# Research on Lane Changing Scenario Analysis and Fusion Decision Model of Intelligent Material Transport Vehicle

**Yongjie Zhang[1,2,*]**

[1]GuangXi Vocational Normal University, Xixiangtang District Luowen Avenue 17, Nanning 530007, China

[2]Key Laboratory of Application Technology of intelligent connected vehicle (Guangxi Vocational Normal University), Education Department of Guangxi Zhuang Autonomous Region, Nanning 530007, China

*Corresponding Author.

### Abstract

With the rapid development of the intelligent material transportation industry and the landing and maturity of the closed road transportation scene, the research and landing of the open road automatic driving transportation scheme has become a hot spot in the current competition of various material transportation industries. Previous studies mainly focus on the optimization of control decisions in the algorithm, which improves the performance but increases the computational cost of the system, which is not conducive to the productization of the system. This paper introduces a networked collaborative material transport architecture based on cloud, road and vehicle to reduce the cost of vehicle environment perception. Through the study of the common scene and dangerous scene of car lane change, the difficulties of automatic driving in lane change technology are analysed, and the steering structure of the four kinds of transport trolleys is compared to study the adaptability of the transport scene. Considering the cost of the main control system, this paper designs a lane change decision model that integrates the rule model and learning model, and tests 11 lane change scenarios in four types of venues in the indoor open test field of the laboratory to detect the lane change safety, decision efficiency, and lane change control smoothness. The results show that the performance of the fusion model designed in this paper does not lose the learning model, and can run on the microcontroller. Compared with the previous schemes, it saves the cost of computing power and provides a reference for the intelligent material transportation scheme of wharf, hospital and production workshop.

**Keywords: Intelligent material transportation; Networking collaboration; Fusion model; Lane change scene**

## 1. Introduction

### 1.1 Background

The State Council's General Office has released the 'New Energy Vehicle Industry Development Plan (2021-2035)[1].' The '2024-2028 China Telematics Industry Investment Planning and Prospect Forecast Report'[2] was issued by a research institute, which analysed the global Telematics industry development and the application of automatic driving technology in the traffic field. The technology is rapidly advancing from closed site testing to open road testing, and from pilot demonstration to commercial operation. The application scenarios for automatic driving include road freight transport, urban travel services, logistics and distribution, in-park transport, port operations, unmanned taxis, unmanned buses, unmanned logistics, unmanned distribution, and more [3]. For industrial logistics scenarios, in addition to the use of AGV and some closed road scenarios have matured, others

are still in manual operation, to achieve the material transport work chain unmanned, safety + reliability + saving money is the premise.

## 1.2 Research Status

The economic value of intelligent vehicle is to replace human drivers to realise automatic driving. For closed and semi-closed structured scenes, intelligent vehicle has been gradually applied and achieved economic results. The unmanned alternative value of open roads, especially complex scenes, has great potential. The research on lane change decision of intelligent material vehicles is the current research hotspot of autonomous driving.

### 1.2.1 Study of the long tail problem

Ni et al.[4] proposed an improved deep network scene classification method to solve the similarity between different categories and the difference between the same categories in the study of automatic driving scene classification. In order to solve the problem of blind area in 2D environment detection of autonomous driving, Wu et al.[5] proposed a method to realize 3D environment perception by using camera and radar to achieve higher precision environment judgment. Makansi et al.[6] studied the method of learning algorithm training set to compensate the long tail scene to avoid collision accidents caused by dynamic traffic.

### 1.2.2 Decision algorithm improvement

Huang et al.[7] established an end-to-end deep learning decision model of driving state and driving action in the direction of learning algorithm. Based on traffic rules, Bhuiyan et al. [8] designed a rule-driven method based on negative deontic logic ( DDL ) to improve the safety decision-making of autonomous vehicles. In response to the lane change decision scenario, Li et al.[9] studied the minimum risk decision strategy based on deep learning according to static and dynamic scenarios to ensure driving safety. In order to improve the performance of autonomous driving and avoid unpredictable perception errors or measurement noise, He et al.[10] proposed an observation adversarial reinforcement learning algorithm to improve the robustness of lane change strategy to measurement noise. Alam[11] et al. designed a strategy that combines deep learning, random forest ( RF ) and other algorithms for perceptual data fusion to solve the problem of multi-vehicle data fusion. Feng et al. [12] designed a Markov decision process to make the training set information more dense in order to break through the influence of the rarity of safety-critical events on the development of autonomous driving. Arizala et al. [13]designed a finite state machine behavior decision-making architecture based on rule model to solve the complex scene of urban road automatic driving. In order to solve the problem of rapid traffic environment detection in dynamic scenes, Yang et al. [14] designed a complex dynamic traffic environment detection model for unmanned vehicles using YOLOv3 architecture. For the intelligent transportation scene, Fragapane et al.[15] conducted a framework study on the motion control and planning of the transportation robot, and adopted a decentralized decision-making method to achieve interaction and communication with other robots. Wang et al.[16] studied the lane change decision of autonomous driving through a prediction method based on fuzzy inference system ( FIS ) and long short-term memory ( LSTM ) neural network. Bryndin et al. [17] studied the structure of the material transport robot and designed a pneumatic light robot according to the safety problem of material transport. For decision-making algorithms, Mozaffari et al.[18] realized short-term prediction of complex traffic scenarios by studying deep learning. Ji et al. [19] studied the decision-making model of autonomous driving based on game theory through online interaction.

### 1.2.3 Optimization of fusion model

Xuemin Hu et al. [20] summarized the defects of the rule model and the learning model, and designed an imitation learning method to realize the dynamic learning of the model. In order to realize multi-sensor fusion decision, Ren et al.[21] proposed a dual-sensor target classification decision fusion method based on evidence reasoning rules to improve the perception accuracy. Geng et al. [22] found that in the Bayesian hypothesis testing framework, the performance of collaborative decision-making is better with the increase of the number of teams, which provides a new idea for autonomous driving multi-vehicle networked collaboration. Li et al. [23] designed a human-computer interaction fusion model, using linear Gaussian process to establish a trust model to realize the behavior decision of robots in dynamic scenes.

**1.3 Contributions**

There have been many studies on the fusion scheme of automatic driving material transportation scenarios, decision-making algorithms and decision-making models, mainly by increasing the complexity of the algorithm to improve the accuracy of decision-making, but these studies have less consideration for the cost of computing power and the feasibility of system productization, only pursuing performance breakthroughs. The main contributions of this paper include the following aspects:

1) Combined with the conventional lane change and dangerous lane change scenarios of vehicles, combined with previous studies, it is analyzed that the current difficulties of intelligent lane change are mainly the limitations of environmental perception, the limitations of lane change decision models, and vehicle smooth control. Through the design of the material transport vehicle networking collaborative architecture, the pressure of the car 's own sensing perception is reduced, and the multi-directional acquisition of road and environmental information is realized, and the real vehicle verification is carried out in the laboratory test field.

2) By studying five kinds of vehicle steering structures, summarizing the characteristics and applicable scenarios of various steering structures, and verifying the smoothness of steering control through experiments, it is ensured that the steering model studied in this paper conforms to the normal driving experience, and provides reference for material transportation schemes in different scenarios.

3) Simplify the decision model with the idea of algorithm switching. Aiming at the current problem of intelligent material delivery car 's computational cost, complex road safety and long tail problem of open road, this paper studies and improves the lane change decision model, and designs a lane change decision model that integrates rule model and learning model. Compared with previous studies, the fusion model can run the system model only using a microcontroller under the premise of ensuring stable performance and strong adaptability to gray scenes, saving computing power costs.

**2. Architectural Design**

**2.1 Analysis of Vehicle Lane Change Scene**

2.1.1 Conventional lane change

1) Lane Change for Overtaking: When the rear vehicle (main vehicle) detects that the speed of the front vehicle is slow and the following state cannot meet the driving needs of the main vehicle, and the conditions for overtaking are met, the main vehicle should turn on the turn signal, accelerate to overtake the front vehicle by changing lanes on the left, arrive at a safe distance, and then turn on the turn signal again and change lanes on the right to complete the overtaking manoeuvre.

2) Avoiding diversion. When the main vehicle detects an obstacle or a vulnerable traffic group ahead, or when a vehicle on an adjacent road suddenly stops in front of the main vehicle and the main vehicle cannot stop in time to avoid a collision, it will detect if the traffic on the neighbouring road meets the conditions for changing lanes and avoid a collision by changing lanes.

