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RESEARCH ARTICLE

Algorithm Optimization of Computer Simulation Vehicle Driving Simulation System Based on Virtual Reality Technology

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Abstract
The traditional automobile driving simulation system has the problems of low calculation efficiency and lack of realism. The traditional automobile driving simulation system with low computational efficiency and lack of realism limits the learning effect. Through virtual reality technology, vehicle driving can be simulated. By optimizing the algorithm of simulating vehicle driving simulation system, the preference of testers for driving style is investigated and the driver's preference style is determined. Finally, through the automatic driving simulation test method based on genetic algorithm, the key scenes can be divided into 11 different types, and the Euclidean distance of these 11 types is analyzed. Most drivers prefer a more conservative autonomous driving style. When analyzing 11 key scenario types, the Euclidean distance between scenario 2 and scenario 3 is the smallest, which is 33 m, and the maximum Euclidean distance between scenario 6 and scenario 11 is 91 m. The difference between scene 2 and scene 3 is the smallest, while the difference between scene 6 and scene 11 is the largest, and there are differences between each scene. Through virtual reality technology and algorithm optimization, the performance and user experience of driving simulation system are improved.

Keywords Virtual Reality Technology · Computer simulation · Autonomous driving · Vehicle driving simulation system · Questionnaire survey

Abbreviations

TORCS	The open racing car simulator
VTORCS	Visual open racing car simulator
AI	Artificial Intelligence
MIL	Model in the loop
SIL	Software in the loop
VIL	Vehicle in the loop
IO	Input/Output
LiDARs	Light Detection and Ranging
UI	User Interface

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1 Introduction

Traditional vehicle driving simulation systems have many problems, such as low computational efficiency, insufficient realism, and limited learning effectiveness [1, 2]. Optimizing the algorithm of computer simulation vehicle driving simulation system based on virtual reality technology can improve the performance and user experience of the simulation system, and achieve a more efficient and realistic driving learning environment. This paper emphasizes the importance of a virtual driving simulation system in a driver training simulator. By improving the fidelity and personalized experience, the training effect can be improved, so that drivers can better adapt to real road conditions, thus enhancing driving skills and improving safety. At present, there are still significant safety issues in the process of automatic to manual vehicle control conversion. Developing models and computer simulations for automatic vehicle control transitions can help designers alleviate these issues, but only if accurate models are used. McDonald A D identified articles describing automatic vehicle takeover or driver modeling research through systematic methods and believed that the driver's response between manual emergency situations and automatic takeover is similar, with delays [3]. Li L proposed a type of human driving system that enables autonomous vehicles to make decisions like humans. This method used a convolutional neural network model to detect, recognize and extract the input road scene information captured by vehicle sensors. After that, on the basis of these abstractions, the decision system calculated the specific commands to control the vehicle. The experimental results demonstrated the effectiveness and robustness of this method [4]. Based on the methods of deep learning and reinforcement learning, Li D studied vision-based automatic driving. Li D decomposed the visual-based lateral control system into perception modules and control modules. To improve data efficiency, a deep reinforcement learning environment VTORCS (visual open racing car simulator) based on the open racing car simulator (TORCS) was proposed. By using an open racing simulator, people can train intelligent agents using images or inputs measured by various physical sensors, or evaluate perception algorithms on the simulator. Li D believed that the perception module can show good performance, and the controller can well control the vehicle to travel along the track center under the condition of visual input [5]. As an emerging and rapidly developing field, autonomous vehicle has attracted extensive attention due to their futuristic driving experience. Although the rapid development of deep sensors and machine learning methods has greatly promoted research on autonomous driving, existing autonomous vehicles do encounter some unavoidable accidents in road testing. The main reason is the misunderstanding between the auto drive system and human drivers.

As a method, vehicle driving virtual reality can create a calm and focused experience for passengers and autonomous vehicle occupants one day. Paredes P E conducted research on understanding the effects of car motion and determining parameters such as simulation length to avoid physical discomfort. Quantitative and qualitative insights indicated that calm in car virtual reality applications are very suitable for automotive environments [6]. Lack of trust or acceptance of technology is a fundamental issue that may hinder the spread of autonomous driving. Technological advancements, such as the full-size windshield display of augmented reality assistive devices, may help provide users with better system understanding. Wintersberger P raised the question of whether augmented reality assistance is possible to increase user acceptance and trust by communicating system decisions. To prove this hypothesis, Wintersberger P conducted two driving simulator studies, and the quantitative results showed that adding other invisible traffic objects (such as dense fog) or displaying upcoming driving movements while sitting backwards are feasible methods to improve user acceptance and trust. The application of augmented reality, especially with the emergence of more powerful, lightweight, or integrated devices, is a great opportunity for autonomous driving and has high potential [7]. To achieve the goal of complete automation, it is important to understand the working principle of AI (Artificial Intelligence) in the auto drive system. Ma Y investigated current practices by analyzing the main applications of AI in supporting autonomous driving, to understand how to use AI and what are the challenges and issues related to implementation. Based on the exploration of current practice and technological progress, potential opportunities for the integration of AI with other emerging technologies were further proposed [8]. The progress of AI has really stimulated the development and deployment of autonomous vehicle in the transportation industry. Driven by big data generated by various sensing devices and advanced computing resources, AI has become an important part of autonomous vehicle to sense the surrounding environment and make appropriate decisions in motion. In the past, the solutions mainly focused on model design and autopilot conversion. However, the lack of accurate model may lead to inevitable accidents, and the misunderstanding between automatic driving system and human drivers is still the main safety problem. This paper makes up for these shortcomings through virtual reality technology and algorithm optimization, and proposes an improved simulation system to improve performance and user experience.

This article optimized the design of a computer simulation vehicle driving simulation system based on virtual reality technology through computer simulation vehicle driving simulation system and virtual reality technology algorithm optimization. Through virtual reality technology and algorithm optimization, this paper improves the performance and user experience of a computer-simulated vehicle driving simulation system. Through a questionnaire survey, the driver's preference is studied, the key scenes are classified by genetic algorithm, and the scene differences are analyzed by Euclidean distance. It is found that most drivers prefer a conservative autopilot style. The contribution of this paper is to propose a personalized simulated driving learning environment, improve the system performance by optimizing the algorithm, and deeply analyze the driving style preferences among different scene types, so as to provide strong guidance for the future development of automatic driving system.

2 Methods

2.1 Optimization of Virtual Scene Generation Algorithm

By improving the virtual scene generation algorithm, a new method for constructing 3D models is proposed, which can improve the rendering speed and fidelity of 3D models. The main research content includes optimizing the loading and rendering process of scene models to achieve fast and realistic scene construction. In the past, its practicality was questioned due to its high cost and technical difficulties. In recent years, with the continuous development of computer technology and the continuous improvement of hardware facilities, virtual driving technology has gradually entered people's lives. Due to the increasing dependence of unmanned driving experiments on virtual simulation scenarios, the traditional scenario counting method based on expert experience can no longer meet the actual testing needs [9]. The automatic generation of scenes based on digital virtual simulation has the advantages of scene diversity, high danger, strong interpretability, and high generation efficiency. It is of great significance for improving the safety and reliability of autonomous driving experiments and is currently a research hotspot in the field of vehicle intelligent control [10, 11].

