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Intersection Information Modelling and Case Analysis under the Dual Drive of Path Guidance and Scenario Constraints

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ABSTRACT

This study proposes a novel intersection-centric information framework, offering a new perspective and a practical approach to enabling autonomous vehicles (AVs) to navigate intersections safely and efficiently. While high-definition (HD) maps provide rich spatial information for autonomous driving, their excessive data volume often leads to increased computational burden and delays, particularly in intersection environments where timely positioning, perception, and decision-making are critical. To address this issue, we introduce the Road-Lane-Device-Scenario (RLDS) model, which separates and extracts key static and dynamic intersection elements, focusing on essential semantic features such as lane topology, traffic signal logic, and right-of-way rules. This targeted framework introduces an innovative approach to reduce data redundancy, thereby providing significant potential for enhancing the efficiency and intelligence of information processing and decision-making in autonomous driving systems. By effectively addressing the critical bottlenecks associated with intersection scenarios, the proposed framework demonstrates strong potential for practical application, enabling safer, more reliable, and more efficient autonomous vehicle operations in complex urban environments.

KEYWORDS

high-definition map; intersection information; Road-Lane-Device-Scenario (RLDS) model; autonomous driving; traffic and transportation.

1. INTRODUCTION

In the road traffic environment, intersections serve as critical nodes where vehicles, often of diverse types and travelling from multiple directions, converge and interact, inherently giving rise to potential conflict zones. The complexity and dynamic nature of real-time driving scenarios at intersections significantly increase the likelihood of traffic accidents. Accordingly, enhancing traffic efficiency and ensuring driving safety at intersections represent pressing challenges that must be addressed to advance the reliable deployment of autonomous driving technologies.

Owing to the diversity, complexity, real-time constraints, and multi-layered right-of-way rules inherent in intersections, the challenges associated with motion planning, decision-making, and control for autonomous vehicles are substantially greater at intersections than along ordinary road segments [1, 2]. The diversity of intersections is reflected not only in their structural forms, such as cross intersections, T-junctions, and Y-junctions, but also in the complexity of dynamic traffic scenarios, including diverging, crossing, and merging manoeuvres [3]. The overall complexity is further amplified by the heterogeneity of traffic participants, movement patterns, and decision-making mechanisms. Typical traffic participants include pedestrians, motor vehicles, and non-motorised vehicles, each contributing to the unpredictability of intersection environments [1, 4]. Moreover, movement modes range from walking to driving, while decision-making processes encompass both human cognitive judgments and algorithm-driven decisions executed by AV systems [5].

The real-time characteristics of intersections are manifested in the continuous and rapid fluctuations of traffic information, which are influenced by dynamic factors such as traffic control measures, weather conditions, traffic incidents, and right-of-way adjustments for emergency or special-purpose vehicles. The multi-constrained nature of right-of-way rules is particularly evident in the complex priority allocation among different traffic participants. For example, at intersections without traffic signals, vehicles are required to yield to pedestrians, while left-turning vehicles must give way to oncoming traffic proceeding straight [6, 7].

The diversity and complexity of driving scenarios at intersections present significant challenges to the safe and efficient navigation of AVs. HD maps serve as a crucial source of environmental and navigational information for autonomous driving systems. Bosch proposed the Local Dynamic Map (LDM), which is divided into four layers based on the frequency of data changes: permanent static data, transient static data, transient dynamic data, and highly dynamic data [8]. Liu Jingnan et al. proposed a four-layer data logical structure, including a static layer which contains roads, lanes, and traffic facilities; a real-time data layer, containing information such as traffic restrictions, traffic flow, and parking data in service areas; a dynamic data layer encompassing pedestrian and vehicle data; and a user model layer that incorporates driving experience data [9]. Jiang Kun et al. proposed the Tsinghua map model, which consists of seven layers: road layer, traffic information layer, road-lane connection layer, lane layer, map feature layer, dynamic objects container layer, and intelligent decision support layer [10]. Zhang Fengyuan et al. presented the Open HD map Service Model, which includes the static map layer, dynamic data layer, and real-time data layer [11].

These models primarily focus on the elements themselves from a global perspective, without sufficient consideration of local contexts or the interrelationships among elements that are critical for autonomous driving. Moreover, their effectiveness in addressing the intricate and highly dynamic conditions commonly encountered at local intersections remains limited. In particular, under rapidly evolving real-time traffic environments, the massive volume of HD map data imposes considerable computational demands, hindering the timely processing of dynamic intersection information. This limitation compromises the ability of HD maps to provide sufficient support for fine-grained, real-time driving decisions at intersections [12, 13].

Therefore, this study proposes an intersection-oriented information framework, termed the Road-Lane-Device-Scenario (RLDS) model, which is designed to enhance the efficiency of data processing and computational performance at intersections within autonomous driving systems. This framework offers a novel approach to achieving safer and more efficient autonomous vehicle navigation in complex intersection environments, and provides a practical reference for such applications. Compared with conventional global HD maps, the RLDS model focuses on extracting targeted, intersection-specific information with reduced data volume, thereby enabling faster information processing and more efficient decision-making by the autonomous driving system. Moreover, the framework demonstrates superior adaptability to diverse intersection scenarios, facilitating more precise path planning and refined vehicle control within localised intersection areas.

This paper is organised as follows: Section 2 describes the HD map and the intersection information model. Section 3 introduces the key points and technologies of the intersection information model. Section 4 presents the experimental results and analysis of the proposed intersection information in a simulation environment. Section 5 provides the conclusions.

2. MODEL DESCRIPTION

This section establishes the foundational concepts by providing an overview of high-definition maps, followed by a detailed explanation of the intersection information model, emphasising its key elements and structural composition. Additionally, a brief comparison is included to highlight the key differences between these two types of models.

2.1 High-definition maps

Generally, HD maps are distinguished by their superior accuracy, rich information content, and high update frequency [14]. These maps provide highly precise and detailed static road information, including road networks, lane configurations, traffic infrastructure, and points of interest (POIs), as well as dynamic elements such as vehicles, pedestrians, and evolving traffic scenarios [15]. Moreover, HD maps integrate user-specific information, such as vehicle attributes and driving preferences, to support personalised applications [16, 17].

By comprehensively combining static, dynamic, and user-related data, HD maps effectively mitigate perception blind spots inherent in both onboard and roadside sensors, while addressing limitations caused by occlusions of road surface markings [18, 19]. Consequently, HD maps provide a reliable and holistic source of road and traffic information. In addition, the incorporation of user information enables HD maps to support personalised route planning and decision-making processes, thereby enhancing the operational safety and efficiency of autonomous vehicles.

As critical nodes where traffic flows intersect and converge, intersections inherently introduce significant complexity, thereby placing higher demands on the capabilities and precision of HD maps. To address these challenges, an intersection-focused information framework has been developed based on HD maps, leveraging detailed HD map models to efficiently and accurately extract localised environmental information relevant to intersection driving scenarios. This targeted framework is designed to support safe and efficient vehicle manoeuvring through complex intersection environments [20, 21].

In such scenarios, the initial step for autonomous vehicles is to infer their intended route, specifically determining which exit or connecting road they will take upon entering the intersection. Once the target road is identified, the vehicle must further decide whether to execute a left turn, right turn, or proceed straight ahead. To ensure smooth navigation, the vehicle is required to pre-emptively perform lane-changing manoeuvres in accordance with traffic signs and road markings, thereby aligning its position with the intended path [22]. The complexity of decision-making and path planning for autonomous vehicles varies considerably across different types of intersections. Particularly in unregulated intersections where traffic signals, signage, or pedestrian crossings are absent, the unpredictability of surrounding traffic participants significantly amplifies the challenges associated with safe and reliable vehicle decision-making [23].