3) Lane Change Deceleration. If the main vehicle detects that it is travelling at a speed lower than the recommended speed for the current lane or if it is about to make a turn or exit the current road, it should check if the neighbouring lane meets the conditions for changing lanes. If so, the main vehicle should decelerate and complete the lane change.

4) Turning and changing lanes. When the main car in the intersection, T-shaped intersection, or roundabout intersection and other roads with road branching, according to the path instructions need to change the direction of travel, the main car detects the oncoming direction, neighbouring roads, the same road behind the traffic in line with the conditions of the turn, the main car to play the turn signals and complete the steering action.

5) Road narrowing and widening. When the vehicle enters or leaves a toll booth, or passes through a maintenance section, the road narrows or widens. The main vehicle, according to the driving needs, or to meet the driving safety requirements, detects that the traffic around the vehicle meets the conditions for changing lanes, turns on the turn signals and completes the lane-changing action.

2.1.2 Dangerous lane change

1) Lane change in congested road. In congested roads, drivers often attempt to change lanes to alleviate traffic. However, if adjacent drivers do not yield by slowing down or stopping, collisions can occur, further exacerbating the congestion.

2) Changing lanes immediately when the vehicle starts. If a vehicle changes lanes immediately upon starting, it increases the risk of collision with vehicles coming from the rear of the neighbouring lane who may not have enough time to react.

3) Frequent lane changing in rainy and foggy weather. Frequent lane changes in rainy and foggy weather can lead to reduced accuracy and delayed recognition of road signs, traffic signs, pedestrians, and other vehicles due to the interference of rain and fog on machine vision and radar. This increases the risk of collisions.

4) Lane changing in curves. When a vehicle is travelling in a curve, the camera and radar have a sensing blind spot, which can cause incorrect distance judgement of surrounding vehicles.

5) Lane changing on inclines.

6) Due to the gradient, vehicle acceleration and braking may not be as sensitive or accurate as on straight roads, increasing the risk of collisions when changing lanes.

## 2.2 Difficulties in Changing Lanes with Smart Cars

2.2.1 Difficulties in environmental perception

Environment perception mainly uses cameras, radars and high-precision maps. The camera is easily limited by blind spots, fog, rain, light, and reflection, resulting in inaccurate or even unrecognizable lane lines, vehicle speed and position, speed limit signs, prohibited signs, and recognition of the road ahead. Radar is easy to be affected by sunlight to produce noise. Different lidars are too close to cause confusion between the transmitted and received pulses. Rain, fog, and exhaust noise are also easy to interfere with laser detection of targets. The high-precision map is ideal in the closed road scene. The open road scene is limited by inter-satellite interference, environmental impact, etc., and the accuracy will also be affected.

2.2.2 Difficulties in decision-making on lane change

At present, the automatic driving lane change decision system is mainly divided into two categories. One is the rule model algorithm. The rule model can solve the driving decision of 80 % open road scene and 95 % closed road scene, but the rule model is difficult to cover all gray scenes. The second is to use the learning algorithm. The learning algorithm can better adapt to the gray scene, but the learning algorithm needs to rely on very large and comprehensive learning data, otherwise it cannot achieve the desired effect. The learning algorithm has high requirements for the computing power of smart cars. On the basis of increasing the landing cost of smart cars, due to the inexplicability of its model, some users do not trust its security.

2.2.3 Difficulties in control and implementation

Currently, the issue with automatic driving control is the deviation between the actual driving trajectory and the expected trajectory caused by closed-loop control errors and delays in lateral and longitudinal speed and displacement. Implementing a control system with a short response time, complex algorithm, and high-frequency data closed-loop feedback can often result in a bulky and costly system, which is not suitable for small and medium-sized intelligent material vehicles.

## 2.3 Design of the NetLink Collaboration Architecture

The intelligent material transport trolley is designed to transport materials in docks, hospitals, and production workshops. It can also automate feeding and unloading based on the manipulator's requirements. In closed road sites, the trolley can reduce sensor input and make efficient traffic decisions through network interconnections between vehicles, roads, and clouds. In open road scenarios, automatic driving may face challenges related to vulnerable traffic groups and long tail traffic issues. Conventional lane change scenarios, which include lane change overtaking, intersections controlled by traffic lights, unprotected left turns, and right turns without traffic light

control, are relatively easier to handle due to their frequent occurrences and clear traffic regulations. The term 'long tail scene' refers to a wide variety of low probability or sudden occurrences, such as vehicles running red lights, pedestrians crossing the road, traffic at intersections damaged by traffic lights, and vehicles parked by the side of the road. These scenes are not easily predictable and can be difficult to manage due to their diverse nature. Addressing these challenges is crucial for the successful implementation of intelligent material transport trolleys. This paper presents a networked collaborative architecture for the intelligent material carrier car transportation system, as illustrated in Figure 1.
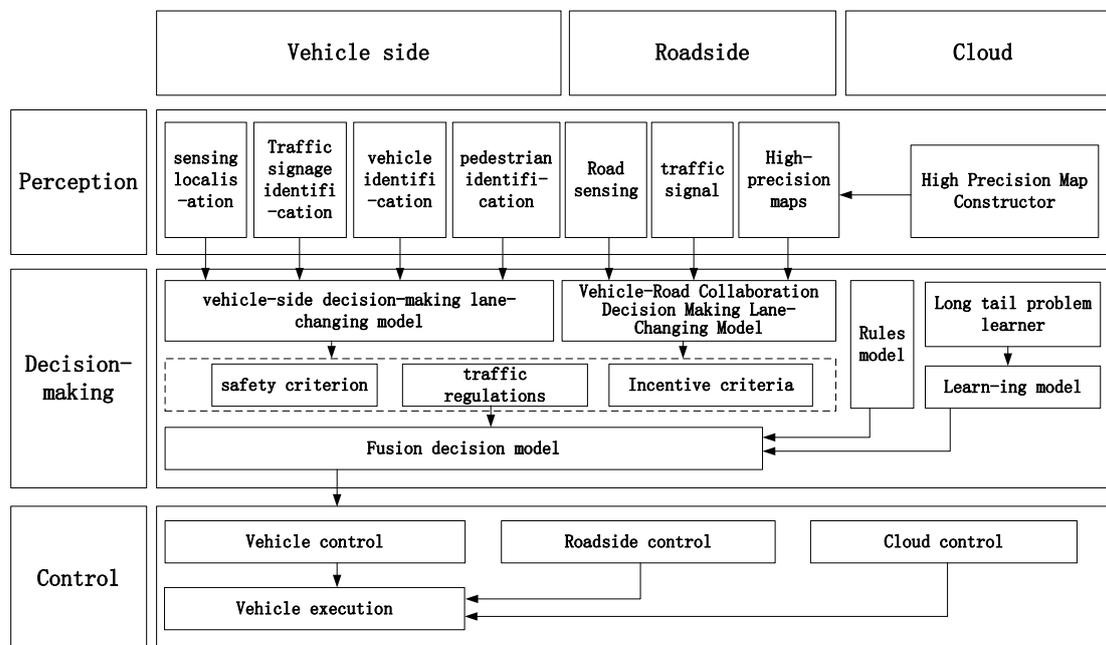


Figure 1. Collaborative architecture of intelligent material transportation network

The architecture is designed to accommodate both closed and open road scenes. It is vertically divided into vehicle side, roadside, and cloud, and horizontally divided into perception, decision-making, and control. In the perception layer, the vehicle terminal performs sensor data fusion. This includes perceptual positioning, machine vision traffic sign recognition, road vehicle recognition, and road pedestrian and traffic vulnerable group recognition. The sensor fusion information is then transmitted to the vehicle terminal decision-making lane change model. The perception layer's road end detects traffic through roadside facilities and synchronizes real-time traffic signal information with the high-precision map maintained by the cloud. The fused sensing data is then imported into the vehicle-road collaborative decision-making lane change model. The models for vehicle terminal decision-making lane change and vehicle-road cooperative decision-making lane change construct a treatment decision model based on safety, traffic, and incentive criteria. These models are integrated with the rule and learning models issued by the cloud. If the rule model satisfies the decision-making requirements, it is used for decision-making. When the environment is grey, the learning model is utilised, and the fusion decision model sends the decision to the vehicle control layer. The vehicle then executes the motion according to the control instructions from the vehicle side, roadside, and cloud.