To obtain the motion trajectory of objects in the scene, it is necessary to have a clear understanding of the object's coordinate system. Compared to the world coordinate system in the scene, the car model is relatively independent. To facilitate control and output data, a local coordinate system can be constructed on the car. The motion of the car can be understood as moving or rotating around the X, Y, and Z axes, respectively, and synthesized, as shown in Fig. 1.

The local coordinate system of the car established in Fig. 1 is fixed on the car. When the car model moves relative to the world coordinate system in the virtual scene, it can be seen as a combination of the following movements: ① longitudinal movement of the car forward and backward; ② the left and right lateral movement of the car; ③ the inclination of the car; ④ the roll motion of a car.

Among these four actions, only the first one is caused by changes in the coordinate system of the vehicle throughout the entire scene. The other three movements are completed by the car rotating around each axis of the local coordinate system [12]. Therefore, for the convenience of observation, this article fixed the observation viewpoint on the rear of the vehicle and used the same local coordinates.

Use virtual reality technology to create a realistic driving simulation environment, including virtual roads, traffic signs, vehicle models and so on. Recruit participants for the driving simulation test. In the experiment, the driving behavior data of participants were recorded, including acceleration, braking, steering and so on. At the same time, virtual reality technology is used to collect their reaction data in different situations, such as reaction time and behavior in case of emergency.

By analyzing the collected driving behavior data, the driving algorithm of the simulation system is optimized, and the parameters of the simulation environment are adjusted in real time according to the preferences of participants. The automatic driving strategy is coded into genes, and the fitness function is designed according to the performance index. Through the evolution of genetic algorithm, the automatic driving strategy is continuously improved.

2.2 Vehicle Physical Model Optimization

The occurrence of traffic safety accidents not only has a significant impact on individuals but also relates to the safety and stability of the entire society. In terms of optimization algorithms for car physical models, the focus is on improving the realism and stability of car driving simulation [13, 14]. The main research content includes improving car motion models, car collision detection algorithms, car handling models, etc., which can improve the accuracy of car motion simulation and improve car driving safety.

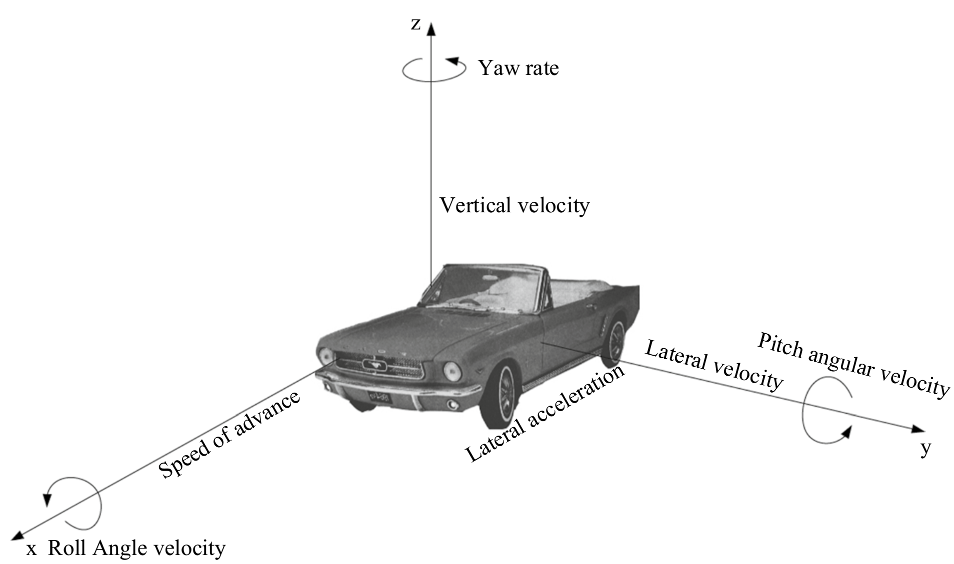


Fig. 1 Automotive local coordinate system

The main safety hazards of driving a car are: the impact on the surrounding environment is ignored before the car starts, and the driver's driving position in the car limits the range of vision. Therefore, before the car starts, the driver needs to have a certain understanding of the surrounding environment of the vehicle. Observing the car before driving can better grasp the distance between the car and fixed objects around it, so that there would be no scratches or collisions [15]. Motor vehicles do not maintain appropriate spacing while driving, resulting in most traffic accidents, while rear-end collisions are caused by drivers not maintaining a safe distance while driving. In the process of vehicle operation, if the appropriate distance cannot be maintained, the safe Braking distance of the vehicle would be lost. Especially at night, if the driver is stimulated by the light emitted by the target car, it would directly affect the driver's vision, leading to traffic accidents. The uneven speed of vehicles is also the main cause of vehicle collisions, especially rear-end accidents. Generally speaking, this situation is more common among inexperienced novice drivers [16, 17]. They have just started driving their vehicles, so when faced with various conditions on the road, they are prone to panic and feel very nervous. It is easy to focus on the process of driving the vehicle and neglect the safe distance between them and the vehicles ahead, especially in complex road surfaces and situations with a large number of vehicles, which can lead to traffic safety accidents.

In addition, the technical safety issues of automobiles are also an important factor leading to automobile safety accidents. Cars are a type of transportation that requires attention to maintenance and repair. Regular maintenance and repair can improve their safety in use. Different models and brands of vehicles meet different technical standards, so maintenance and repair should be carried out according to the characteristics of the vehicle [18]. For the collision process of a car, it can be divided into three parts, and the specific stage diagram can be shown in Fig. 2.

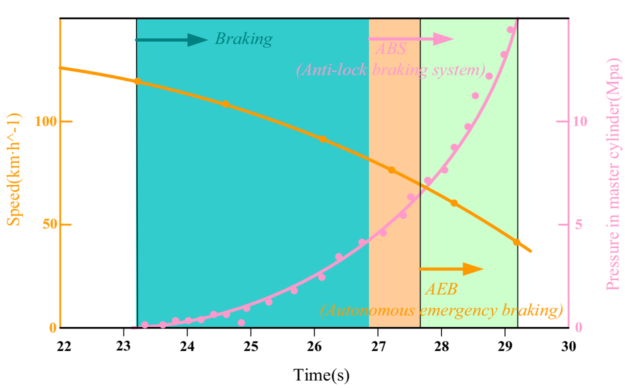


Fig. 2 Stage diagram before car collision

To accurately reflect the driving condition of a car in the event of a traffic accident, it is necessary to analyze the parameters such as driving speed and front wheel angle. Hyundai Motor Company has adopted a technology called Ackerman steering technology. The Ackermann steering technology can be shown in Fig. 3.