Road, lane, and device information provides comprehensive and fine-grained descriptions of road geometry, lane configurations, traffic signs, and pavement markings, thereby supporting both global and local path planning for autonomous vehicles, as illustrated in *Figure 1*. Intersection scenarios, however, introduce inherent complexity. They encompass a wide range of intersection types, including T-junctions, four-way intersections, and complex multi-lane configurations. Moreover, these scenarios are characterised by the presence of diverse traffic participants and highly dynamic traffic conditions that evolve throughout the different phases of vehicle traversal through the intersection.

In this study, the intersection scenario is systematically divided into three distinct phases: diverging, crossing, and merging, based on the typical process by which vehicles enter, navigate, and exit an intersection. Intersections are characterised by a comprehensive set of driving rules and detailed spatial elements, including obstacles, channelisation markings, medians, and roundabouts. Autonomous vehicles must continuously adapt their driving behaviour by integrating this static spatial information with dynamic, real-time traffic conditions.

To address the complexity of intersection environments, this study proposes an information framework for autonomous driving at intersections, referred to as the Road-Lane-Device-Scenario (RLDS) Model. This framework is designed to provide autonomous vehicles with comprehensive and fine-grained information regarding road geometry, lane configurations, traffic signs, and pavement markings. By incorporating this multi-dimensional information, the RLDS model aims to enhance vehicle decision-making, mitigate potential conflicts within intersections, and ultimately improve overall traffic safety and operational efficiency.

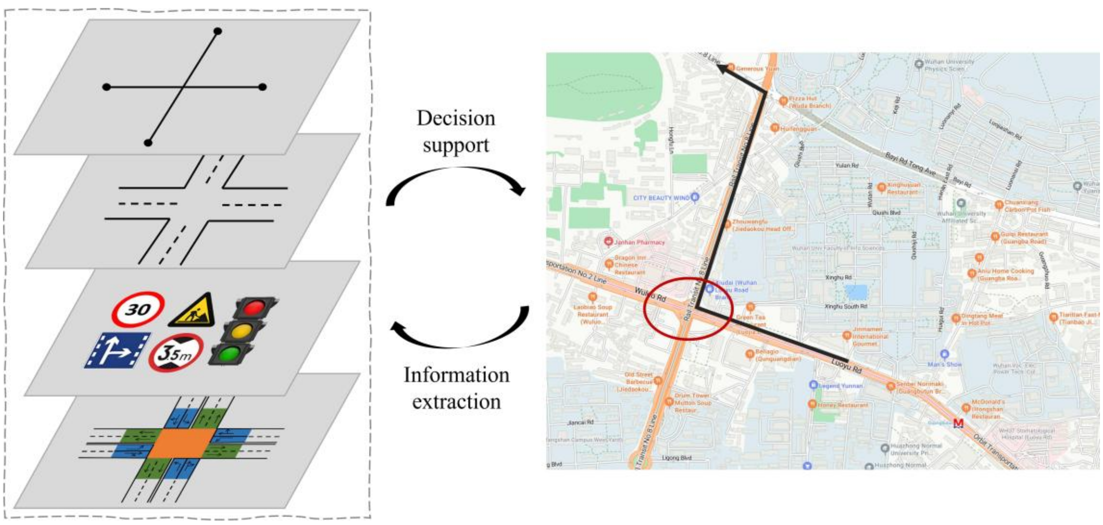


Figure 1 – The RLDS model and its role in global planning

2.2 Road-Lane-Device-Scenario (RLDS) model

The Road-Lane-Device-Scenario (RLDS) model consists of four key components: road network, lane network, traffic control devices, and intersection scenarios, as shown in *Figure 2*. The road network provides macro-level route planning for autonomous vehicles, while the lane network constrains vehicle trajectories at the micro level, enabling precise lane-level navigation. Traffic control devices, such as signals, regulate vehicle behaviour, requiring stops at red lights and permitting movement during green lights. Intersection scenarios define the three stages during which a vehicle enters, traverses, and exits an intersection, where potential conflicts with other traffic participants may occur. Moreover, by integrating key technologies such as traffic rule enforcement and road priority allocation, autonomous vehicles can achieve safer and more efficient intersection navigation.

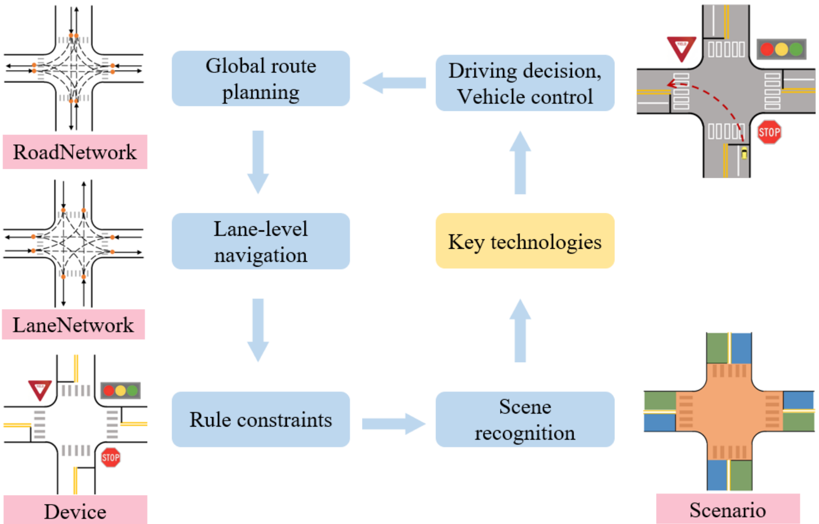


Figure 2 – Logical structure of the RLDS model

This study employs the Unified Modeling Language (UML) to organise data, encapsulating intersection-related information within a package named RLDS, which contains four sub-packages: RoadNetwork, LaneNetwork, TrafficControlDevice, and Scenario. Each sub-package contains several feature classes, as shown in *Figure 3*.

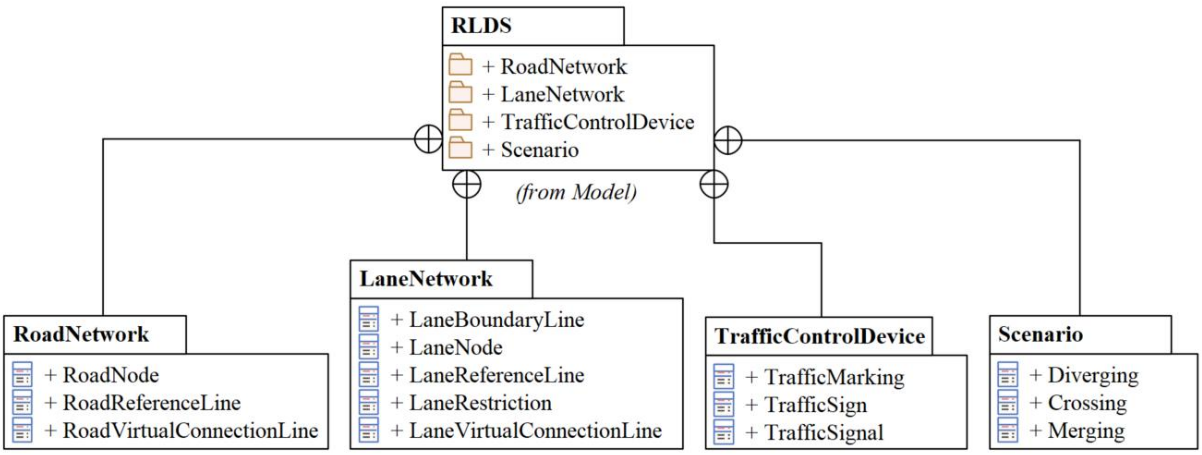


Figure 3 – Data structure of the RLDS model

Among these, the road network provides the macro-level foundation for autonomous vehicle path selection and serves as the structural basis of the intersection information framework. Specifically, the road network encompasses essential elements such as road reference lines, road virtual connection lines, and road nodes. The topological structure of intersections can be effectively represented, as illustrated in *Figure 4*.