For the closed road scene, there are no vulnerable groups to interfere with transportation since the route is relatively fixed. To reduce camera input, RFID and electromagnetic coils can be laid on the site instead of relying on machine vision to identify roads, vehicles, and vulnerable groups. By synchronising traffic signals in real-time and downloading a high-precision map through the cloud, the buried navigation equipment enables stable medium-low speed transportation. A rule-based decision model can be implemented for standardised closed road scenes.

For open road scenes, the method of solving the sensing blind area often adopts the method of adding sensors, multi-angle and multi-position placement of camera sensors, and deployment of lidar or millimeter-wave radar. In terms of decision-making model, how to achieve high-security, low-latency, and high-stability lane-changing

decisions while controlling costs is one of the keys for unmanned vehicles to achieve landing in material transportation vehicles.

## 3. Model Design

### 3.1 Steering Structure

3.1.1 Steering model with suspension

The most common steering system is front wheel steering. As shown in Figure 2, the car steers the driving path. In the case of the front-wheel steering car, the rear wheel does not turn, so the steering centre is roughly on the extension line of the rear axle. There is also a four-wheel steering system. In a four-wheel steering car, the rear wheels are steered in the opposite direction and the steering centre is closer to the car body than in a front-wheel steering car. When steering at low speed, if the front wheel steering angle of both cars is the same, the steering radius of the 4WD car is smaller, the inner wheel difference is smaller and the steering performance is better. Although the four-wheel steering system has certain advantages in cornering, it is mainly used in high-end cars due to its high cost and complex structure.



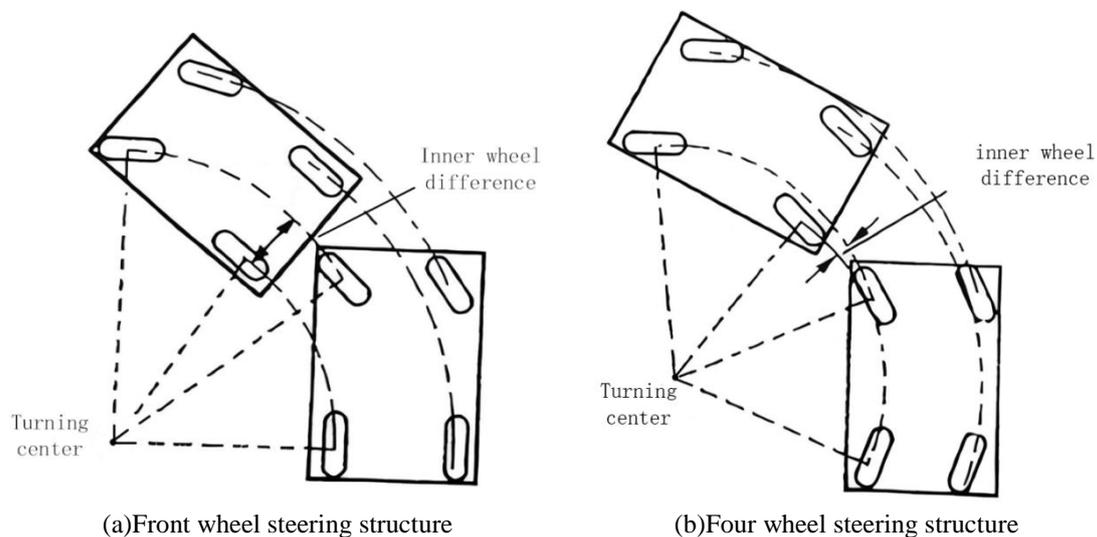(a)Front wheel steering structure       (b)Four wheel steering structure

Figure 2. Suspension steering structure

The intelligent material car, when using the front wheel steering scheme, realizes the vehicle turning by controlling the tire angle[24]. $e_1$ is set as the lateral error ( the distance between the center of mass of the vehicle and the center of the lane ), $e_2$ is the heading error, the longitudinal speed of the vehicle is $v_x$, and the turning radius of the vehicle is R. It can be obtained :

The angular velocity required for the body to turn the desired angle is

$$\dot{\phi}_{des} = \frac{v_x}{R} \tag{1}$$

The required lateral acceleration is

$$a_{ydes} = \frac{v_x^2}{R} = v_x \dot{\phi}_{des} \tag{2}$$

The lateral acceleration error is

$$\ddot{e}_1 = a_y - a_{ydes} = (\ddot{y} + v_x\dot{\phi}) - \frac{v_x^2}{R} = \ddot{y} + v_x(\dot{\phi} - \dot{\phi}_{des}) \tag{3}$$

The lateral velocity error is

$$\dot{e}_1 = \dot{y} + v_x(\phi - \phi_{des}) \tag{4}$$

The heading error is

$$e_2 = \phi - \phi_{des} \tag{5}$$

Joint correlation formula is

$$\text{m}(\ddot{e}_1 + v_x \dot{\varphi}_{des}) = \dot{e}_1\left[-\frac{2C_{af}}{v_x} - \frac{2C_{ar}}{v_x}\right] + e_2\left[2C_{af} + 2C_{ar}\right] + \dot{e}_2\left[-\frac{2C_{af}l_f}{v_x} + \frac{2C_{af}l_r}{v_x}\right] +$$

$$\dot{\varphi}_{des}\left[-\frac{2C_{af}l_f}{v_x} + \frac{2C_{af}l_r}{v_x}\right] + 2C_{af}\delta \tag{6}$$

$$I_z\ddot{e}_2 = 2C_{af}l_f\delta + \dot{e}_1\left[-\frac{2C_{af}l_f}{v_x} + \frac{2C_{ar}l_r}{v_x}\right] + e_2\left[2C_{af}l_f + 2C_{ar}l_r\right] +$$

$$\dot{e}_2\left[-\frac{2C_{af}l_f^2}{v_x} - \frac{2C_{ar}l_r^2}{v_x}\right] - I_z\ddot{\varphi}_{des} + \dot{\varphi}\left[-\frac{2C_{af}l_f^2}{v_x} - \frac{2C_{ar}l_r^2}{v_x}\right] \tag{7}$$

Let the vehicle system state equation be :

$$\dot{X} = AX + Bu \tag{8}$$
$$Y = CX + Du \tag{9}$$

The dynamic model of steering control can be obtained by combining :

$$\frac{\text{d}}{dt}\begin{bmatrix} e_1 \\ \dot{e}_1 \\ e_2 \\ \dot{e}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\dfrac{2C_{af}+2C_{ar}}{mv_x} & \dfrac{2C_{af}+2C_{ar}}{m} & \dfrac{-2C_{af}l_f+2C_{ar}l_r}{mv_x} \\ 0 & 0 & 0 & 1 \\ 0 & -\dfrac{2C_{af}l_f-2C_{ar}l_r}{I_zv_x} & \dfrac{2C_{af}l_f-2C_{ar}I_r}{I_z} & -\dfrac{2C_{af}I_f^2+2C_{ar}l_r^2}{I_zv_x} \end{bmatrix}\begin{bmatrix} e_1 \\ \dot{e}_1 \\ e_2 \\ \dot{e}_2 \end{bmatrix} +$$

$$\begin{bmatrix} 0 \\ \dfrac{2C_{af}}{m} \\ 0 \\ \dfrac{2l_fC_{af}}{I_z} \end{bmatrix}\delta + \begin{bmatrix} 0 \\ \dfrac{-2C_{af}I_f+2C_{ar}l_r}{mv_x} - v_x \\ 0 \\ -\dfrac{2C_{af}l_f^2+2C_{ar}l_r^2}{I_zv_x} \end{bmatrix}\dot{\varphi}_{des} \tag{10}$$

Among them, $C_{af}$ and $C_{ar}$ are the lateral stiffness of the front and rear wheels, $l_f$ is the front suspension length, and $l_r$ is the rear suspension length.

3.1.2 Differential steering model

For the Mecanum wheel structure, the principle of movement is to rotate the two wheels on the same side of the vehicle in opposite directions, so that the forces along the front and rear are offset and the lateral forces have exactly the same direction. The mecanum wheel is an omnidirectional wheel that can move in all directions. It consists of a hub and a roller around the hub. The angle between the axis of the wheat wheel roller and the axis of the hub is 45 degrees. On the rim of the hub there are many small wheels, i.e. rollers, arranged at an angle so that the small wheels can slide sideways. The principle of the Mecanum wheel steering is shown in Figure 3.

