iv/pulls/2409/map/lanelet2_extension/docs/extra_regulatory_elements/ (accessed on 25 December 2024).

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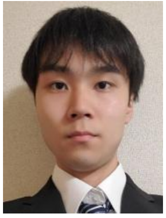

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