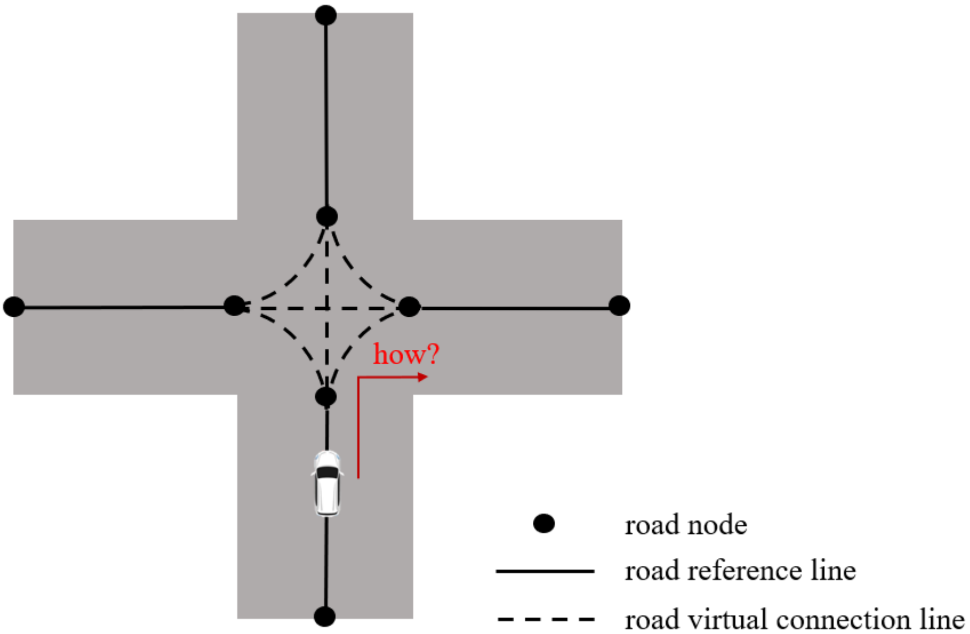


Figure 4 – Schematic diagram of the road network at the intersection

The road reference line is a linear abstraction of a physical road segment, capturing the geometric characteristics of the roadway between two adjacent road nodes along the direction of traffic flow. It contains multiple attributes, including road identifier (ID), road name, road type, road material, and geometry.

Road virtual connection lines, although not physically present in the real world, are introduced within the road network to construct the topological structure of intersections. These lines contain attributes such as a unique ID and geometric properties, which support the logical representation of connectivity within the intersection.

Road nodes serve as the endpoints of both road reference lines and virtual connection lines, marking positions where structural or attribute changes occur along the roadway. Each node is defined by a unique ID and geometric attributes.

The data structure of the RoadNetwork is illustrated in *Figure 5*.

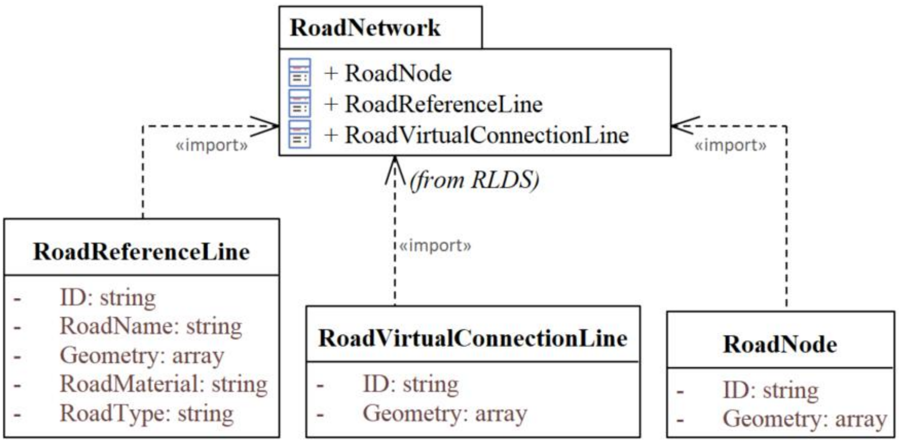


Figure 5 – Data structure of the RoadNetwork

The lane network regulates the operational boundaries of autonomous vehicles at a mesoscopic level, providing a more refined and detailed representation of the broader road network. It delineates the precise spatial limits within which autonomous vehicles can safely navigate and provides high-precision reference information to support path planning and vehicle control. The lane network consists of several key elements, including lane boundaries, lane reference lines, lane virtual connection lines, lane nodes, and lane restrictions. The topological structure of intersections can be effectively represented within the lane network, as illustrated in *Figure 6*.

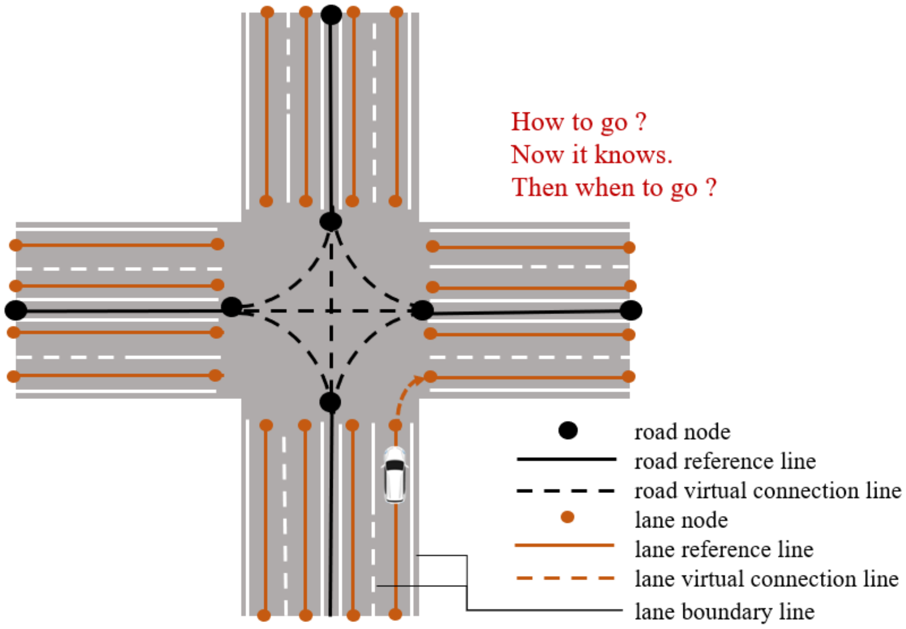


Figure 6 – Schematic diagram of the lane network at the intersection

Lane boundaries define the physical drivable area of each lane, constraining vehicle movement and preventing unintended lane departures. These boundaries are characterised by unique identifiers and geometric attributes.

The lane reference line serves as a linear abstraction of a physical lane segment, capturing its geometric trajectory. It contains attributes such as lane identifier (ID) and geometry.

Lane virtual connection lines, though not physically present, are introduced to construct the topological structure of intersections within the lane network. These lines are similarly defined by unique identifiers and geometric properties, facilitating logical connectivity at intersections.

Lane nodes represent the start and end points of lane reference lines or lane virtual connection lines, marking locations where structural or attribute changes occur along the lane. They are assigned unique identifiers and geometric descriptions.

In addition, lane restrictions define specific scenarios in which vehicular movement within a lane is limited. These restrictions include attributes such as restriction periods, restricted areas, permitted travel directions, and applicable speed limits.

The data structure of the LaneNetwork is illustrated in *Figure 7*.

