Research on Safety Testing Method for Autonomous Driving Based on Visual System in Complex Urban Road Conditions

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Abstract

With the rapid development of autonomous driving technology, its safety issues have increasingly attracted attention. Through in-depth analysis of autonomous driving technology, this paper focuses on combing the role of the Vision System in the autonomous driving system architecture, and points out its key position in information perception, environmental modeling, and decision planning. The existing safety test methods are systematically evaluated, and their limitations in adapting to rapidly changing driving environments are identified. Aiming at the specific needs of the visual system, a new safety test method framework is proposed, covering Data Preparation, Testing Process, Evaluation Metrics and other aspects. It provides a new theoretical basis and practical guidance for autonomous driving safety testing assisted by the visual system, and promotes the further development of this field.

Keywords Autonomous Driving; Security; Testing Methods; Accident Vision

1 Introduction

With the rapid advancement of science and technology, autonomous driving technology has gradually become an indispensable part of modern transportation systems, especially in the context of Intelligent Transportation System and Smart City construction. The application prospect of autonomous driving is becoming more and more important [1]. However, with the widespread application of this technology, the accompanying safety issues have become increasingly prominent, triggering widespread concern in academia and industry. Research on autonomous driving safety test methods in complex urban traffic scenarios has become an important issue that researchers and engineers urgently need to solve [2].

2 Overview of Autonomous Driving Technology

Autonomous driving technology integrates sensors, computer vision, artificial intelligence, and control systems to realize autonomous vehicle driving. Its core includes environmental perception, decision planning and control execution. Autonomous driving technology has great potential in improving traffic efficiency, reducing accidents, and promoting the development of smart cities. In the future, it is expected to be widely used in passenger cars, commercial vehicles, and specific fields. In order to adapt to the increasingly complex urban traffic conditions, the research on safety testing technology of autonomous driving technology is particularly important.

3 Application of Vehicle-Road Collaboration and Visual System Fusion in Autonomous Driving

In the development of autonomous driving technology, the visual system, as a key sensor, plays a vital role in realizing vehicle-road collaboration. It captures information about the surrounding environment through cameras, and uses image processing algorithms to analyze this information, so as to realize the recognition and tracking of other vehicles, pedestrians, traffic signs and obstacles. Specifically, as follows:

3.1 The Role of the Vehicle End

Environmental perception and target recognition: It can identify the driving state, distance, speed, etc. of the vehicle in front, and provide a basis for following, overtaking and other operations. It can also detect pedestrians, traffic signs and traffic lights, such as reminding vehicles in time when pedestrians cross the road, and making accurate responses to red lights, speed limit signs, etc., to ensure driving safety and compliance.

Lane detection and keeping: Recognize lane lines, help vehicles keep driving in the lane, and enable vehicles to accurately drive along the lane in complex road sections such as curves and forks, reducing lane departure, deviation and other situations, and reducing the risk of traffic accidents.

Auxiliary automatic driving decision-making: Provide rich visual information for the automatic driving system, such as identifying obstacles and construction areas on the road, so that the vehicle can plan the route in advance and make decisions such as deceleration and avoidance, thereby improving the reliability and safety of automatic driving.

3.2 The Role of the Roadside

Traffic flow monitoring: The visual recognition system installed at intersections or road sections can monitor traffic flow, vehicle type, speed, etc., provide data support for traffic management, help optimize traffic signal timing, and alleviate congestion.

Event detection and early warning: It can monitor abnormal events such as traffic accidents and vehicle breakdowns in real time, and notify the traffic management department and nearby vehicles in time, which is convenient for rapid processing and reduces the impact on traffic.

Interaction and collaboration with vehicles: The road-side visual recognition system transmits the recognized information, such as road conditions ahead, traffic control information, etc., to the vehicles through the Internet of Vehicles technology, assisting vehicles to make better decisions and realizing efficient collaboration of vehicle-road information.