(a)Straight principle          (b)Transverse principle          (c)Principle of in-situ steering
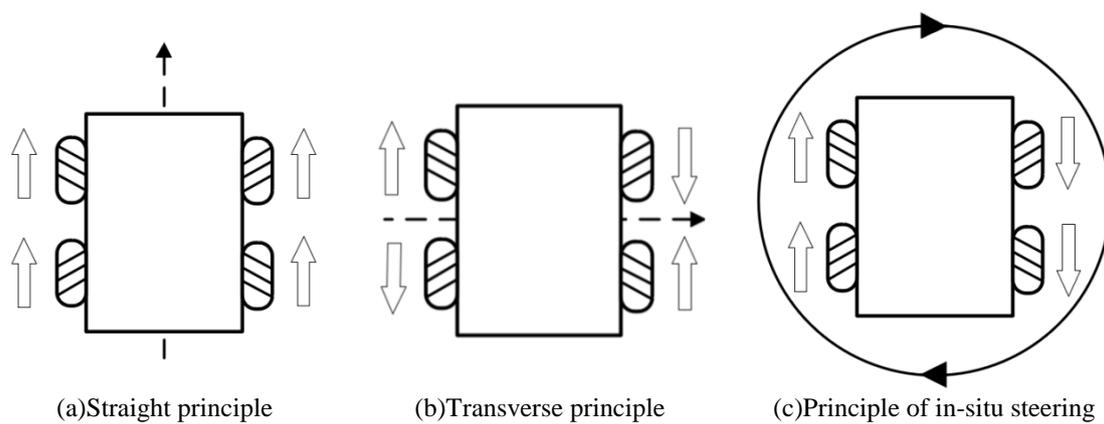
Figure 3. Mecanum wheel steering structure

With the rubber wheel sliding steering structure, when the vehicle turns, the inner tyre must travel a shorter arc, while the outer tyre must travel a longer arc. Because the wheels are fixed to the vehicle chassis, they cannot rotate at exactly the same speed and direction, so relative sliding occurs. The inner tyre slides relative to the ground to compensate for the difference between the inner and outer tyres, thereby achieving steering. The principle of rubber differential steering is shown in Figure 4.



(a)Straight principle          (b)Lane changing principle          (c)Principle of in-situ steering
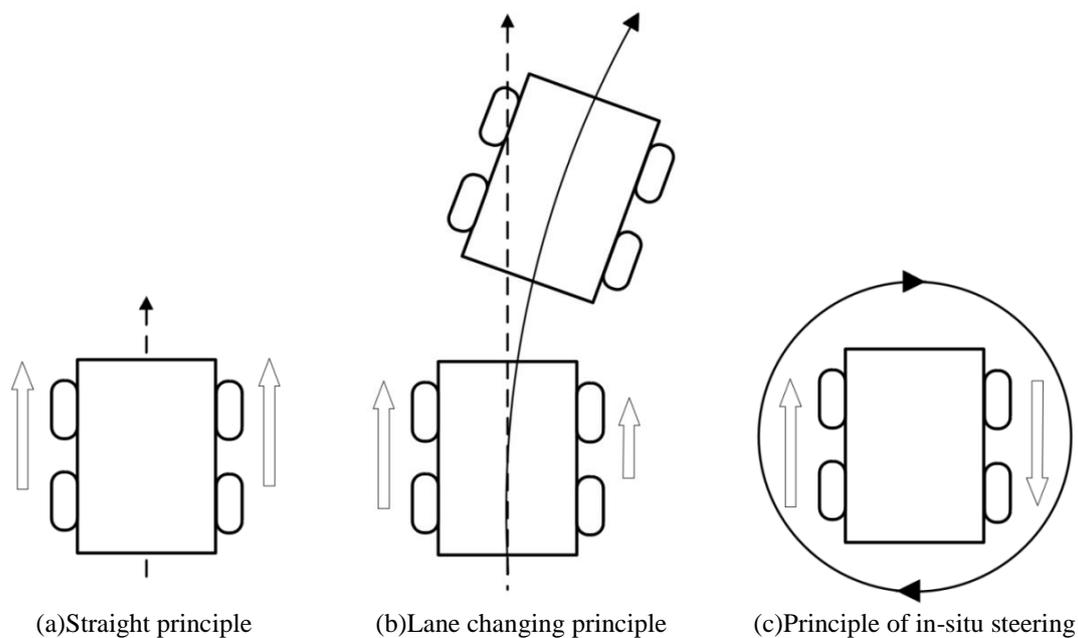
Figure 4. Rubber wheel sliding steering structure

For the rubber wheel differential steering structure, only a pair of wheel axles are fixed, and they are also the wheels responsible for steering. Several other pairs of wheels are usually freely rotating, such as the universal wheel, bull 's-eye wheel, not involved in steering. In differential steering, when the vehicle turns, the moving direction of the driving wheel and the rotation plane are indeed the same, so the tire responsible for steering will not slide. Because the drive wheels are fixed and responsible for steering, they achieve speed difference through differential device or electronic control system when turning, so that the inner drive wheels slow down or stagnate, while the outer drive wheels continue to drive, so as to realize the steering of the vehicle. The differential steering structure of the rubber wheel is shown in Figure 5.

(a)Bovine eye wheel structure    (b)Lane changing principle    (c)Principle of in-situ steering
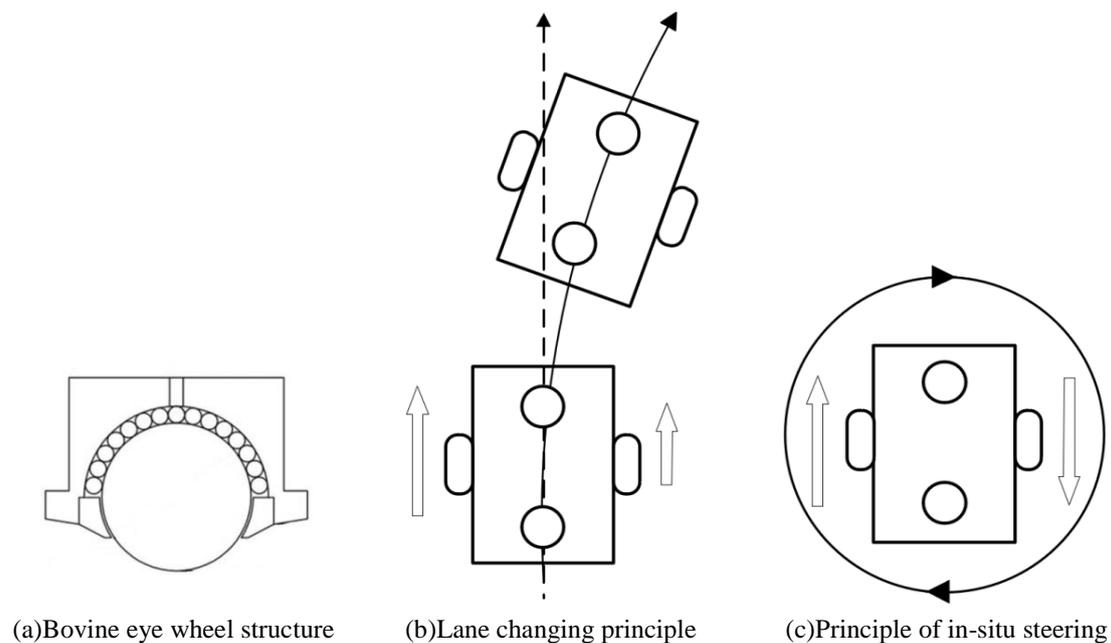
Figure 5. Rubber wheel differential steering structure

3.1.3 Comparison of steering structure

This paper presents two main categories and five commonly used structures for steering material transportation. The scenarios for material transportation vary depending on the structure used. Table 1 shows a comparison of the five steering structures.

Table 1. Comparison of steering structure

| Model name | cornering ability | weight capacity | cost | Difficulty of control | Applicable Scenarios |
|---|---|---|---|---|---|
| Front wheel steering with suspension | medium | strong | rather high | medium | Large and medium-sized material transport vehicles, long-distance transportation of large items in terminals, warehouses, etc. |
| Four-wheel steering with suspension | rather high | relatively strong | High | rather difficult | |
| Mecanum Wheel | High | medium | Low | simple | Small and medium-sized material transport trolley, in the hospital, production workshop material transport. |
| Rubber wheel sliding steering | High | weak | Low | simple | |
| Rubber wheel differential steering | High | weak | Low | simple | |

The comparison shows that different control structure models are suitable for different material handling scenarios, and appropriate schemes should be selected according to the scenarios and requirements.