Before the emergence of this technology, cars often used single hinge chain steering, which can achieve consistent inner and outer steering trajectories, but also has certain drawbacks. The Ackermann steering system can effectively overcome the shortcomings of a single articulated steering system and steer the car by reducing the turning radius of the inner tire compared to the outer tire [19].

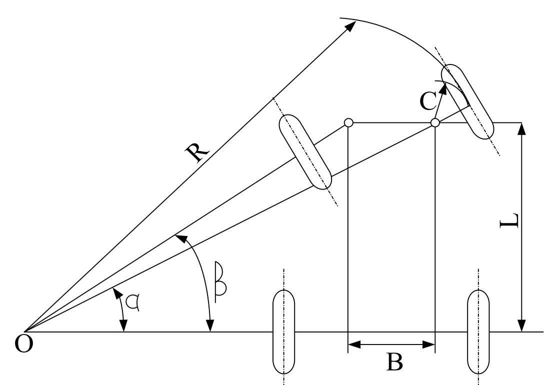


Fig. 3 Ackermann steering technology

2.3 Optimization of Intelligent Driving Algorithms

Autonomous driving technology in automobiles is a new way to improve traffic efficiency and alleviate traffic congestion, and is also one of the key technologies to achieve intelligent transportation. Due to the certain risks associated with the driving behavior of drivers, unmanned driving technology needs to be widely applied on the premise of safety and stability. Research has shown that to ensure the reliability of autonomous vehicles and enable them to cope with various situations on the road network, at least hundreds of millions, or even billions of kilometers of testing mileage are required, which is clearly impossible to achieve solely through real vehicle testing [20]. On this basis, the article proposed an intelligent driving simulation system based on a multi-objective programming method. The main research contents include improving the road planning algorithm, establishing the traffic flow model, designing the interactive traffic flow model, and building a more intelligent road traffic system.

Improvement of road planning algorithm: The A* (A Star) algorithm is the most representative heuristic search algorithm. According to the needs of path planning and actual tasks, adjustments need to be made to indicators such as path length, planning efficiency, and the number of inflection points.

The establishment of interactive traffic flow models and design: The research and development of unmanned driving systems include the development of software and hardware, system design and decomposition, testing and validation, etc. Due to the differences in requirements at each stage, simulation systems are often based on different platforms, resulting in issues such as time asynchrony and data incompatibility. For this reason, a set of technical system can be built to realize the combination of offline and real-time, software simulation and Hardware-in-the-loop simulation, virtual simulation and real vehicle test, so as to meet the life cycle requirements of the unmanned driving system. For the test objects at different stages, the automatic driving simulation test schemes are also different, including model in the loop (MIL), software in the loop (SIL), Hardware in the loop (HIL) and vehicle in the loop (VIL). Although the hardware and Input/Output Interface (IO) interfaces of actual vehicles have gradually been introduced, which can make the simulation closer to the performance of real vehicles under low-cost and small-scale conditions, the driving environment always requires simulation [21]. The model of the autonomous driving environment sensor can be shown in Fig. 4.

Common environmental sensors in unmanned driving systems include various types of cameras, millimeter-wave radars, LiDARs (Light Detection and Ranging), positioning devices, and wireless communication devices. Their modeling must be based on basic physical laws to simulate [22]. Environmental sensors typically consist of a detection device and a signal processing device, each of which can output a detected signal.

2.4 User Experience Optimization

Improving user interaction and feedback systems can enhance user experience and learning outcomes. The specific content includes improving user interface design, interactive devices, and feedback mechanisms, and allowing users to participate more intuitively and conveniently in driving simulations, thereby improving efficiency [23]. The user interface design is shown in Fig. 5.

Under autonomous driving conditions, the driver is both an operator and a decision-maker, while the vehicle controls the brakes and throttle based on the driver's perception and judgment of the surrounding environment. Therefore, the driver has expectations for every step of the car's movement.

For the auto drive system, the current driver's identity is the co-driver. At this time, the driver in the car is no longer the driver who performs various operations on the vehicle. The driver's role now is like a coach when learning the driver's license. The driver would not participate in the decision-making and operation of the vehicle at all. The driver is more likely to experience as a supervisor. The changes brought about by autonomous driving can be seen in Table 1.

On this basis, combined with methods such as user interviews, expert surveys, and questionnaire surveys, the influencing factors on the user experience of autonomous vehicles are studied [24]. On this basis, scientific decisions are made at various research and development stages by refining user requirements to ensure the achievement of the final design goals and continuous updates and updates are carried out.

In this paper, virtual reality technology is used to optimize the algorithm of computer simulation vehicle driving simulation system. First, the fidelity and rendering speed are improved by improving the virtual scene generation algorithm. Then, the key scenes are classified by genetic algorithm to investigate the driving style preference of the experimenters. Finally, Euclidean distance is used to analyze the differences between different scene types. Methods Focus on improving system authenticity, intelligent decision-making ability and user experience, and provide a basis for personalized driving learning.