Visual recognition technology plays a vital role in vehicle-road collaboration, but it also faces many difficulties.

Firstly, at the technical level, the visual recognition and perception accuracy of vehicle-road collaboration is affected by the external environment. In case of heavy rain, thick fog, and heavy snow, the accuracy of the visual system will be significantly reduced. At the same time, complex environments, such as road construction and a large number of obstacles, will also interfere with the visual system's recognition of targets, resulting in inaccurate or missing information.

Secondly, the visual systems and vehicle-road collaboration equipment of different manufacturers have differences in interfaces, protocols, etc., making it difficult to achieve seamless connection and collaborative work, and there are system compatibility and interoperability problems.

Thirdly, the data collected by the visual system involves the privacy of vehicles and pedestrians. If security measures are not in place during data transmission, storage and use, it is easy to cause data leakage and lead to security risks and privacy issues.

4 Research on Automatic Driving Safety Test Methods

Under the background of the increasing development of autonomous driving technology, the safety test related to it has become more and more important [5]. Due to the complexity of the ADS (Automated Driving System) and the dynamic and changeable environmental characteristics, its safety not only involves the evaluation of single technical parameters, but must comprehensively consider the interaction between people and vehicles, and the relationship between vehicles and the environment [6]. The accident rate is an important indicator to measure the safety of autonomous vehicles. According to statistics, although autonomous driving technology has shown potential in reducing the accident rate, once a system failure or decision-making error occurs, the consequences may be more serious. Therefore, timely and comprehensive safety testing is undoubtedly the prerequisite and foundation for ensuring public safety.

4.1 Analysis of Existing Test Methods

With the increasing maturity of autonomous driving technology, safety test methods are diversified and have become the core link to evaluate the reliability of autonomous driving systems [7]. This section will deeply analyze the different methods currently used in autonomous driving safety testing, and explore their advantages, disadvantages and shortcomings in practical applications, which will provide data support and theoretical basis for proposing new methods later [8].

For the detection accuracy of the autonomous driving system, using test automation technology, the accuracy of the test reaches 90.55% [9]. The acquisition of this data reflects the excellent performance of the system in environmental perception under specific test conditions. However, it is worth noting that although the accuracy rate is high, the accuracy rate may be affected by various factors in actual deployment, such as changing weather conditions, different road complexity, and the degree of sensor optimization. At the same time, the detection accuracy of the autonomous driving system has increased by 3%, which shows that the system has made certain progress in actively adapting to environmental changes and continuously optimizing algorithms. Continued investment in algorithm optimization and hardware upgrades in the future will be the key to improving the accuracy of the system.

The false detection rate of the system needs to be carefully evaluated. The data shows that the false detection rates are 19.67%, 7.52% and 22.05% respectively [11]. A high false detection rate may lead to frequent false warnings from the system, which will affect the safety and convenience of automatic driving. Therefore, in the process of visual algorithm training and optimization, we must pay attention to the accuracy and diversity of data to reduce false detection and improve the reliability of the overall system.