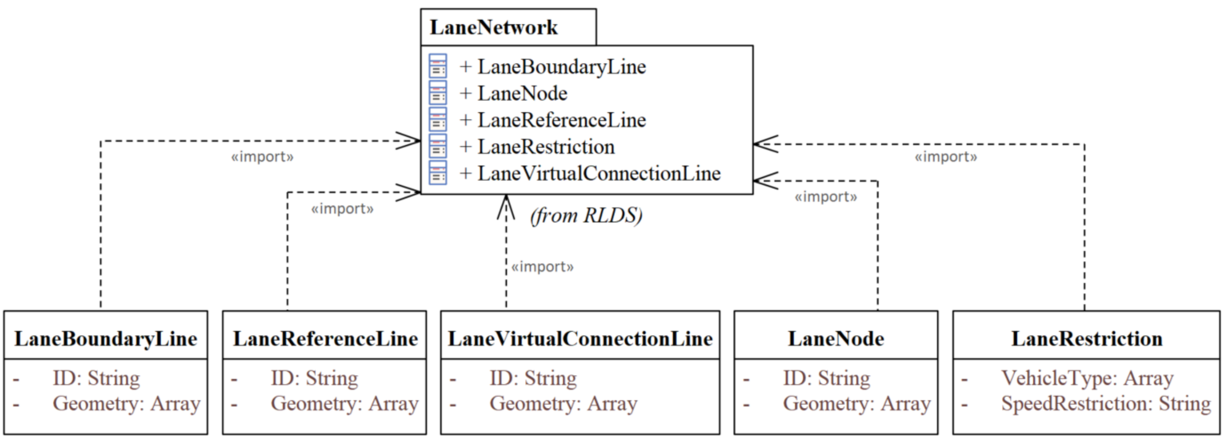


Figure 7 – Data structure of the LaneNetwork

Traffic control devices include traffic signs, traffic markings, and traffic signals, serving as critical visual elements for regulating and guiding vehicular behaviour, as illustrated in *Figure 8*.

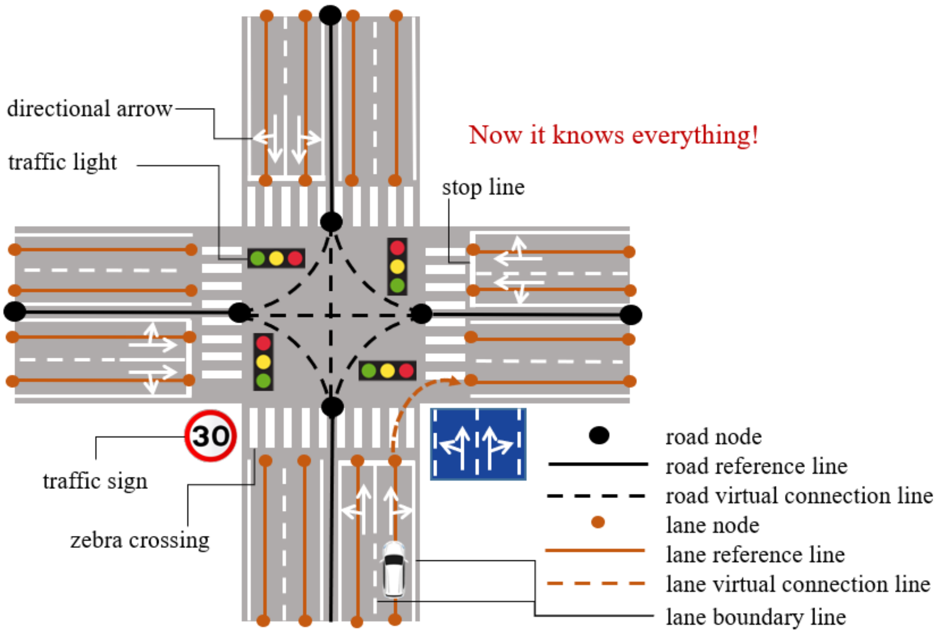


Figure 8 – Schematic diagram of some markings at the intersection

Traffic signs can be broadly categorised into warning signs, regulatory signs, and special information signs. Warning signs are designed to alert drivers to potential hazards ahead, such as sharp curves, pedestrian crossings, and accident-prone areas. Regulatory signs impose mandatory constraints on vehicle behaviour, including speed limit signs, no-overtaking signs, and no-left-turn or no-right-turn signs. Special information signs provide supplementary information to assist drivers in specific situations.

Traffic markings at intersections include stop lines, zebra crossings, directional arrows, channelisation markings, and reversible lane markings, all of which play essential roles in organising traffic flow and enhancing operational safety. As direct visual representations of traffic regulations, traffic markings provide autonomous vehicles with interpretable guidance, explicitly delineating travel directions, turning positions, and lane change boundaries, offering precise spatial references for vehicle decision-making and ensuring that they can safely pass through intersections.

Traffic signals include traffic lights and electronic displays. Traffic lights regulate the temporal right-of-way, while electronic displays provide real-time traffic conditions. For instance, vehicles are only permitted to proceed when the corresponding lane traffic light displays a green light.

The data structure of the TrafficControlDevice is illustrated in *Figure 9*.

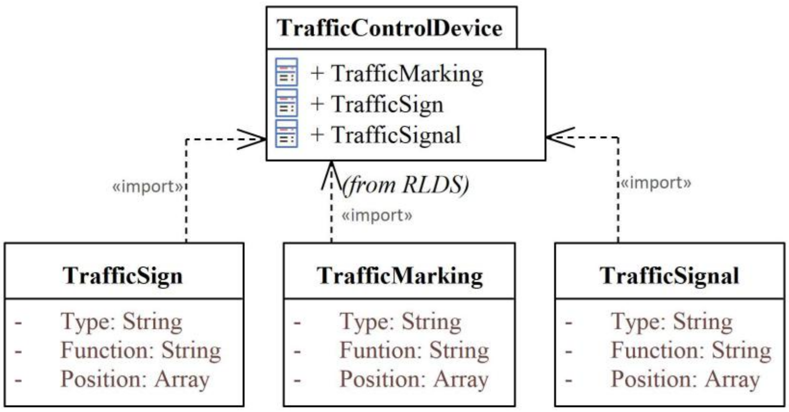


Figure 9 – Data structure of the TrafficControlDevice

Equipped with prior knowledge of road networks, lane networks, traffic signs, and traffic regulations, autonomous vehicles are capable of determining their intended routes under typical road conditions. However, when navigating intersections, autonomous vehicles encounter a highly variable and unpredictable dynamic traffic environment. Consequently, vehicles must not only rely on static information but also account for the influence of dynamic factors encountered at different stages of intersection traversal.

To address these challenges, this study systematically divides the intersection driving process into three distinct scenarios based on typical vehicle behaviour at intersections: the diverging scenario, the crossing scenario, and the merging scenario, as illustrated in *Figure 10*. This phased classification provides a structured basis for understanding the spatiotemporal dynamics of intersections and supports more adaptive and reliable vehicle decision-making.

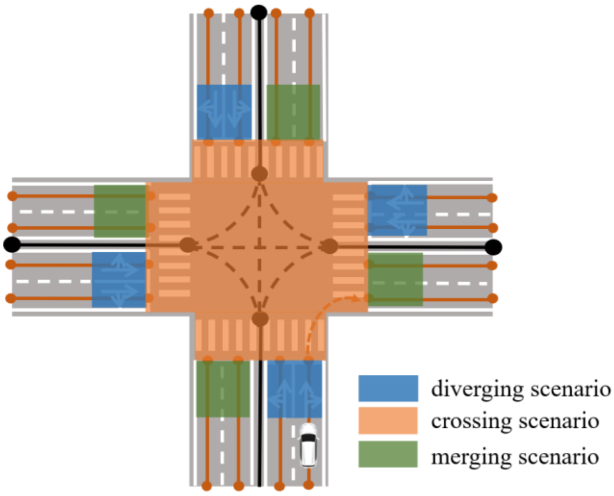


Figure 10 – Schematic diagram of intersection scenario division

The diverging scenario describes situations in which vehicles entering an intersection from the same approach are dispersed into multiple directions or lanes based on their intended routes. The crossing scenario refers to situations where vehicles approaching the intersection from two or more different roads intersect and must execute left turns, right turns, or proceed straight. The merging scenario occurs when vehicles from different directions or lanes converge onto a shared lane or roadway after passing through the intersection.