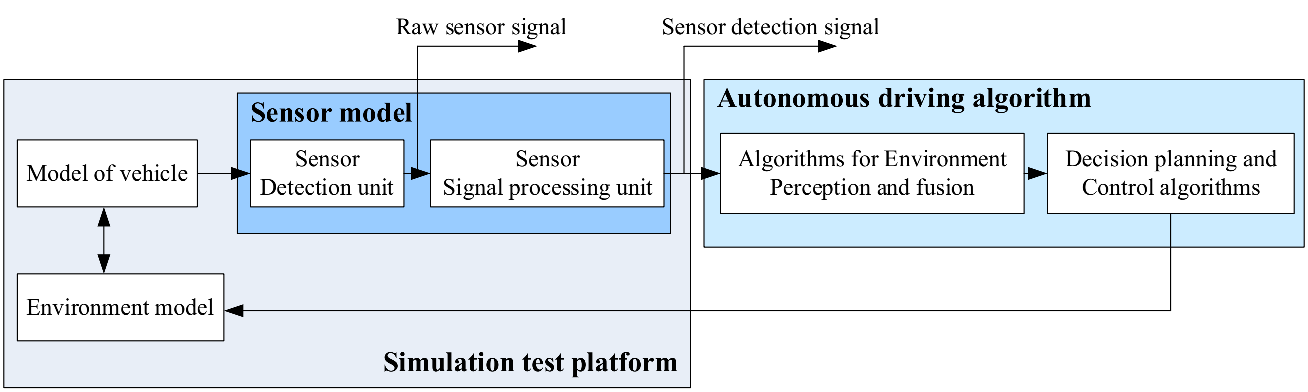


Fig. 4 Model of autonomous driving environment sensors

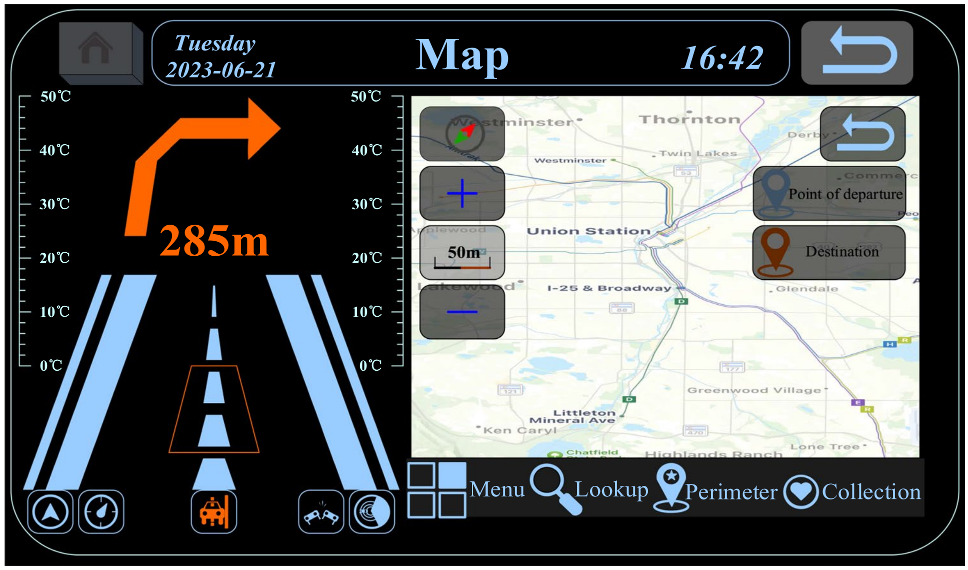


Fig. 5 User interface design

Table 1 Changes brought about by autonomous driving

	Manual driving	Autonomous driving
User identity	Operator, Decision maker	Helper, Supervisor
Angle of evaluation	How well the vehicle responds to user commands	How close the vehicle dynamic control is to the driver control
User expectations	Clearly understand the vehicle's next steps	They don't know what to do next, so they need to pass it to the user through the User Interface (UI)

The algorithm optimization process in this paper includes improving the virtual scene generation algorithm, optimizing the vehicle physical model algorithm, intelligent driving algorithm and user experience algorithm. By improving the virtual scene generation algorithm, 3D model rendering is accelerated and improved. The optimization of the vehicle's physical model algorithm aims to improve the realism and stability of driving simulation. The optimization of intelligent driving algorithms emphasizes improving the autonomous decision-making and intelligent interaction ability of the system. The optimization of the user experience algorithm focuses on improving user interface design, interactive equipment and feedback mechanism to enhance user participation and convenience. This series of optimization has deepened the performance and user experience of the driving simulation system through virtual reality technology.

3 Results

3.1 Simulation of Autonomous Driving Scenarios

A six-degree-of-freedom driving simulation device is established, including seat, steering wheel, pedal, virtual reality headset and so on. Ensure that the device can provide a realistic driving simulation experience, including road vibration, acceleration feedback, etc. Participants are required to complete the obstacle avoidance test on the simulated driving device according to their normal driving habits. The test includes obstacle avoidance behavior when encountering obstacles, such as avoiding obstacles or slowing down to avoid. Record the data during driving, such as speed, acceleration, steering angle, etc. According to the data recorded during driving, such as acceleration, braking force and steering angle, the driving performance of participants is quantitatively evaluated.

In the test, participants need to perform obstacle avoidance behaviors in the face of obstacles, including avoiding obstacles or slowing down. Data records during driving include parameters such as speed, acceleration and steering angle. By analyzing the recorded data such as acceleration, braking force and steering angle, the driving performance of participants is quantitatively evaluated.

The simulated driving test was conducted by participants on a six degree of freedom simulated driving device, requiring them to complete obstacle avoidance tests according to normal driving habits. Driving style should comply with the following two points: 1) Driving style varies depending on individual or group; 2) Driving style is a habit that should be a more stable driving behavior. There are generally three ways to drive: “radical”, “conservative”, and “average”. In terms of driving style, it is mainly measured by subjective statement scales and driving performance.

In terms of driving behavior characteristics, several indicators were selected, including average speed, average acceleration/deceleration, maximum acceleration, minimum deceleration, maximum speed, and standard deviation of acceleration. Automatic driving scene simulation refers to the use of Vehicle dynamics simulation software to build a two-way four lane highway scene. In the simulation scenario, the background vehicle was driving at a constant speed of 78 km/h, and the simulated vehicle was autonomous. It approached the vehicle in front at a higher speed and switched to overtaking after reaching certain conditions. Figure 6 shows the driver’s direct forward view of the simulated vehicle.

The vehicle model, trajectory planning, motion control and driver model of automatic driving are all carried out in the Vehicle dynamics simulation software. This experiment provided two types of autonomous driving modes and compared the differences in four aspects: different average vehicle speeds, different lane-changing times, lane-changing trajectory curves, and maximum lateral acceleration. The differences between the two driving styles of autonomous driving design are shown in Table 2.

The average speed of the aggressive driving style is 92.3 km/h, while the average speed of the conservative driving style is 78 km/h. This shows that drivers with aggressive driving style are more inclined to drive at higher speed, and may pay more attention to reaching their destinations quickly, while conservative drivers pay more attention to safety and stability, so the speed is slower. Curvature indicates the degree of turning when a vehicle changes lanes. Drivers with aggressive driving style tend to have a sharper curve when changing lanes, while conservative drivers prefer a smooth curve. Drivers with aggressive driving style are more inclined to high-speed and rapid driving behavior, and are more willing to bear higher lateral acceleration, while conservative drivers pay more attention to safety, stability

Table 2 Differences between the two styles in autonomous driving

Parameters	Aggressive driving style	Conservative driving style
Average vehicle speed	92.3 km/h	78 km/h
Start lane change time	3.6 s	15.9 s
Curvature of lane-changing trajectory	0.036	0.0109
Maximum lateral acceleration	4.36 m/s^2	2.61 m/s^2

and caution, with slower speed and need more time to make driving decisions.