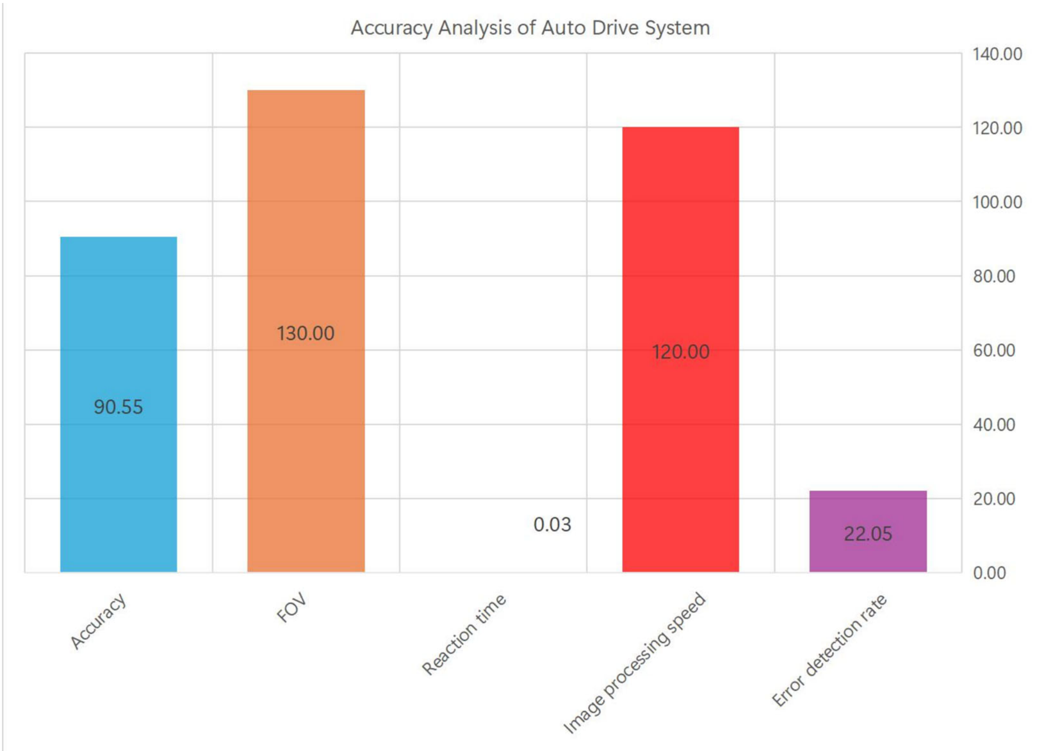

Fig. 1. Analysis of Detection Accuracy of Autonomous Driving System

The FOV (Field of View) of the visual system is another important safety test parameter. In this study, the FOV data is quantified into multiple different values such as 30°, 60°, 100°, 130°and 190° [10]. The breadth of the FOV directly affects the perception ability of the autonomous driving system to the surrounding environment. A larger range of FOV enables the system to more comprehensively identify potential obstacles and driving risks. However, the expansion of the field of view may introduce a large amount of irrelevant information, thereby affecting the accuracy and response speed of recognition. Therefore, how to balance the detection range and information processing efficiency when designing a visual system is an urgent technical challenge to be solved.