**3.2 Steering decision fusion model**

The Behaviour Decision Module is the brain of the vehicle. Making the right decision is key to avoiding collisions and completing the lane change and transport task. For closed roads or structured scenes, the use of rule models can meet the needs of lane changing. More typical is the AGV car, which navigates the driving path by laser or electromagnetic wire, and combines the high-precision map of the site to achieve good material delivery planning. For the open road scene, due to the influence of traffic vulnerable groups and special environment, there may be a long tail scene that is not under the preset rules. If the learning algorithm model is adopted, there will be higher requirements for the computing power system of the material delivery vehicle, and the volume and cost of the material delivery vehicle will increase. This is the main reason why the learning model is still at the research stage in the material handling scene and has not yet landed. In addition, the learning model is not omnipotent. The premise that the learning model can get the right decision is that the training sample coverage is wide enough and the scene

contains integrity[25]. However, the long-tail effect of open roads is characterised by the unpredictability of the scene, so the learning model must have the ability to learn continuously and the appropriate safe driving protection mechanism. Considering the peculiarity of the car's computing power cost and the long tail effect, this paper designs a fusion model. The detailed process is shown in Figure 6.
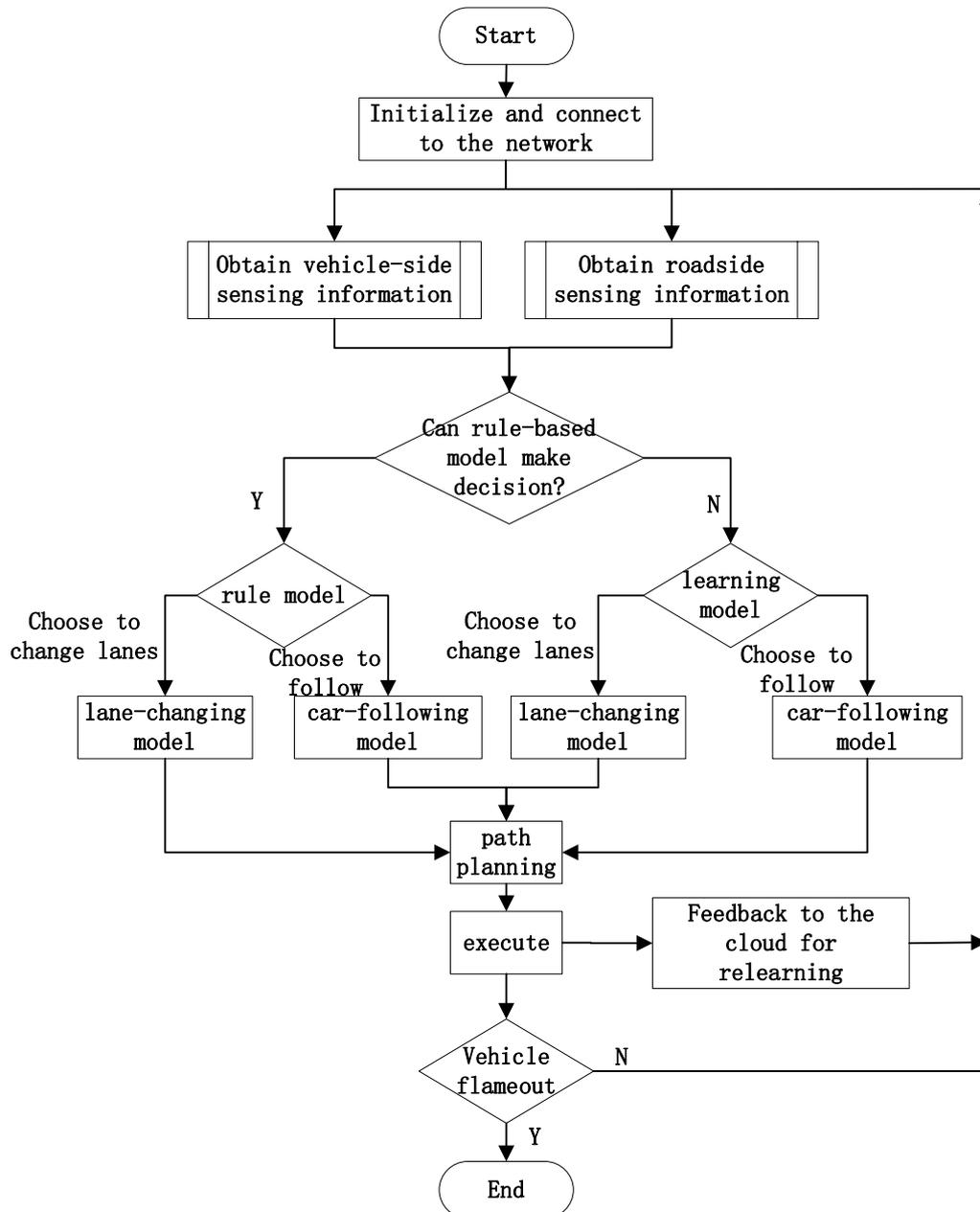


Figure 6. Execution process of lane change decision fusion model

The trolley starts to initialise the whole vehicle system and sensor configuration and connects to the main material handling control system to receive the material handling task. Depending on the accepted task scenario, the trolley connects to the roadside sensor system. After completing the initialisation and network connection, the trolley starts to move on the road according to the material handling request or instruction. During the driving process, the trolley receives sensor information from the on-board sensor system and the roadside sensor system about the vehicle itself, the environment around the vehicle and the route to the material delivery destination, including the trolley's own speed, acceleration, positioning, the situation of the surrounding vehicles, the situation of the vulnerable groups on the road, the obstacles on the road and maintenance barricades, and the traffic lights. The car sensor fusion module regulates and fuses the sensor information, and then imports the car rule model, and if the preset rules are

capable of decision, the car makes a decision according to the instructions of the rule model. If the decision result is to change lane, the car enters the lane change model and implements the corresponding lane change path planning according to the steering structure used, and if the decision result is to follow the car, the car enters the following model. If the preset rule model is unable to make a decision on the current situation, the learning model will make a decision. Unlike the decision execution of the rule model, the learning model will provide feedback after the decision execution of the learning model, and the feedback information will be transmitted to the cloud to re-learn and perfect the model, and the content of the feedback will include whether the vehicle has a collision or not, whether it violates traffic rules or not, and whether it deviates from the planned route, and so on. The vehicle will be able to make a decision about the current situation if it is in violation of the rules. The process from sensing to decision making is performed in a loop until the car reaches the destination or the car switches off before the process is terminated. The model is able to solve 90% of the structured rule scenarios with minimal computational cost, and then switch the learning model at the right time to cope with less frequent long-tail effects and grey scenarios not covered by the rules, and perform self-improvement of the model through continuous learning.

## 4. Experiments and Analysis

### 4.1 Experiment Scene

The test scenarios include overtaking lane change ( a ), avoidance lane change ( b ), deceleration lane change ( c ), turning lane change ( d ), road narrowing and widening lane change ( e ), congestion section lane change ( f ), vehicle starting immediately lane change ( g ), frequent rain and fog weather lane change ( h ), curve lane change ( i ), uphill and downhill lane change ( j ), traffic vulnerable group interference lane change ( k ).

### 4.2 Experimental Site

This article uses laboratory indoor open roads. The area of the test site is 1300 m2, and the real scene of the test site is shown in Figure 7 below. The test site contains 18 major road scenarios for connected intelligent vehicles, equipped with a scaled-down traffic light system and a traffic indication system.