Autonomous driving adopted rule-based decision-making and used time to collision (TTC) to represent the initial lane change time:

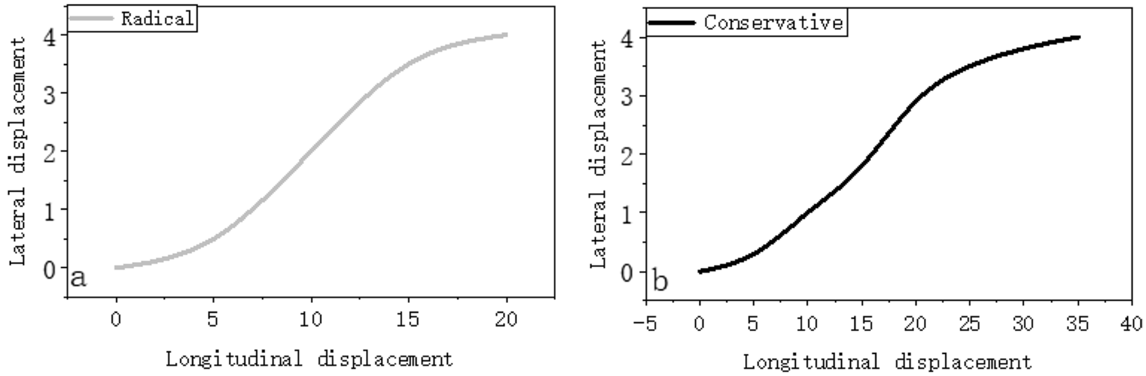
$$TTC = \Delta x/\Delta v \tag{1}$$

The trajectory planning adopted the connection of two arcs, and the curvature of the trajectory varied due to different driving modes. In the vehicle Dynamic simulation software, the driver’s single-point forward-looking model was established, and the target tracking control was realized. The trajectory maps of different driving styles are shown in Fig. 7.

Figure 7a shows a set of radical experiments, while Fig. 7b shows a set of conservative experiments. Five individuals were arranged on a driving simulator to conduct aggressive and conservative experiments, each lasting approximately 3 min. Before and after the experiment, a questionnaire survey was conducted on five participants to evaluate their subjective trust. The content of the autonomous driving assessment scale mainly includes the reliability, ability, predictability, comprehensibility, familiarity, purpose/motivation, and overall level of autonomous driving. The survey results are shown in Table 3.

The researchers gave the testers a questionnaire before and after the experiment. The results showed that four testers trusted a more conservative style autonomous driving,

Fig. 6 Driving perspective of simulated vehicles



(a) Radical style **(b)** Conservative style

Fig. 7 Trajectory maps of different driving styles (a) Radical style. (b) Conservative style

Table 3 Post experiment questionnaire survey results

Title	Tester1	Tester2	Tester3	Tester4	Tester5
Number of obstacles hit	B	A	C	B	A
How easy it is to drive to the finish line	C	A	D	B	C
Think of your driving skills	C	B	B	D	C
Before that drive strategy	D	A	F	D	E
In this experiment	A	B	D	A	B
After familiarization with the experiment, compared to the state before the experiment	B	A	D	A	B
The driving style before that	A and E	A and F	B and C	E and F	A and E

while one tester trusted a more aggressive style autonomous driving.

3.2 Scene Generation Under Autonomous Driving

In this paper, the longest road was selected from the M map in the simulation platform for testing, and the road scene was generated to realize the long-distance test of the auto-drive system. On this basis, a genetic algorithm-based autonomous driving simulation test method was adopted to conduct simulation tests on autonomous driving vehicles, and the simulation test results were evaluated. In each case, the vehicle was set as the primary vehicle and connected to the unmanned driving system. A collision detector was installed on the main vehicle to monitor the safety of unmanned vehicles. Based on the driving trajectory of secondary vehicles and the design defects of unmanned driving systems, the detected safety violations were classified.

By comparing the automated driving simulation test method based on a genetic algorithm with the existing advanced automated driving simulation scene generation technology, it was proved that the automated driving simulation test method based on a genetic algorithm is effective and progressiveness. The baseline method selected in this paper was an open-source automatic driving test technology based on a search method and a software toolkit for formal analysis of AI-based network physical system.

Open source search-based autonomous driving testing technology that uses genetic algorithms to evolve the motion of secondary vehicles to expose their safety violations. The software toolkit for formal analysis of AI (AI) based network physical system can generate test scenarios by optimizing sampling in the feature space, so as to discover the properties of the system that violate the defined rules (the rules defined here are to avoid collision with secondary vehicles). On this basis, the performance evaluation results of the genetic algorithm-based autonomous driving simulation testing method and two benchmark testing methods under the same working conditions were compared, and their effectiveness in generating key scenarios, efficiency in generating and operating, impact on autonomous driving, and differences in generating key scenarios were analyzed. Through the automated driving simulation test method based on a genetic algorithm, the key scenarios can be divided into 11 different types. Type 1 is shown in Fig. 8.

Figure 8 shows type 1: collision between main and secondary vehicles. When the main vehicle moved along the track, the secondary vehicle would enter the front of the