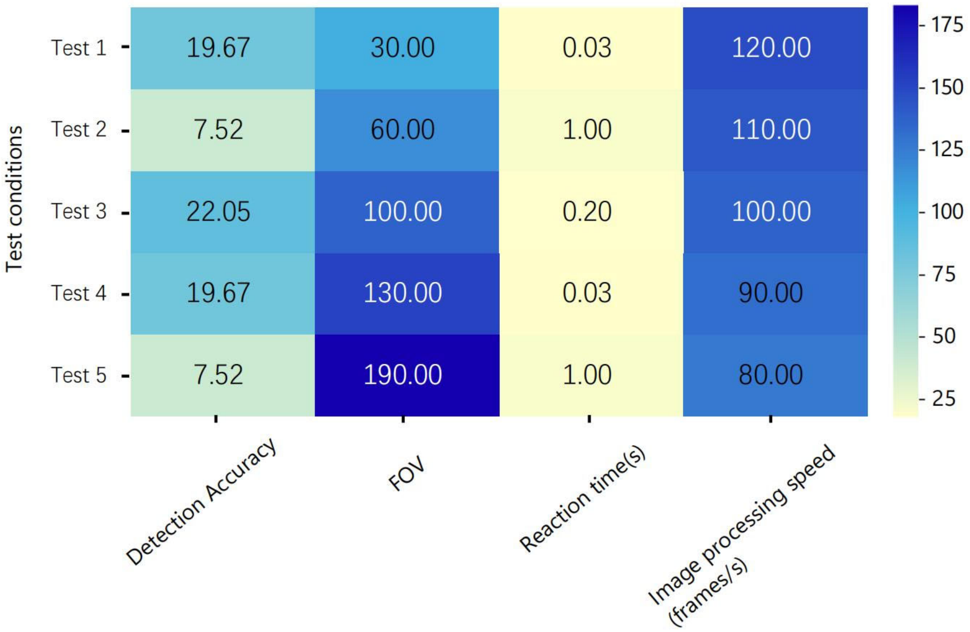

Fig. 2. Visual System Field of View and Impact

On the Response Time index, the system shows response times of 0.03 seconds, 1 second and 0.2 seconds, showing its important role in real-time performance. For autonomous driving systems, a very short response time is obviously more ideal. The rapid response mechanism can not only improve driving safety, but also enhance the comfort of passengers. It should be noted that the optimization of response time needs to find an appropriate balance between algorithm efficiency and computing resources to avoid resource waste and computing bottlenecks.

The automatic driving visual processing speed is another key indicator that cannot be ignored. In this study, the image processing speed of the system reaches different heights, including 120, 110, 100, 90 and 80 frames/second. A higher image processing speed means that the system can be more agile when dealing with complex and changeable road conditions information. However, it should be pointed out that when facing fast-moving scenes, whether the improvement of image processing speed can timely support decision-making will directly affect the safety of the vehicle.

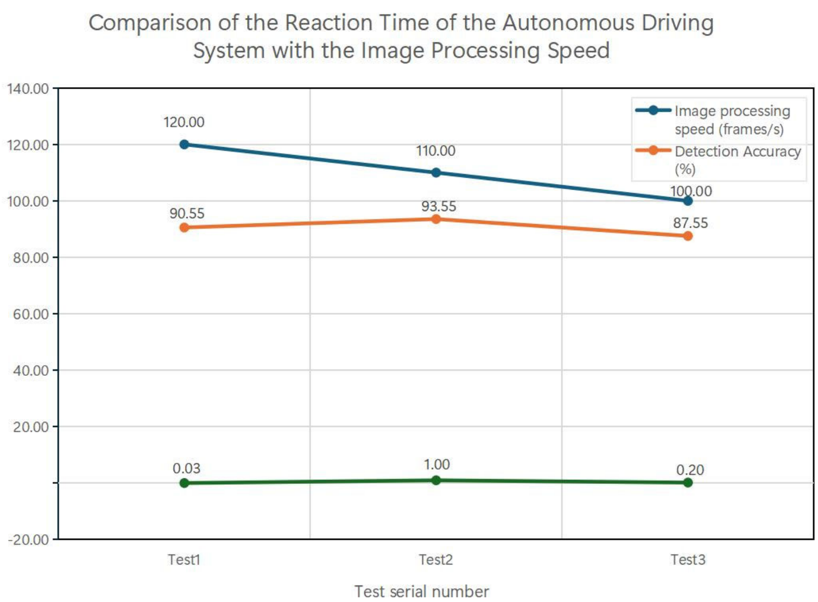

Fig. 3. Comparison of Reaction Time and Image Processing Speed of Autonomous Driving System

Although the current autonomous driving safety test methods have certain theoretical and practical basis, they still face many challenges, such as the improvement of accuracy, the optimization of FOV and processing speed, the reduction of reaction time and the control of false detection rate. Future research should focus on overcoming the shortcomings of existing methods through continuous iteration of algorithms and technological innovation, so as to realize safer and more efficient autonomous driving technology.

4.2 Discussion on Vehicle-road Collaboration Based Visual System Test Method

In order to comprehensively and deeply explore the automatic driving safety test method of visual system in complex vehicle-road collaboration scenarios, it is necessary to clarify the key role and function of the visual system in automatic driving first [12]. Modern autonomous vehicles usually rely on a variety of sensors to acquire environmental information, among which visual sensors (such as cameras) are responsible for identifying and classifying the target objects in the environment (such as pedestrians, vehicles, traffic signs, etc.). Therefore, effectively evaluating the accuracy and reliability of the visual system, as well as its performance in complex environments, is the basis for improving the safety of autonomous driving [13].