(a)Bottom layer of testing field



(b)Top layer of testing field



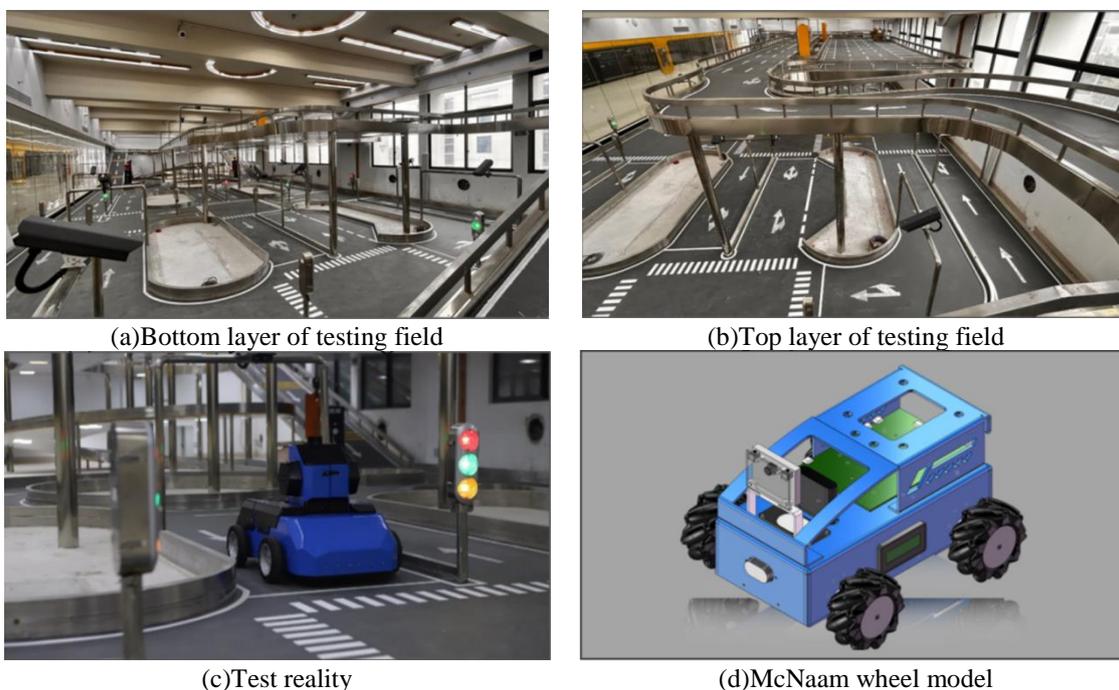(c)Test reality



(d)McNaam wheel model

Figure 7. Indoor test field

The lane change test performed in this paper includes the main road types, including gates, junctions, roundabouts, straight roads, etc.[26]. The road structure is shown in Figure 8.

(a)Drive out,drive into the gate                    (b)Intersection

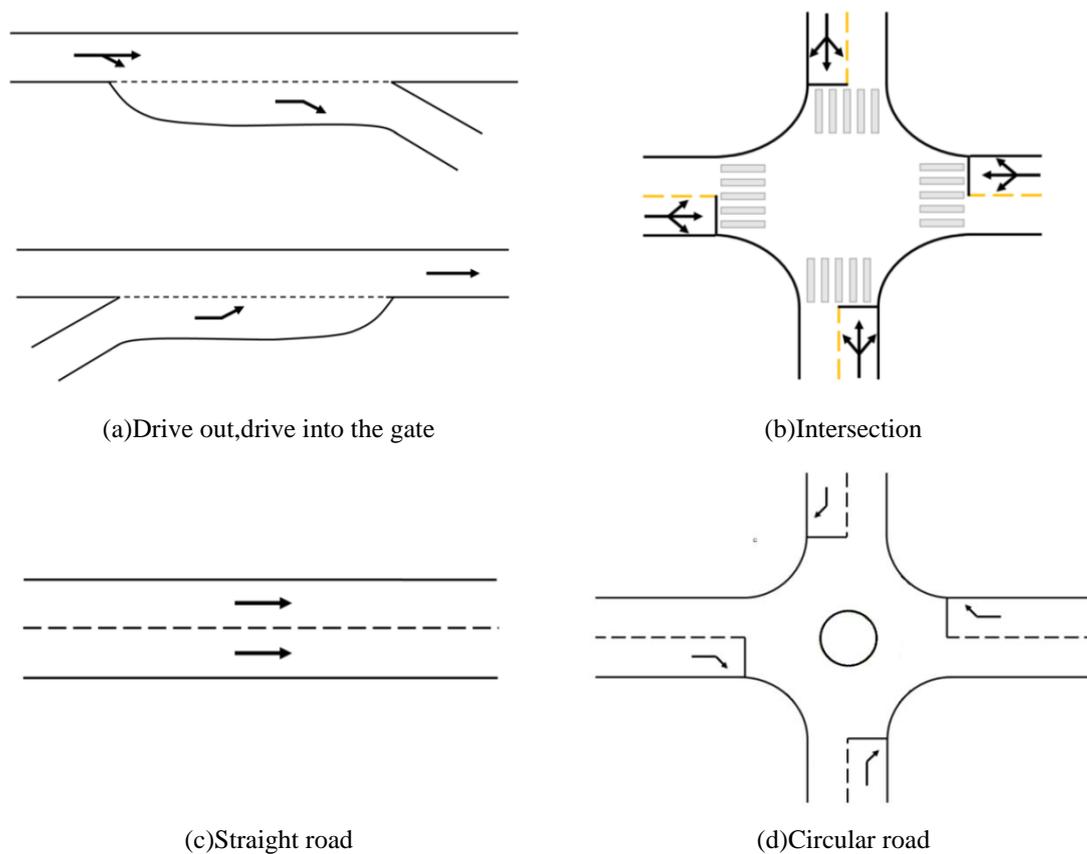(c)Straight road                    (d)Circular road

Figure 8. Test Road

Ramps are divided into entry ramps and exit ramps. They are the auxiliary connecting sections of the main lines, which can be 'level ramps' or 'interchange ramps'. Intersections bring together the traffic flow in four directions, which can easily become the prone point of traffic congestion and accidents. The straight road has the characteristics of a single direction of travel, clear road markings, variable number of lanes, no turning signs, stable driving speed, large traffic flow and high safety requirements. The roundabout generally has a central island setting, which has the characteristics of single phase driving and intersection weaving.

**4.3 Experimental Method**

In this paper, a front-wheel steering vehicle and a four-wheel wheat-wheel steering vehicle are tested for real vehicle lane change. When using the learning model test, the NVIDIA system is used as the main control. When using other model tests, the Arduino mega2560 microcontroller is used as the main control. The vehicle is connected to the laboratory road-end sensing system and the cloud sensing system through the mqtt interface. The interface connects the laboratory road-end sensing system and the cloud sensing system. The vehicle uses the rule model, the learning model, and the fusion model to compare and test each scene on the test road. Each scene is tested 20 times. For the scene where the traffic vulnerable group interferes with the lane change, the simulated pedestrian sudden probe, vehicle retrograde, and vehicle red light are used for testing.

**4.4 Experimental Results and Analysis**

4.4.1 Lane-change safety experiment

The test results of 20 times in each scene are recorded. The collision, violation of traffic instructions, and deviation from the planned driving route during the lane change process of the vehicle are all failures. The test failure ratio ( number of failures / number of tests ) is recorded for each scene. The scene number is consistent with the 4.1 in this article. The experimental results of the front wheel steering trolley are shown in table 2 below.

Table 2. Front wheel steering car experimental record

| Rule model | a | b | c | d | e | f | g | h | i | j | k | l |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Learning model | 0/20 | 0/20 | 0/20 | 0/20 | 2/20 | 1/20 | 0/20 | 5/20 | 1/20 | 2/20 | 1/20 | 2/20 |
| Fusion model | 0/20 | 1/20 | 0/20 | 0/20 | 1/20 | 0/20 | 0/20 | 3/20 | 0/20 | 3/20 | 1/20 | 0/20 |
| Rule model | 0/20 | 0/20 | 0/20 | 0/20 | 1/20 | 0/20 | 0/20 | 4/20 | 0/20 | 1/20 | 0/20 | 1/20 |

It is evident that the performance of several models for rain and fog special weather scenarios is suboptimal, primarily due to inaccurate sensor perception. To enhance performance, sensor hardware improvement or recognition algorithm optimization is necessary. The rule model exhibits a more robust decision-making ability for conventional scenarios and performs well in conventional lane change scenarios. However, when dealing with complex or unstructured scenarios, such as road narrowing, widening, and congested road sections, the decision-making error rate is significantly reduced. Although the overall decision error rate is lower in the learning model than in the rule model, some simple scenarios may still result in mistakes due to insufficient training samples. The fusion model has a lower overall decision error rate compared to the rule model and the learning model. Additionally, it has a more stable performance in conventional lane change scenes. Upon monitoring the model's usage records, it was found that 90% of the rule model scenes can complete the decision when the fusion model is used, resulting in saved computing resources for the system. In summary, the fusion model is superior to the rule model and the learning model in terms of decision security and stability. Additionally, the system's computational cost is higher than that of the rule model but lower than that of the learning model.

The experimental results of the Mecanum car are shown in table 3 below.