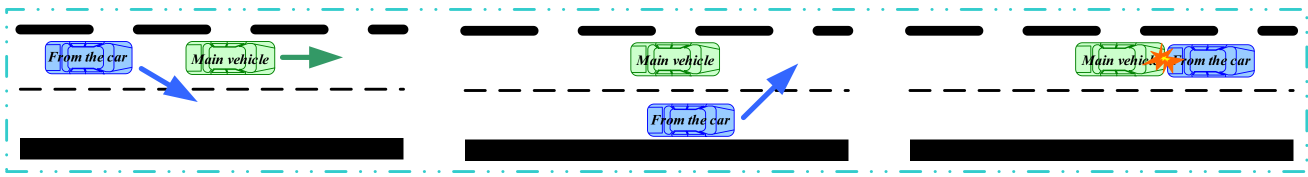


Fig. 8 Key scenarios for type 1

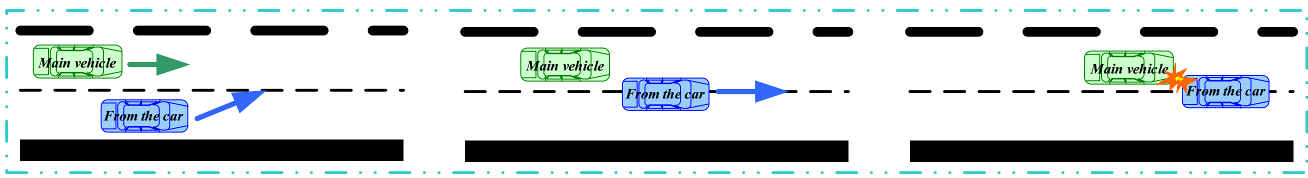


Fig. 9 Key scenarios for type 2

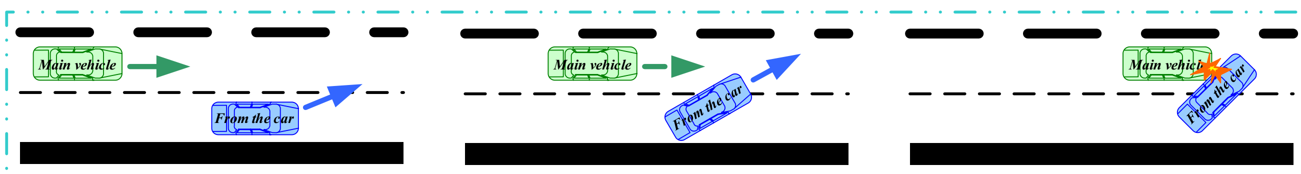


Fig. 10 Key scenarios for type 3

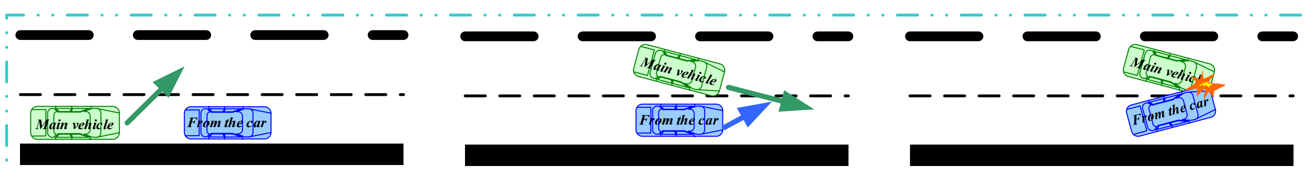


Fig. 11 Key scenarios for type 4

main vehicle in a short period of time, and then broke, resulting in a rear collision accident of the auto drive system. Through analysis, it was found that due to the inability of the main vehicle's warning module to alert the overtaking intention of the secondary vehicle, the main vehicle did not slow down in a timely manner during driving, resulting in a rear-end collision with the vehicle. Type 2 is shown in Fig. 9.

Figure 9 shows type 2: side collision between the main vehicle and the secondary vehicle. After analysis, it was found that the secondary vehicle was occupying the main driving lane. Although the main driving perception module can detect the position of the secondary vehicle, it cannot accurately identify the size of the secondary vehicle, resulting in scratches. Type 3 is shown in Fig. 10.

Figure 10 shows type 3: the main vehicle was driving along the lane separation line, and the secondary vehicle collided with the adjacent vehicle due to deceleration. Through analysis, the prediction module made incorrect predictions about the trajectory of the secondary vehicle and identified the trajectory of the secondary vehicle in the lane on the right side of the main vehicle. Based on the current speed of the second train, a prediction was made on whether the second train can achieve lane changing. However, the speed of the second car suddenly decreased, so when the second car reached the main driver's lane, it is already late, and a collision would occur. Type 4 is shown in Fig. 11.

Figure 11 shows type 4: collision caused by overtaking of the main vehicle. Through analysis, the main vehicle perception module perceived that the next vehicle ahead was stationary, and the planning module re-planed the current path. After receiving the overtaking command, the control module performed overtaking, and the original stationary state in the secondary vehicle changed to a lane change. However, the collision occurred due to the failure to update the path planning in a timely manner. Type 5 is shown in Fig. 12.

Figure 12 shows type 5: two secondary vehicles collided while changing lanes to the front of the main vehicle road at the same time, next to the main vehicle. Through analysis, it was found that although the decision-making module correctly recognized the motion trajectory of the secondary vehicle based on the perception of the main vehicle, it did not accurately identify the size of the vehicle. Therefore, although the vehicle slowed down, it still collided with one of the secondary vehicles. Type 6 is shown in Fig. 13.

Figure 13 shows type 6: the main vehicle collided with the secondary vehicle during deceleration and cutting during the following process. Through analysis, it was found that the perception module of the driver's vehicle detected that the vehicle ahead was changing lanes. The prediction module determined whether the vehicle ahead can complete the lane change process quickly based on the current vehicle's driving speed, direction, etc., while the planning module failed to update the vehicle's driving trajectory in a timely manner, resulting in vehicle collisions. Type 7 is shown in Fig. 14.

Figure 14 shows type 7: two secondary vehicles driving in front of the main vehicle. Secondary vehicle 1 was located in the lane adjacent to the main vehicle, while secondary vehicle 2 was located in the same lane as the main vehicle. When secondary vehicle 1 was inserted between secondary vehicle 2 and the main vehicle, a collision occurred. After analyzing the main vehicle, the perception module mistook the two secondary vehicles for one and identified a part of secondary vehicle 1 and 2 as the same, resulting in a collision. Type 8 is shown in Fig. 15.

Figure 15 shows type 8: when the main vehicle was following and the previous secondary vehicle was constantly changing lanes, a collision occurs. Through the analysis of the dynamic changes of secondary vehicles, it was found that the prediction model of the main vehicle cannot accurately predict secondary vehicles when the dynamic changes of the vehicles were significant. At the same time, due to the inability of the positioning module to accurately determine the position of the secondary vehicle, the planning module cannot timely draw the distance from the previous vehicle, resulting in collisions between the main vehicle due to insufficient avoidance time. Type 9 is shown in Fig. 16.

Figure 16 shows type 9: three cars were moving forward on the same lane, with the main car behind them. The secondary vehicle 1 following in the middle temporarily changed lanes, resulting in a collision between the