This study shows that the target recognition rate of the visual system shows significant differences in different environments and conditions [14]. The business meaning behind these data can be analyzed from multiple dimensions.

5 Design of Visual System Based Safety Test Method

In the field of modern intelligent transportation, the development of autonomous driving technology has aroused widespread attention and research [15]. The core of this technology lies in the realization of safe and reliable control of vehicles in complex traffic environments through various sensors and algorithms. The importance of its safety test, especially in the automatic driving visual system, has become increasingly prominent [16]. With the rapid development of deep learning and computer vision technology, the safety test method of the automatic driving visual system urgently needs to be updated and optimized according to the characteristics of emerging technologies [17].

In the architecture of the automatic driving visual system, the data acquisition module is responsible for real-time acquisition of environmental information, while the information processing module processes the data from sensors (such as cameras and lidar) through image recognition, object detection and other technologies [18]. However, the effectiveness and stability of these technologies may face many challenges in different lighting conditions, weather factors and complex traffic conditions. Therefore, the safety test method not only needs to test the accuracy of the algorithm but also needs to verify its Robustness under various uncertain factors.

5.1 Test Data Preparation

Table 1. Overview of Automatic Driving Safety Test Method Framework Based on Visual System

Module	Technology	Test method	Evaluation index
Data acquisition	Information processing		
Visual system	Camera, lidar	Image recognition, target detection Hybrid test	Accuracy, robustness, scene adaptability
Safety test		Algorithm evaluation	Scene adaptability
Test environment	Simulation environment	Simulation evaluation	Performance
	Real environment	Comprehensive test	Environmental adaptability
Data analysis	Real-time data feedback	Dynamic adjustment	Safety standard

In order to systematically discuss the implementation path of the automatic driving safety test method, this paper starts with the necessity of safety test, analyzes the existing test methods and identifies their limitations. The existing methods often rely on the simulation environment for testing, which may not be able to fully reflect the complexity of the real scene. For example, evaluating the performance of the visual system only through simulation may not be able to capture the problems of visual information loss or misidentification that may occur in extreme cases. Therefore, it is particularly important to explore a comprehensive test scheme based on the Real-World Scenario.

Next, the test method of the visual system is discussed, and a hybrid testing strategy is suggested, that is, combining simulation test and real vehicle test. By designing a comprehensive test framework, including test data preparation, test process and evaluation index, the reliability and safety of the visual system in different scenarios can be evaluated more effectively. This framework should be able to cover multi-dimensional tests from static scenes to dynamic scenes, so as to ensure that the impact of different environmental factors on the visual system can be fully evaluated. For example, in a specific urban traffic environment, a real scene test including obstacles, pedestrians and other vehicle driving conditions can be designed to verify the adaptability of the automatic driving system under complex conditions.

Finally, the design of the visual system-based safety test method is not only limited to the construction of the theoretical framework, but should constantly optimize the test strategy through a large amount of data analysis and feedback of experimental results. At the same time, combining with advanced artificial intelligence technology in the field, it is helpful to improve the intelligence and comprehensiveness of the test, so as to ensure that the driving safety during automatic driving reaches a higher standard. When carrying out future research, we should deeply explore how to use real-time data to dynamically adjust the test strategy, so as to cope with the rapid changes in technology development.

5.2 Test Process and Evaluation Index

In the field of autonomous driving, the design of safety test methods based on visual system is a key link to ensure the efficient and safe operation of autonomous driving vehicles [19]. For the establishment of the test method framework, it is necessary to construct a systematic evaluation index and process to ensure that the visual system shows the expected safety and reliability in complex environments [20]. The following content will systematically analyze the various steps of the test process, and discuss in detail the evaluation indexes that need to be defined, so as to comprehensively evaluate the safety performance of the visual system in different scenarios.