In particular, within crossing scenarios, the density of diverse traffic participants, including pedestrians, motor vehicles, and non-motorised vehicles, is typically high. The behavioural diversity and dynamic variability of these participants significantly increase the complexity of the traffic environment, posing substantial challenges to the safe navigation of autonomous vehicles and the development of intelligent transportation systems. Under such conditions, the efficiency with which intersection information is acquired and processed directly influences the accuracy of autonomous vehicle decision-making and control, ultimately affecting the safety and operational efficiency of intersection traversal.

To address these challenges, this study incorporates three key dynamic elements that significantly influence vehicle behaviour at intersections: pedestrians, vehicles, and obstacles into the scenario data structure to support real-time decision-making for AVs. The data structure of the Scenario is illustrated in *Figure 11*.

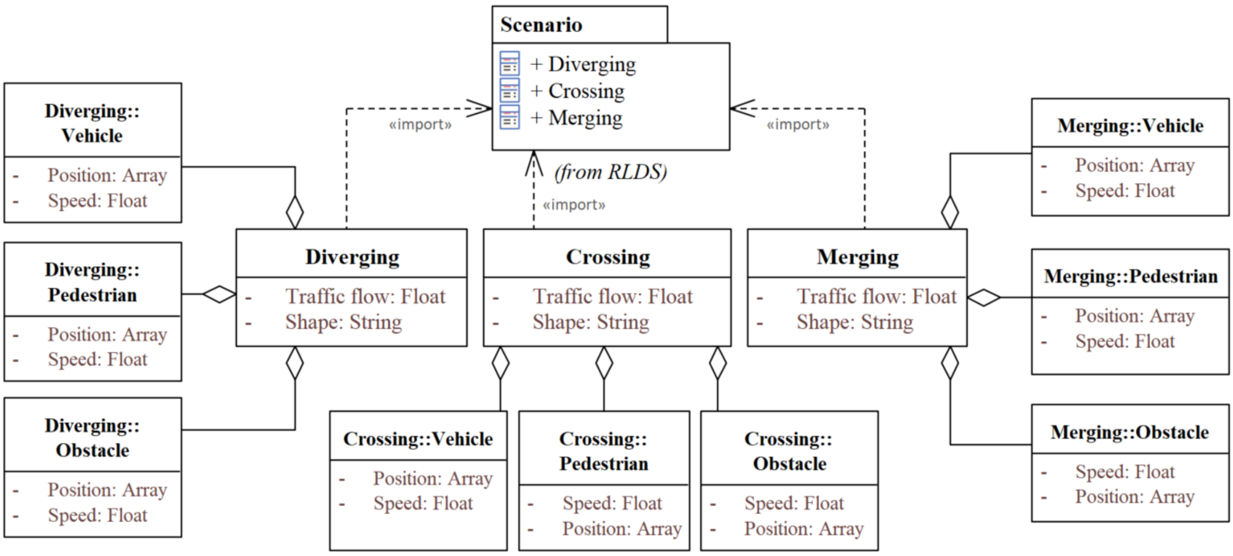


Figure 11 – Data structure of the Scenario

2.3 Comparison between the HD map model and the RLDS model

This study compares the HD map model and the RLDS model from four dimensions, including data scope, model structure, data update mechanism, and applicable scenarios, as shown in *Table 1*. Regarding data scope, HD map models aim to comprehensively delineate all environmental elements for autonomous driving, whereas the RLDS model concentrates exclusively on the essential components of intersections. In terms of model structure, HD map models are generally organised in hierarchical layers, while the RLDS model primarily focuses on the semantic relationship network among intersection elements. With respect to the data update mechanism, HD maps typically require full-element updates, while the RLDS model is designed for efficient incremental updates. Consequently, HD map models provide the fundamental support for global path planning in autonomous driving, while the RLDS model offers critical real-time support for local navigation and intersection decision-making.

Table 1 – Comparison between the HD map model and the RLDS model

Comparison dimensions	HD map model	RLDS model
Data scope	Full elements	Key elements
Model structure	Hierarchical layers	Relationship network
Data update mechanism	Full element update	Incremental update
Applicable scenario	Global navigation planning	Local navigation decision

3. KEY POINTS AND TECHNOLOGIES

This section primarily focuses on the key technologies associated with the intersection information model, detailing the rule constraints they impose on autonomous vehicles and clarifying how the RLDS model supports local navigation decision-making and vehicle control.

3.1 Traffic rules constraints

Traffic regulations are fundamentally established to standardise and constrain the behaviour of traffic participants, thereby ensuring the orderly and safe operation of transportation systems, particularly at intersections where diverse traffic participants converge. Within intersection environments, specific traffic rules govern the movement of different entities, including pedestrians, motor vehicles, and non-motorised vehicles, effectively mitigating the risk of traffic conflicts and accidents [24, 25].

The road network, lane network, and device information collectively provide static spatial constraints that reflect traffic regulations and guide vehicle navigation within intersections [26]. In particular, lane guidance rules stipulate that once an autonomous vehicle determines its intended route based on road network information, it must operate strictly within designated motor vehicle lanes. Moreover, the vehicle is generally required to remain within the physical boundaries defined by lane markings throughout its passage, as illustrated in *Figure 12*.

Within the marking information, different types of road markings impose specific and distinct behavioural constraints on vehicle operations. For example, a solid white line indicates that lane changes are strictly prohibited, whereas a dashed white line permits lane changes under appropriate conditions. A double solid yellow line delineates a two-way traffic division and explicitly prohibits crossing over to the opposite lane. In contrast, a solid-and-dashed line allows lane changes from one direction while restricting them from the other, providing asymmetric control of traffic flow.

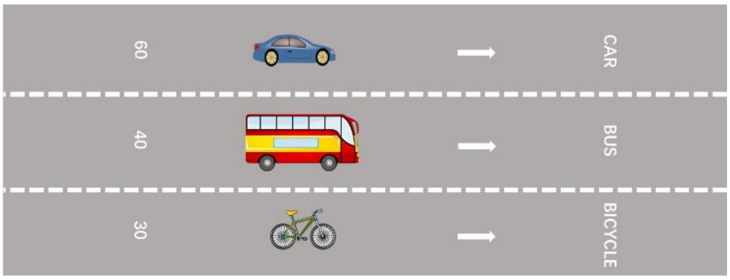


Figure 12 – Restrictions on vehicle travel caused by lane lines and markings

In addition, stop lines at signalised intersections require vehicles to come to a complete stop prior to crossing the intersection when the corresponding traffic signal displays a red light. Beyond pavement markings, traffic signs further constrain vehicle behaviour. For instance, speed limit signs mandate that vehicles maintain speeds below a specified threshold, while yield signs require autonomous vehicles to give priority to pedestrians or other vehicles when they are detected within or approaching the intersection area.

The correct interpretation and compliance with these marking and signage regulations are essential for ensuring the safe, lawful, and efficient operation of autonomous vehicles, particularly in the highly complex and dynamic environments of intersections.

In addition to these static constraints, dynamic traffic information, including traffic signal states, temporary control instructions, the behaviour of surrounding vehicles, and the presence of pedestrians or non-motorised traffic, further imposes real-time constraints on vehicle decision-making and trajectory control. For instance, traffic light signals directly determine whether a vehicle is permitted to enter or proceed within the intersection, while temporary lane closures or emergency vehicle priority dynamically alters right-of-way distributions. The integration of both static and dynamic traffic information is therefore essential for autonomous vehicles to achieve safe, lawful, and efficient navigation in complex intersection environments.

3.2 Priority division of right-of-way

In intersection scenarios, the presence of diverse traffic participants significantly increases the likelihood of conflicts, as some road users do not obey traffic rules [27, 28, 29]. The establishment of a structured intersection information framework provides the foundation for systematically analysing and comparing right-of-way priorities, thereby facilitating the mitigation of potential conflicts among different traffic participants.

From a road-level network perspective, vehicles travelling on main roads are generally granted priority in merging scenarios, while vehicles entering from minor roads are required to yield, as shown in *Figure 13*. At the lane-level network, left-turn manoeuvres usually demand greater time and spatial resources within the intersection, posing additional operational challenges for autonomous vehicles. When a dedicated left-turn lane is present, vehicles making left turns generally have priority during the corresponding green signal phase. In contrast, when left turns are executed from shared lanes, vehicles are required to yield to oncoming traffic before completing the manoeuvre.