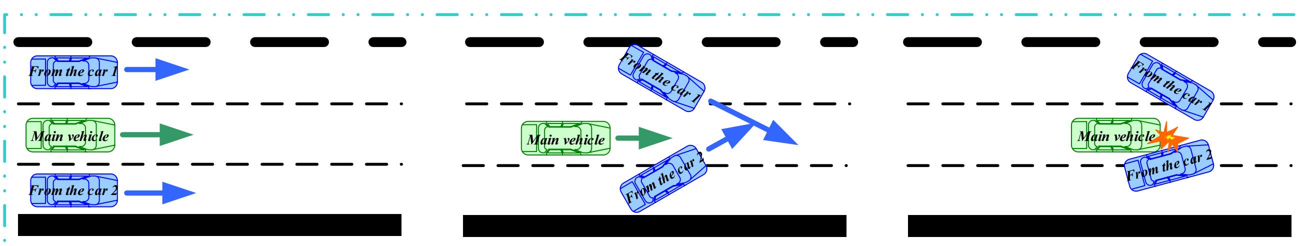


Fig. 12 Key scenarios for type 5

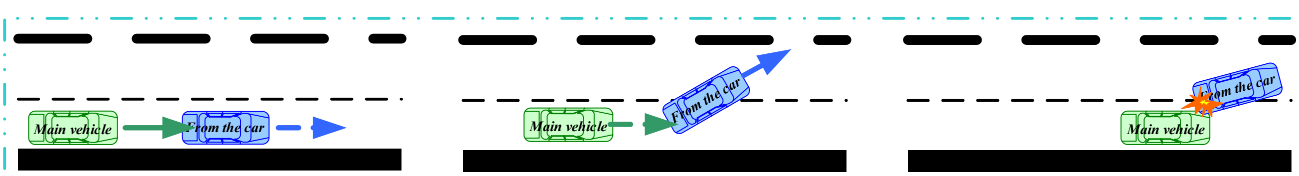


Fig. 13 Key scenarios for type 6

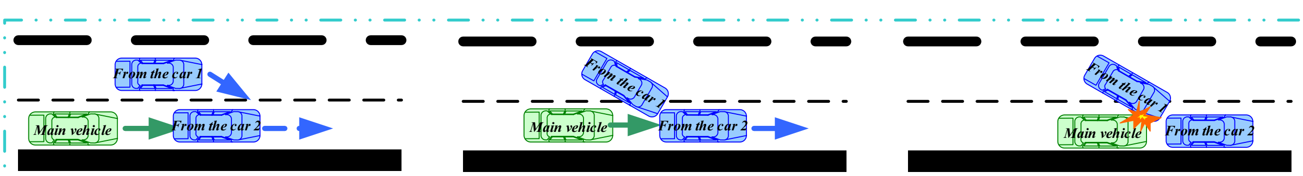


Fig. 14 Key scenarios for type 7

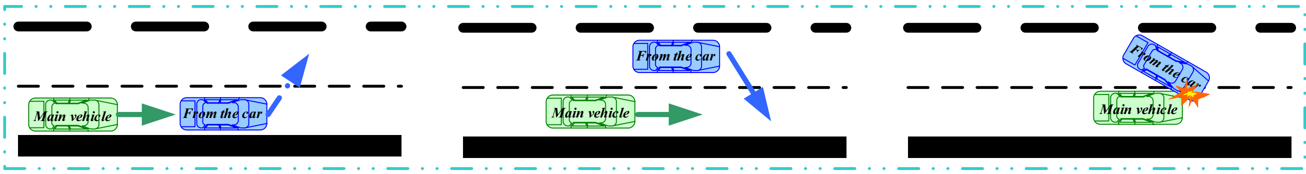


Fig. 15 Key scenarios for type 8

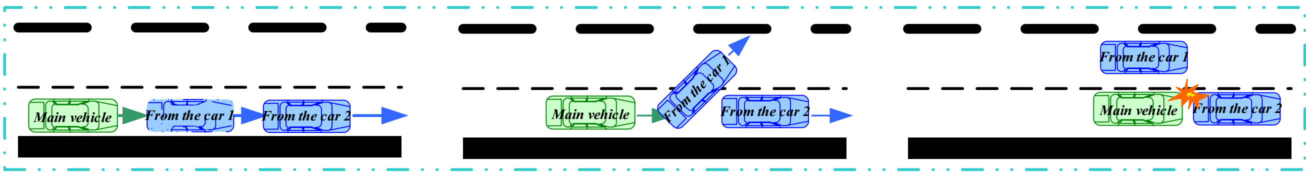


Fig. 16 Key scenarios for type 9

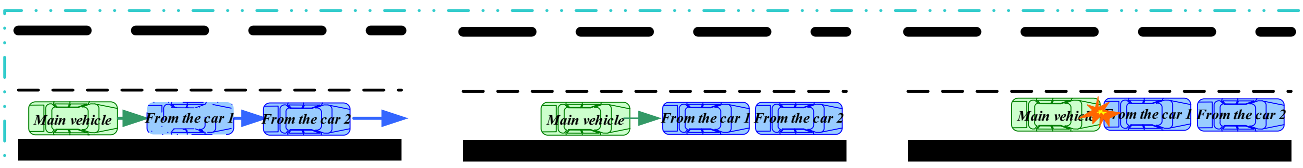


Fig. 17 Key scenarios for type 10

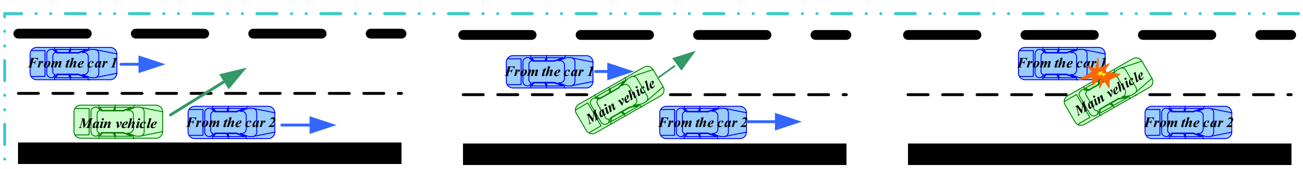


Fig. 18 Key scenarios for type 11

main vehicle and the secondary vehicle. According to the analysis, the perception module of the main vehicle could perceive the foremost secondary vehicle 2 due to being obstructed by secondary vehicle 1, but it also did not maintain a distance from secondary vehicle 1. So, if the secondary vehicle changes lanes and the speed of the secondary vehicle is faster than the speed of the secondary vehicle, a collision would occur when the speed of the secondary vehicle slows down. Type 10 is shown in Fig. 17.

Figure 17 shows type 10: three cars collide with each other repeatedly while driving in a straight line on the same lane. After analysis, it was found that this was because the car did not maintain sufficient safety distance. Therefore, during the emergency braking of the second car 1, although the main car had already detected the emergency braking of the previous second car 1, the braking distance between the main car and the previous car was too small, resulting in a collision. Type 11 is shown in Fig. 18.

Figure 18 shows type 11: the main vehicle attempted to overtake the secondary vehicle 2, but collided with the secondary vehicle 1 on the left lane. According to analysis, when the main vehicle operation planning module replanned the overtaking route, the secondary vehicle 1 on the adjacent lane accelerated due to the perception module not updating in a timely manner, resulting in delayed path planning and ultimately a collision.

3.3 Scenarios Under Autonomous Driving

Based on the eleven key scenarios generated in the previous text, this article analyzed these eleven key scenarios using Euclidean distance. In Euclidean distance, the larger the distance, the greater the difference in key scene types. Figure 19 shows the Euclidean distance analysis between key scenarios of each type and their respective types. The horizontal axis represents the key scenarios of each type, and the vertical axis represents the Euclidean distance (m).

Through the Euclidean distance results in Fig. 19, it can be analyzed that there was a minimum Euclidean distance of 33 m between type 2 and type 3, which also indicated that the scene difference between type 2 and type 3 was the smallest; there was a maximum Euclidean distance of 91 m between type 6 and type 11, indicating that the scene difference between type 6 and type 11 was the greatest. The average Euclidean distance between different types of scenes was 73.225 m. Through the Euclidean distance between different scenes, it can also be concluded that there were differences and no completely consistent scenes among different scene types. Through genetic algorithm and Euclidean distance analysis, it is revealed that most drivers prefer a conservative automatic driving style, which provides substantial guidance for system optimization.