Multi-dimensional evaluation index system

According to the evaluation index system and systematic test process framework designed for the safety test of the automatic driving visual system, refer to the functional safety standard conforming to ISO 26262 and the automatic driving grading requirements of SAE J3016:

Table 2. Evaluation Index System of Automatic Driving Safety Coefficient

No.	Test items	Index	Value
1	Perception ability benchmark	Target detection confidence	≥98% @100m
		Continuous frame accuracy of multi-target tracking	F1-score≥0.95
		Intersection ratio of semantic segmentation	IoU≥0.85
		Lane line detection lateral deviation	≤15cm@80km/h
2	Depth of environmental understanding	Light adaptation	10^5 lux dynamic range coverage
		Extreme weather recognition retention rate	≥85% in rain, fog and snow scenes
		Road topology reconstruction accuracy	3D positioning error ≤0.1m
		Dynamic object intention prediction accuracy	Pedestrian / vehicle ≥92%
3	Fault response ability	Monocular failure compensation time	＜200ms
		Sensor pollution recovery ability	Function retention rate when 50% of dirt is covered
		Data conflict arbitration success rate	≥99.9% in multi-sensor fusion scene
4	Boundary condition processing	Tunnel light and dark transition adaptation time	＜0.5 seconds
		Strong light glare suppression ability	Retain effective pixels ≥80%
		Extreme weather penetration coefficient	Detection distance when the visibility of thick fog is 50m
5	Continuous operation stability	24-hour continuous operation attenuation rate	Performance degradation ≤3%
		Thermal defocus compensation ability	-30℃~85℃ temperature drift compensation accuracy
		Vibration environment robustness	Function integrity under 5-500Hz random vibration
6	Safety redundancy mechanism	Consistency of heterogeneous algorithm cross-validation	≥99.5%
		Spatiotemporal synchronization fault tolerance threshold	Clock offset ＜1ms
		Effectiveness of emergency state downgrade strategy	L3→L2 transition success rate
7	Interpretability measurement	Visual decision visualization confidence	Driver understanding ≥90%
		Risk prediction advance amount	Warning time of dangerous scene ≥2.5 seconds
		Clarity of takeover request	Multi-modal prompt misreading rate ≤1%

1）Perception ability benchmark test method

Target detection confidence test: On a long straight test road, place multiple different types of targets (such as vehicles, pedestrian dummies, etc.) at a distance of 100m. The autonomous driving vehicle travels at a specified speed, and the detection device is used to record the detection of the target by the vehicle sensor, and the proportion of the number of targets with the target detection confidence ≥98% to the total number of targets at this distance is calculated.

Continuous frame accuracy of multi-target tracking: In a simulated urban traffic scene, set up multiple moving targets (such as multiple driving vehicles, multiple walking pedestrians, etc.). During the driving of the autonomous driving vehicle, continuous frame images or data are collected. By comparing the tracking results of the algorithm with the actual target position, quantity and other information, the F1-score value is calculated to evaluate the continuous frame accuracy of multi-target tracking.

Intersection ratio of semantic segmentation: Construct a variety of scene elements (such as roads, buildings, vegetation, vehicle etc.). Collect continuous frame images or data during the driving of the autonomous driving vehicle and calculate the IoU value by comparing the segmentation results of the algorithm with the actual image information to evaluate the accuracy of semantic segmentation.

Lane line detection lateral deviation: Clear lane lines are set up on a standard test road. The autonomous vehicle drives at a speed of 80 km/h, and its actual position relative to the ideal lane line position is recorded in real-time using high-precision positioning equipment (such as differential GPS). The lateral deviation between the two positions is then calculated.

2) Environmental Understanding Depth Test Method

Lighting Adaptability: In a lighting laboratory, simulate various lighting conditions ranging from very low light (such as 0.1 lux) to extremely high light (10^5 lux). The autonomous vehicle is driven in the simulated environment to test the impact of different lighting conditions on the vehicle's sensors and algorithms, particularly for target detection, recognition, and other functions. The test verifies whether the system can cover the dynamic range of 10^5 lux.