The explicit representation of such road-level and lane-level priority rules within the intersection information framework is essential for supporting safe, efficient, and legally compliant decision-making for autonomous vehicles in complex intersection environments.

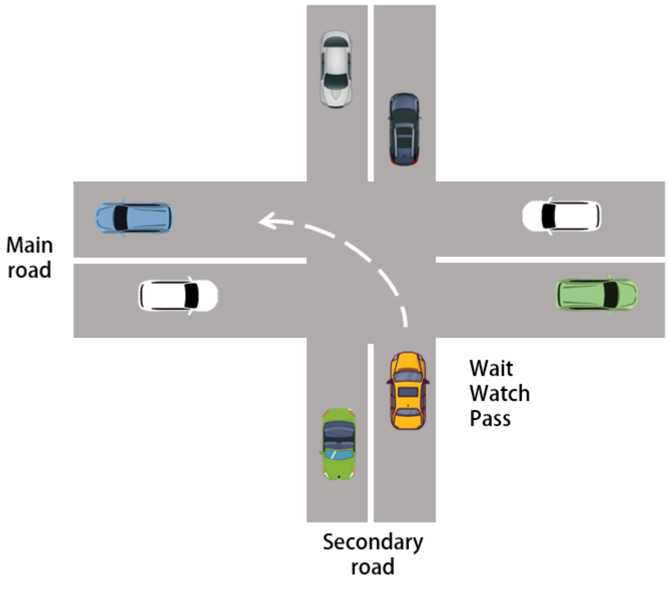


Figure 13 – Diagram of an AV turning left onto the main road at an intersection without traffic lights

Concerning intersection markings, when both traffic signals and stop lines are present, vehicles are required to come to a complete stop at the stop line during a red signal phase and yield to pedestrians occupying the crosswalk. Even in the absence of traffic signals, the presence of a marked crosswalk necessitates that vehicles yield the right-of-way to pedestrians crossing at the intersection.

The road network defines the overall structural layout and hierarchical relationships within the intersection, thereby shaping global right-of-way priorities. The lane network further constrains vehicle trajectories and establishes lane-level movement priorities for vehicles navigating through the intersection. Intersection markings provide explicit visual cues to ensure compliance with traffic regulations, ultimately influencing the actual right-of-way order of traffic participants.

To achieve safe and efficient navigation in complex intersection environments, autonomous driving systems must comprehensively integrate information from these three components (i.e., road network, lane network, and markings) to make context-aware and rule-compliant driving decisions.

3.3 Conflict zone prediction and risk avoidance

In the context of autonomous driving and intelligent transportation systems, intersections represent critical spatial points where vehicles, vulnerable road users, and pedestrians converge from multiple directions, substantially increasing collision risks [30]. The specific locations within intersections where potential collisions may occur are defined as conflict points, while the broader spatial regions encompassing these locations are referred to as conflict zones [31, 32, 33].

Within the proposed intersection information framework, the system integrates multi-source trajectory data and traffic regulation information to simulate interactions among various traffic participants. By analysing the real-time positions of road users in conjunction with the applicable traffic rules, the system can proactively predict potential conflict zones and issue early warnings before vehicles enter these high-risk areas.

Based on the typical movement patterns of vehicles through intersections, conflict scenarios are primarily concentrated within three critical regions: diverging areas, crossing areas, and merging areas. Accurate identification and prediction of these regions are essential for enhancing the situational awareness of autonomous vehicles and ensuring safe, efficient navigation in complex intersection environments.

As core components of HD maps, the road network, lane network, and markings, when integrated with diverging, crossing, and merging scenarios, provide essential support for the accurate prediction and effective avoidance of conflict zones. This capability is primarily reflected in the following aspects.

The road network defines the geometric structure and topological relationships of the roadway system, encompassing attributes such as road classifications, intersection types, connectivity patterns, and intersection geometries (e.g., four-way intersections, T-junctions, and roundabouts). Through topological analysis of the road network, the system can identify convergence areas where traffic flows from different directions intersect, enabling the recognition of potential conflict zones at a mesoscopic scale.

The lane network offers a more refined, lane-level representation of the road network, incorporating detailed information for each lane, including lane direction, lane type (e.g., through lane, left-turn lane, right-turn lane), lane width, boundary type (solid or dashed lines), and lane priority. By providing high-resolution, lane-level navigation information, the lane network enables precise vehicle trajectory localisation and facilitates the identification of potential conflict points with microscopic spatial accuracy.

Markings, including traffic signs, traffic signals, and road surface markings, provide explicit and structured guidance on traffic regulations for vehicles. Traffic signs function as essential navigational and regulatory aids, while road markings, such as channelisation lines, lane dividers, and pedestrian crosswalks, assist autonomous driving systems in accurately identifying potential conflict points among vehicles, pedestrians, and other road users.

By leveraging real-time traffic signal data, the system can calculate permissible time windows for vehicle passage in different directions, predict potential conflict scenarios, and dynamically adjust vehicle speed or determine the optimal crossing time based on the signal countdowns. In scenarios where traffic signals are absent, the system must rely on the perception of dynamic traffic scene information, such as the movement of surrounding vehicles, pedestrians, and non-motorised traffic, to anticipate and mitigate potential conflicts. This integrated utilization of static markings and dynamic perception is essential for enhancing the safety and efficiency of autonomous vehicle operations in complex intersection environments, as illustrated in *Figure 14*.

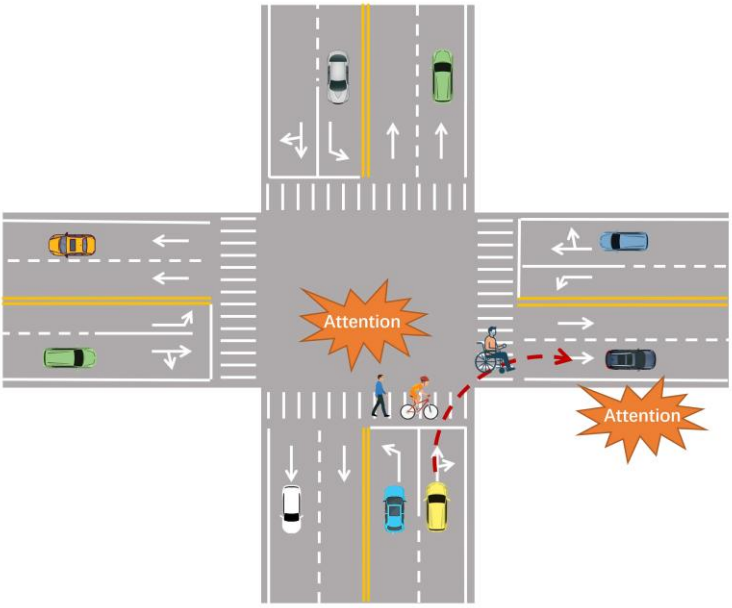


Figure 14 – Potential conflicts when AV turns right at the intersection

The road network, lane network, and traffic sign information collectively impose structural and regulatory constraints on vehicle trajectories, enabling the prediction of potential conflict zones under different scenario modes, such as diverging, crossing, and merging scenarios. By analysing vehicle trajectories within these spatial and regulatory constraints, specific potential conflict points can be inferred, facilitating proactive risk assessment and collision avoidance planning.

These three information sources play complementary roles in conflict zone prediction, collectively enhancing the situational awareness, safety, and decision-making capabilities of autonomous driving systems in complex intersection environments. The road network provides macro-level structural and topological information, delineating the overall geometric layout and connectivity of the intersection. The lane network offers fine-grained, lane-level guidance for precise trajectory planning and vehicle localisation. Meanwhile, traffic signs and road markings ensure strict compliance with traffic regulations, providing explicit visual cues for vehicle behaviour control.