4 Discussion

It is very important to create a computer simulation vehicle driving simulation system through virtual reality technology and algorithm optimization. The system not only provides a highly realistic driving experience but also can personalize and simulate the driving style to meet the needs of different drivers. Different drivers have obvious differences in driving styles, and these styles are relatively stable for a period of time. This provides a strong support for the personalized customization of the automatic driving system, and the automatic driving strategy can be adjusted according to the driver's preferences and habits. By using genetic algorithm and Euclidean distance analysis, we successfully classified different driving scenarios and found that most

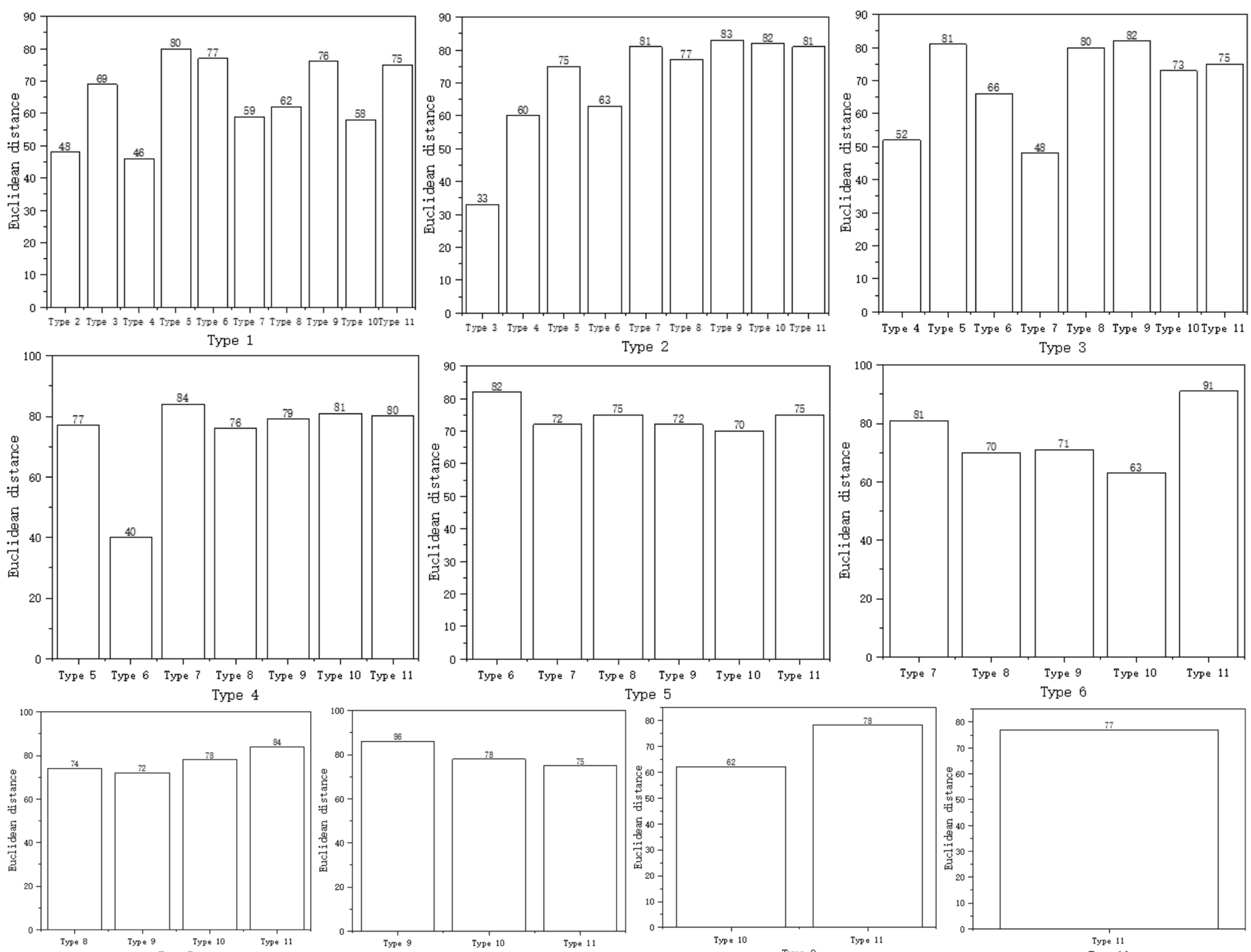


Fig. 19 Euclidean distance between different key scenarios

drivers prefer a conservative autonomous driving style. This provides guidance for the development of automatic driving system in the future, which can better adapt to the diverse driving situations in the real world and improve safety and performance. Through virtual reality technology and algorithm optimization, this paper successfully improves the performance of computer-simulated vehicle driving simulation system. It is found that most drivers prefer a conservative autonomous driving style, which provides guidance for future system development. This paper provides personalized driving experience with high fidelity through collaborative optimization of virtual reality technology and algorithm. Compared with the previous studies, this study deeply explores the driver's preference and stable driving style, and provides a new perspective for the development of automatic driving system. The successful application of genetic algorithm and Euclidean distance analysis makes the scene classification more accurate and provides empirical support for system adjustment. This research result is expected to promote the development of automatic driving system in a direction closer to the individual needs of drivers and improve safety and performance in diversified driving situations.

5 Conclusions

This article analyzed and introduced the algorithm optimization of the simulated vehicle driving simulation system. Under the algorithm optimization of the simulated vehicle driving simulation system, by introducing the optimization of virtual scene generation algorithm, vehicle physical model optimization, intelligent driving algorithm optimization, and user experience optimization, it was understood that when improving the virtual scene generation algorithm, the main purpose is to improve the scene rendering speed and realism. When optimizing vehicle physical model algorithms, the main purpose is to improve the authenticity and stability of driving simulation. When optimizing intelligent driving algorithms, the main purpose is to enhance the autonomous decision-making and intelligent interaction capabilities of the driving simulation system. When optimizing user interaction and feedback mechanisms, the main goal is to improve user experience and learning outcomes. In the experimental analysis section of the article, it was found that among the two styles of radical and conservative driving, people tend to prefer the conservative style of autonomous driving. In the genetic algorithm-based autonomous driving simulation testing method, key scenarios were divided into 11 different types and analyzed for these 11 types of scenarios. At the end of the article, Euclidean distance analysis was also conducted on key scenarios, and it was found that there is this difference between scenarios. In this paper, the computer simulation vehicle driving system is improved by virtual reality technology and algorithm optimization, and the automatic driving simulation test is carried out by genetic algorithm, and 11 key scenarios are analyzed. The results show that most drivers prefer a conservative autopilot style. This study provides an in-depth understanding of the performance and user experience of driving simulation system and provides guidance for the development of automatic driving systems in the future. Compared with traditional research, this study deeply discusses the driver's preference and stable driving style, which provides a new perspective for the development of automatic driving systems. This paper provides innovative ideas for the optimization of virtual reality technology and genetic algorithm in driving simulation systems. Its personalized driving experience and scene classification method provide empirical guidance for the development of the automatic driving system, which is expected to improve the adaptability of the system in diversified driving situations and promote the safety and performance of intelligent transportation systems. This research result lays a foundation for the practical application of autonomous driving technology in the future. The small number of people surveyed in the article may affect the representativeness of the results. There is a lack of in-depth discussion on the specific implementation details of virtual reality technology and genetic algorithms. Future research can expand the sample size and explore the technical implementation methods in more detail.

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Data Availability The data of this paper can be obtained through the email to the authors.

Declarations

Conflicts of Interest The authors declare no conflict of interest.

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