Table 3. Mecanum car experiment record

| Model | a | b | c | d | e | f | g | h | i | j | k | l |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rule model | 0/20 | 0/20 | 0/20 | 0/20 | 1/20 | 0/20 | 0/20 | 2/20 | 1/20 | 1/20 | 0/20 | 1/20 |
| Learning model | 0/20 | 0/20 | 1/20 | 0/20 | 1/20 | 0/20 | 0/20 | 3/20 | 0/20 | 0/20 | 1/20 | 0/20 |
| Fusion model | 0/20 | 0/20 | 0/20 | 0/20 | 0/20 | 0/20 | 0/20 | 2/20 | 0/20 | 1/20 | 0/20 | 1/20 |

It is evident that the Mecanum car outperforms the front wheel steering car in the rule model, learning model, and fusion model. This is due to the wheat wheel car's slower speed, more convenient steering and lane changing actions, and shorter route. For those prioritising stability, the fusion model is recommended, while those seeking cost control should opt for the rule model.

4.4.2 Networked collaborative experiment

In this paper, WiFi is used as the communication medium, Node-RED is used as the message middleware, MQTT server is built, MQTT client is deployed on both roadside devices and smart cars, roadside facilities and smart cars share road environment information and vehicle driving status and path. This paper compares the efficiency of the fusion model in the lane-changing decision-making of the network-connected cooperative mode and the single-vehicle mode, and conducts 100 real-vehicle experiments on 11 lane-changing scenarios, and records the time difference between the vehicle 's decision-making and the actual implementation of the lane-changing action, that is, the advance decision-making time. The comparison results are shown in Figure 9.
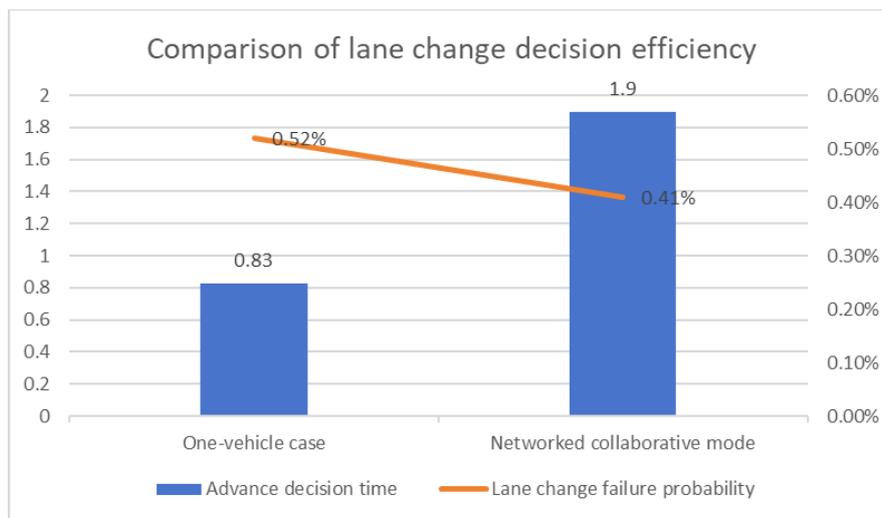
Figure 9. Comparison of lane change decision efficiency

Through comparison, it can be seen that by improving the acquired traffic information dimension and reducing the difficulty of the vehicle 's own sensing perception, the use of the networked collaborative mode can improve the time efficiency of the intelligent vehicle 's lane change decision and reduce the wrong decision.

4.4.3 Lane change control experiment

In this paper, the indoor test field is used to perform the lane change test, and the motion control of the model is repeatedly tested under the condition of ensuring no collision. The vehicle operation status is sampled and collected, including lateral speed, lateral acceleration, longitudinal speed, longitudinal acceleration and so on. The vehicle status data collected by sampling is plotted as shown in Figure 10 below.

By observing the drawing results of the vehicle motion state, it can be seen that the lateral velocity, lateral acceleration, longitudinal velocity and longitudinal acceleration curve of the vehicle lane change trajectory are continuous, smooth and without speed mutation, which meets the requirements of vehicle driving in the real road environment.
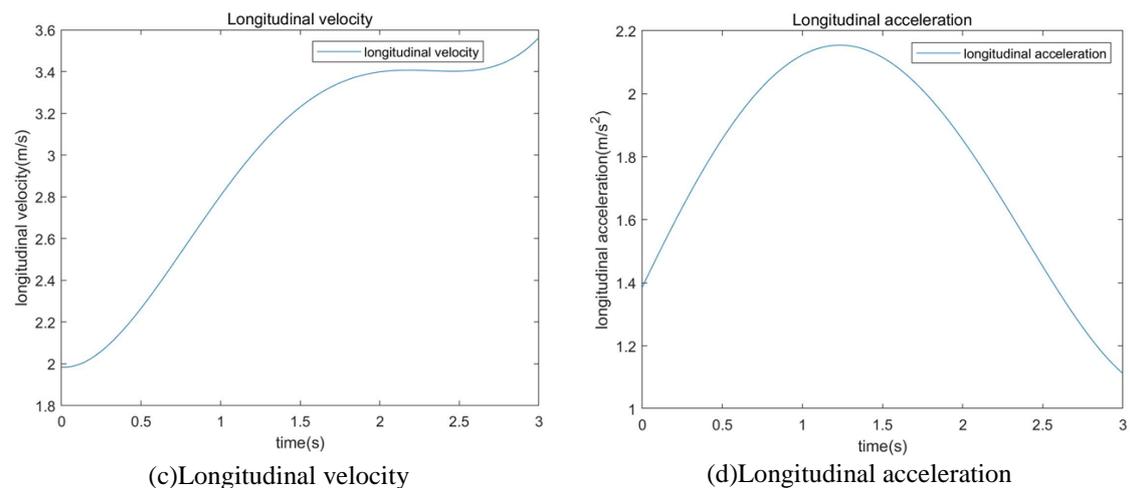


(a)Lateral velocity                      (b)Transverse acceleration

(c)Longitudinal velocity　　　　　　(d)Longitudinal acceleration
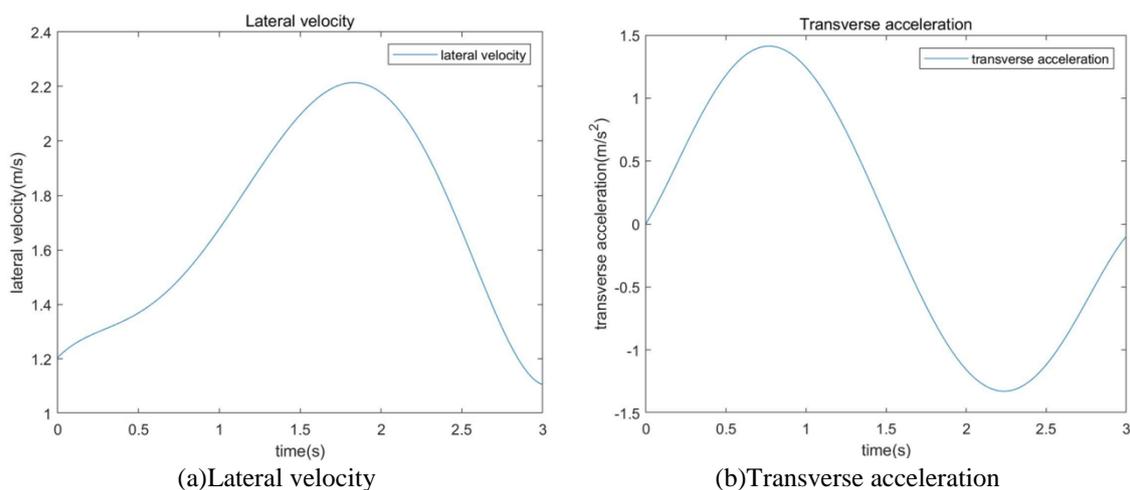
Figure 10. Vehicle lane change state quantity

## 5. Conclusion

### 5.1 Achievement

In this paper, the system architecture of intelligent material transport trolley based on vehicle terminal, road terminal and cloud network is designed. The main innovation of this paper is to analyse and compare the advantages and disadvantages of the steering structure of four kinds of material transport trolley. Aiming at the grey scene and long tail problem of automatic driving, the lane change decision fusion model and strategy process based on rule model and learning model are designed with the idea of model switching. Through the test of 11 scenarios, it can be seen that compared with the single rule model and learning model, the fusion model has lower computational cost and can be realised by using the microcontroller. It has good adaptability to both structured scenes and special scenes. With the help of network coordination, it can also improve decision-making efficiency and reduce decision-making errors. The model meets the requirements of the actual smooth driving control.