Furthermore, scenario-based modelling allows autonomous vehicles to anticipate potential conflicts in advance and implement targeted countermeasures, thereby enabling pre-emptive strategies during actual driving to reduce reaction time and improve operational efficiency. The integration of these multi-source information elements enables autonomous driving systems to more accurately predict potential risks within conflict zones, optimise driving strategies, and enhance overall traffic safety and efficiency in intersection environments.

3.4 Local navigation decisions and vehicle control

Accurately computing the road network and lane network, interpreting the semantics of traffic signs, and predicting potential conflict zones are critical for improving traffic safety, reducing the risk of accidents, and optimising traffic efficiency at intersections [34, 35, 36]. By constructing an integrated Road-Lane-Device-Scenario (RLDS) model, which incorporates information from the road network, lane network, markings, and dynamic scenarios, autonomous vehicles can achieve early awareness of intersection conditions, anticipate potential conflicts, and proactively implement informed response strategies.

Within this framework, the road network provides essential route options for vehicles navigating through intersections, while the lane network offers precise trajectory guidance and boundary constraints for vehicle movement. Traffic signs and markings convey explicit driving regulations, including designated turning lanes, speed limits, and movement restrictions. Meanwhile, dynamic scenario information requires autonomous vehicles to respond in real time to evolving intersection environments, such as the presence of pedestrians, non-motorised vehicles, and other traffic participants. By integrating static structural information with real-time perception, autonomous vehicles are enabled to execute safe, compliant, and adaptive driving behaviours, such as slowing down, yielding, or stopping, thereby enhancing overall safety and efficiency at intersections, as illustrated in *Figure 15*.

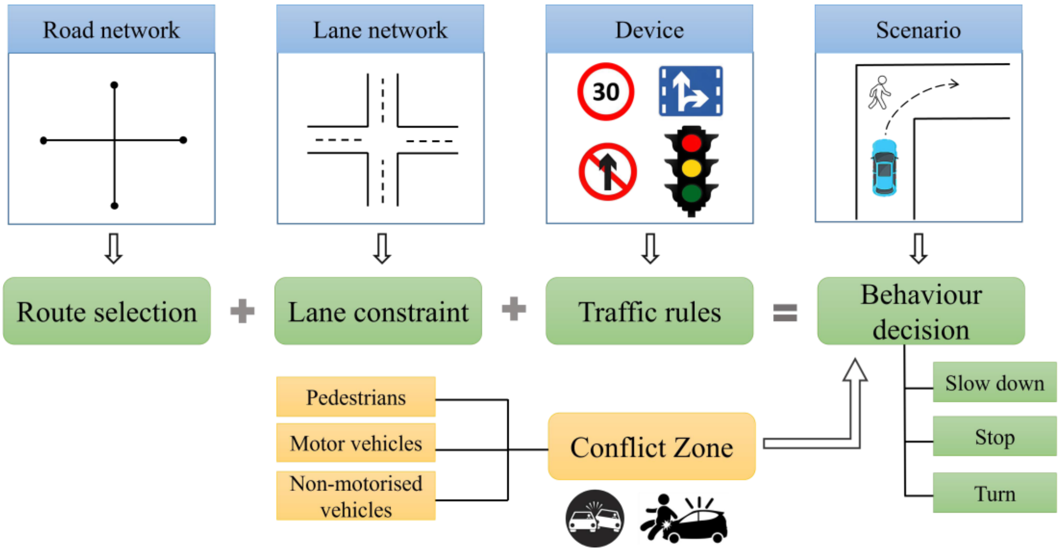


Figure 15 – The role of the RLDS model at intersections

4. EXPERIMENTS

In this study, the driving behaviours of autonomous vehicles are designed based on the three critical stages of diverging, crossing, and merging, to demonstrate the effectiveness and importance of the proposed RLDS model for decision-making at intersections. To validate the model, real-world intersection data collected from the Jiedaokou intersection in Wuhan, China, are utilised, as illustrated in *Figure 16*.

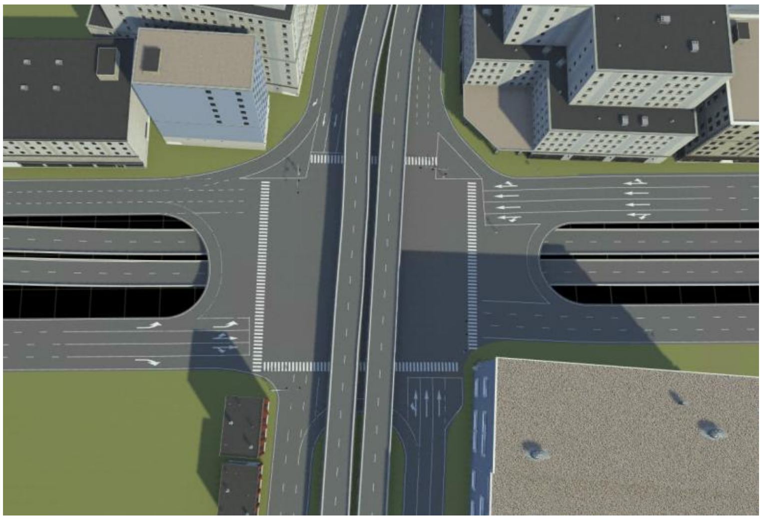
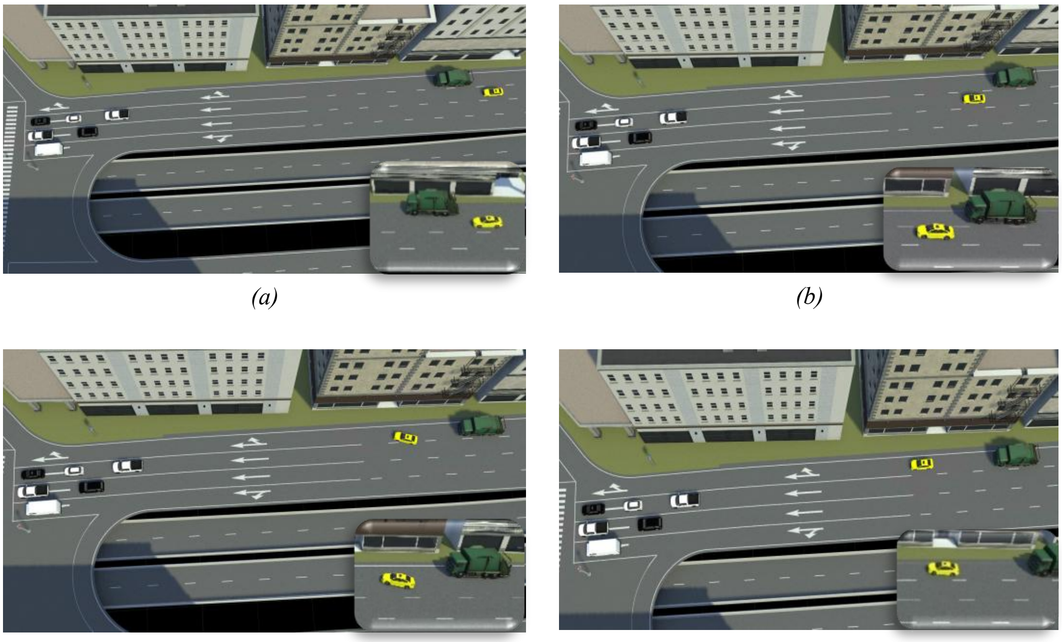


Figure 16 – Jiedaokou in Wuhan, China

According to the path planning results derived from the road network, the autonomous vehicle (yellow car) is required to execute a right turn at the intersection. Based on the arrow markings on the road surface, it is evident that the vehicle is currently traveling within a through lane. Under lane constraints and traffic regulations, the right turn must be completed from a designated right-turn lane. Consequently, the vehicle needs to perform a lane change from the through lane to the right-turn lane, guided by the detailed lane network information.