### 5.2 Implication

The collaborative architecture designed in this paper is suitable for small and medium-sized material handling systems. In the decision model, the rule model is stable and the computation cost is low, but the adaptability to special scenarios is not good. In the learning model, the algorithm has good adaptability to special scenes, but the algorithm interpretation is not good and the model computation cost is high. The fusion decision model designed in this paper can not only make full use of the advantages of the two types of models, but also avoid the disadvantages of the two types of models to some extent. It has the characteristics of good stability, strong scene adaptability and low computational requirements. Combined with the scene adaptability analysis of different steering structures, it provides a reference for the industrial landing of intelligent handling. This research can provide theoretical and practical support for the design and landing of intelligent material handling vehicles and systems in warehouses, shipyards, hospitals and production workshops.

### 5.3 Limitation and future study

Due to the limitation of the indoor test site, this paper can only carry out real-vehicle testing on small material handling vehicles, but not on large and medium-sized material handling vehicles. Due to the limitation of the project cycle, this paper cannot make a comparative study on more fusion model systems. The self-learning rule model and the rule model + networked collaborative model are all ideas to improve the decision-making ability of automatic lane change. The author and the research team will conduct in-depth exploration through follow-up related topics.

## References

[1] Yang Xiulan, 'New Energy Vehicle Industry Development Plan (2021-2035),' Lhasa Daily News, Nov. 03, 2020.

[2] Industrial Research Institute, 'China Smart Car (Intelligent Networked Vehicle) Industry Investment Planning and Prospect Forecast Report, 2024-2028.'

[3] B. Turner, "Logistics 4.0 and the mobile industrial robot," Control engineering: Covering control, instrumentation, and automation systems worldwide, no. 3, p. 69, 2022.

[4] J. Ni, K. Shen, Y. Chen, W. Cao, and S. X. Yang, "An Improved Deep Network-Based Scene Classification Method for Self-Driving Cars," IEEE Transactions on Instrumentation and Measurement, vol. 71, p. 5001614, 2022, doi: 10.1109/TIM.2022.3146923.

[5] Q. Wu, X. Li, K. Wang, and H. Bilal, "Regional feature fusion for on-road detection of objects using camera and 3D-LiDAR in high-speed autonomous vehicles," Soft Computing, vol. 27, no. 23, pp. 18195-18213, Dec. 2023, doi: 10.1007/s00500-023-09278-3.

[6] O. Makansi, Ö. Cicek, Y. Marrakchi, and T. Brox, "On exposing the challenging long tail in future prediction of traffic actors," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 13147–13157.

[7] Z. Huang, J. Zhang, R. Tian, and Y. Zhang, "End-to-End Autonomous Driving Decision Based on Deep Reinforcement Learning," Conference Proceedings Of 2019 5th International Conference on Control, Automation and Robotics (ICCAR), pp. 658–662, 2019, doi: 10.1109/iccar.2019.8813431.

[8] H. Bhuiyan, G. Governatori, A. Rakotonirainy, M. W. Wong, and A. Mahajan, "Driving Decision Making of Autonomous Vehicle According to Queensland Overtaking Traffic Rules," Review OF Socionetwork Strategies, vol. 17, no. 2, pp. 233–254, Oct. 2023, doi: 10.1007/s12626-023-00147-x.

[9] G. Li, Y. Yang, S. Li, X. Qu, N. Lyu, and S. E. Li, "Decision making of autonomous vehicles in lane change scenarios: Deep reinforcement learning approaches with risk awareness," Transportation Research Part C-Emerging Technologies, vol. 134, p. 103452, Jan. 2022, doi: 10.1016/j.trc.2021.103452.

[10] X. He, H. Yang, Z. Hu, and C. Lv, "Robust Lane Change Decision Making for Autonomous Vehicles: An Observation Adversarial Reinforcement Learning Approach," IEEE Transactions on Intelligent Vehicles, vol. 8, no. 1, pp. 184–193, Jan. 2023, doi: 10.1109/TIV.2022.3165178.

[11] F. Alam, R. Mehmood, I. Katib, S. M. Altowaijri, and A. Albeshri, "TAAWUN: a Decision Fusion and Feature Specific Road Detection Approach for Connected Autonomous Vehicles," Mobile Networks & Applications, vol. 28, no. 2, pp. 636–652, Apr. 2023, doi: 10.1007/s11036-019-01319-2.

[12] S. Feng et al., "Dense reinforcement learning for safety validation of autonomous vehicles," Nature, vol. 615, no. 7953, pp. 620-+, Mar. 2023, doi: 10.1038/s41586-023-05732-2.

[13] A. Arizala, A. Zubizarreta, and J. Perez, "A Complete Framework for a Behavioral Planner with Automated Vehicles: A Car-Sharing Fleet Relocation Approach," SENSORS, vol. 22, no. 22, p. 8640, Nov. 2022, doi: 10.3390/s22228640.

[14] S. Yang, L. Gao, and Y. Zhao, "A Detection Model of the Complex Dynamic Traffic Environment for Unmanned Vehicles," IEEE ACCESS, vol. 10, pp. 51873–51888, 2022, doi: 10.1109/ACCESS.2022.3174859.

[15] G. Fragapane, R. De Koster, F. Sgarbossa, and J. O. Strandhagen, "Planning and control of autonomous mobile robots for intralogistics: Literature review and research agenda," European Journal of Operational Research, vol. 294, no. 2, pp. 405–426, 2021, doi: 10.1016/j.ejor.2021.01.019.

[16] W. Wang, T. Qie, C. Yang, W. Liu, C. Xiang, and K. Huang, "An intelligent lane-changing behavior prediction and decision-making strategy for an autonomous vehicle," IEEE transactions on industrial electronics, vol. 69, no. 3, pp. 2927–2937, 2021, doi: 10.1109/TIE.2021.3066943.

[17] E. Bryndin, "Increase of safety use robots in industry 4.0 by developing sensitivity and professional behavioral skills," American Journal of Mechanical and Industrial Engineering, vol. 5, no. 1, pp. 6-14, 2020, doi: 10.11648/j.ajmie.20200501.12.

[18] S. Mozaffari, O. Y. Al-Jarrah, M. Dianati, P. Jennings, and A. Mouzakitis, "Deep learning-based vehicle behavior prediction for autonomous driving applications: A review," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 1, pp. 33–47, 2020, doi: 10.1109/TITS.2020.3012034.

[19] K. Ji, N. Li, M. Orsag, and K. Han, "Hierarchical and game-theoretic decision-making for connected and automated vehicles in overtaking scenarios," Transportation research part C: emerging technologies, vol. 150, p. 104109, 2023, doi: 10.1016/j.trc.2023.104109.

[20] X. Hu, Y. Liu, B. Tang, J. Yan, and L. Chen, "Learning Dynamic Graph for Overtaking Strategy in Autonomous Driving," Ieee Transactions on Intelligent Transportation Systems, vol. 24, no. 11, pp. 11921–11933, Nov. 2023, doi: 10.1109/TITS.2023.3287223.

[21] M. Ren, P. He, and J. Zhou, "Decision fusion of two sensors object classification based on the evidential reasoning rule," Expert Systems with Applications, vol. 210, p. 118620, Dec. 2022, doi: 10.1016/j.eswa.2022.118620.

[22] B. Geng, Q. Li, and P. K. Varshney, "Human Decision Making with Bounded Rationality," 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 5493–5497, 2022, doi: 10.1109/ICASSP43922.2022.9747866.

[23] Y. Li, J. Xu, D. Guo, and H. Liu, "Trust-Aware Human–Robot Fusion Decision-Making for Emergency Indoor Patrolling," IEEE Transactions on Automation Science and Engineering, Jan. 2024, doi: 10.1109/TASE.2024.3350639.

[24] Li Biao and Wang Wei, 'Intelligent Networked Vehicle Modelling and Simulation Technology,' in Intelligent Networked Vehicle Modelling and Simulation Technology, Mechanical Industry Press, 2023, pp. 31-32.

[25] Y. Karl, H. K. Kim, and Y. P. Geum, "A Study on Deep Learning Model Autonomous Driving Based on Big Data," International journal of software innovation, no. 4, p. 9, 2021, doi: 10.4018/IJSI.289174.

[26] China Intelligent Networked Vehicle Industry Innovation Alliance and National Automobile Standard Committee Intelligent Networked Vehicle Sub-Technical Committee, 'Intelligent Networked Vehicle Autonomous Driving Function Test Regulations.' 2018.