As illustrated in *Figure 17a*, the autonomous vehicle is approaching the diverging stage of the intersection. According to traffic regulations, lane changes are prohibited when the lane boundary is marked by a solid white line. Therefore, the vehicle must complete the lane change in advance while travelling along the segment marked with dashed white lines. In *Figure 17b*, the autonomous vehicle accelerates to overtake the garbage truck (green) on its right. After the autonomous vehicle has passed the garbage truck by a certain safe distance, it initiates a lane change to the right, as shown in *Figure 17c*. In *Figure 17d*, the autonomous vehicle successfully completes the manoeuvre.

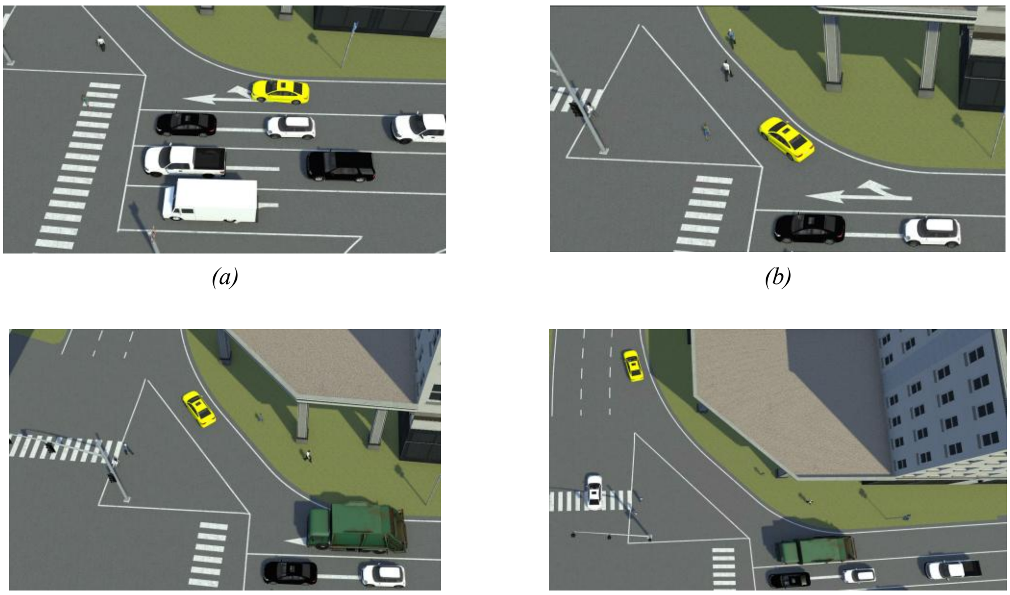


(a) (b)

(c) (d)

Figure 17 – Lane change in the diverging scenario: a) AV is in the straight lane and at the left rear of the garbage truck; b) AV overtakes the garbage truck; c) AV is changing lanes to the right; d) AV has changed to the right-turn lane

During the crossing stage, a potential conflict arises between the AV and pedestrians on the zebra crossing, as illustrated in *Figure 18a*. In compliance with the semantics of the yield sign, the AV is required to come to a complete stop and yield to pedestrians, as shown in *Figures 18b* and *18c*. Once the pedestrians have entirely cleared the crossing area, the AV can proceed, as depicted in *Figure 18d*. Throughout this process, the AV's driving speed must strictly adhere to the speed limit indicated by the corresponding traffic sign, which specifies a maximum speed of 30 km/h. In other words, it must comply with the traffic rules and constraints specified by traffic signs.

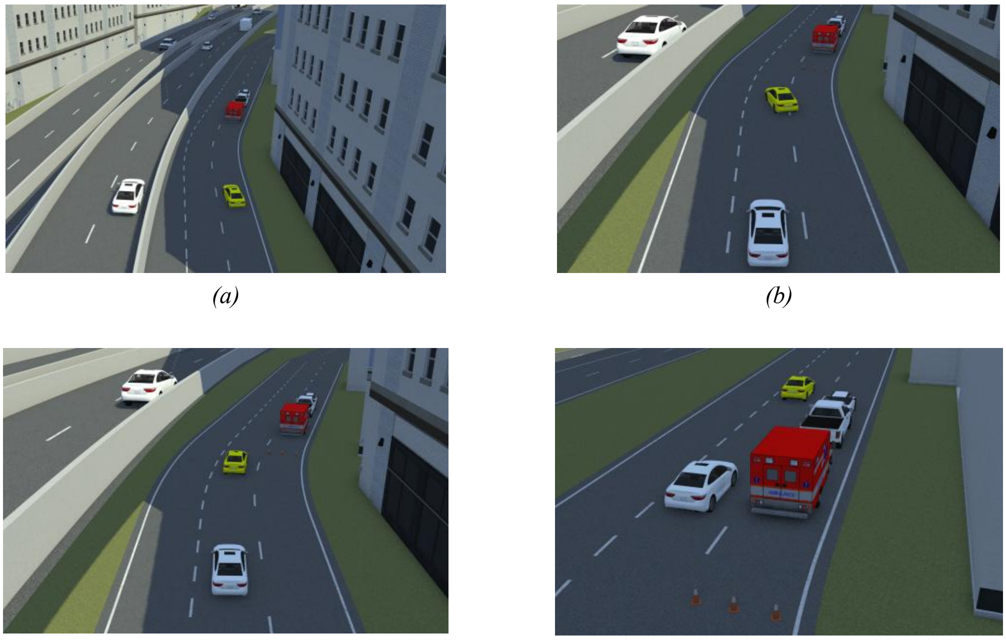


(a) (b)

(c) (d)

Figure 18 – Giving way to pedestrians in the crossing scenario: a) AV is about to turn right; b) AV stops and waits for pedestrians to pass; c) AV starts moving forward; d) AV completes the right turn

After the AV has completed the right turn and merged onto a new road, it detects a traffic accident blocking its current lane, as illustrated in *Figure 19a*. The affected lane is cordoned off by traffic cones, rendering it impassable. Under these circumstances, the AV must make a lane-change decision based on the lane network information and accurately predict the optimal timing for the manoeuvre by considering the dynamic behaviour of surrounding vehicles in the merging scenario. Subsequently, the AV performs the lane change, as depicted in *Figures 19b* and *19c*, and ultimately achieves safe and smooth navigation, as shown in *Figure 19d*.



(a) *(b)* *(c)* *(d)*

Figure 19 – Avoiding traffic accidents in the merging scenario: a) AV is driving in the rightmost lane; b) AV is changing lanes to the left; c) AV completes lane change; d) AV successfully avoids the accident area

Throughout the entire process, the road network, lane network, road markings and scenario information each play distinct yet complementary roles. Their integrated cooperation enables the AV to successfully execute the right-turn manoeuvre.

5. CONCLUSIONS

In this study, an innovative Road-Lane-Device-Scenario (RLDS) model is proposed to highlight the critical roles of road network, lane network, device, and scenario information at intersections. Guided by path planning requirements and scenario constraints, we designed simulation experiments for three scenarios involving autonomous vehicles navigating intersections, based on real-world data collected from the Jiedaokou area of Wuhan.

The results comprehensively demonstrate that the four categories of information (i.e., road network, lane network, device, and scenario) are indispensable for AVs to make informed decisions when navigating intersections, including lane changes, yielding, and obstacle avoidance. This validates the effectiveness of the RLDS model. Considering the inherent data redundancy of HD maps, this research offers a novel approach and practical reference for enhancing the efficiency and decision-making capabilities of autonomous vehicles in intersection environments.

However, the application of the RLDS model in real-world intersection traffic environments still faces several challenges. For example, sudden changes in road and lane information (e.g., road surface damage), limitations in scene perception (e.g., undetected small obstacles), and inefficiencies in information interaction can all affect the performance of autonomous driving at intersections. Although the simulation results demonstrate the effectiveness of the RLDS model, its application in real-world traffic environments remains challenging. Future research will focus on addressing these issues and conducting on-road testing of autonomous vehicles in practical scenarios.

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