Extreme Weather Recognition Retention Rate: In a climate simulation test field, extreme weather scenarios such as rain, fog, and snow are simulated. The autonomous vehicle drives in each of these scenarios, recording its ability to recognize the road, objects, and other elements. The retention rate is calculated based on how well the recognition functions are maintained under extreme weather conditions.

Road Topology Reconstruction Accuracy: In a test area with a known accurate 3D map, the autonomous vehicle reconstructs the road topology in real time during its driving process. By comparing the reconstruction with the precise 3D map, the error in the vehicle's 3D localization is calculated to evaluate the accuracy of the road topology reconstruction.

Dynamic Object Intent Prediction Accuracy: In a simulated traffic scenario, multiple dynamic objects (such as pedestrians and vehicles) are set up, moving according to different behavior patterns (e.g., normal driving, lane change, turning, sudden acceleration/deceleration, etc.). The autonomous vehicle predicts the intent of these dynamic objects in real time, comparing it with their actual behavior, and calculates the accuracy of the intent prediction for pedestrians/vehicles.

3) Fault Response Capability Test Method

Monocular Failure Compensation Time: During the test, the monocular camera of the autonomous vehicle is deliberately disabled (e.g., by obstruction, power failure, etc.), and a high-precision timer is started. When other sensors or algorithms of the vehicle compensate for the monocular camera's function and restore normal target detection and other functionalities, the timer is stopped, and the monocular failure compensation time is recorded.

Sensor Contamination Recovery Ability: Special materials are used to simulate dirt, covering 50% of the vehicle's sensor surfaces (e.g., cameras, radars, etc.). The vehicle then drives through a simulated road scenario. The performance of the sensors before and after contamination is compared (e.g., target detection quantity, accuracy, etc.), and the functionality retention rate is calculated.

Data Conflict Arbitration Success Rate: In a multi-sensor fusion test scenario, sensor data conflicts are deliberately created (e.g., when different sensors have significantly different detection data for the same target). The vehicle's data fusion and arbitration algorithms process the conflicting data, and the success rate of data conflict arbitration is calculated by determining the ratio of successful conflict resolutions to the total number of conflicts.

4) Boundary Condition Handling Test Method

Tunnel Light Transition Adaptation Time: On a test route that includes a tunnel, the autonomous vehicle drives at a specified speed into and out of the tunnel. Using high-precision sensors and a timer, the time it takes for the vehicle to adapt to the new lighting conditions and restore normal target detection (such as sensor and algorithm adjustment to the sudden change in light when entering the tunnel) is recorded, along with the similar adaptation time when exiting the tunnel.

Glare Suppression Ability in Strong Light: In a strong light simulation test environment, intense light sources are used to simulate scenarios such as direct sunlight or high beams from oncoming vehicles. The autonomous vehicle drives while facing this strong light, and its camera images are captured. The proportion of valid pixels (those that are not overexposed or disturbed by glare) in the image is analyzed, relative to the total number of pixels.

Extreme Weather Penetration Coefficient: In a dense fog simulation test field, visibility is set to 50 meters. The autonomous vehicle drives through the area, testing its sensors (such as radar, cameras, etc.) to determine the detection distance of objects ahead, thus assessing the extreme weather penetration coefficient.

5) Continuous Operation Stability

24-Hour Continuous Operation Degradation Rate: The autonomous vehicle is operated continuously for 24 hours in a simulated real-world road environment (such as a combination of city roads, highways, and various road conditions). Every certain period of time (e.g., 1 hour), various performance metrics (such as target detection accuracy, recognition rate, etc.) are recorded and compared with the initial performance metrics to calculate the degradation ratio, i.e., the degradation rate.

Thermal Defocus Compensation Ability: In a high and low-temperature test chamber, the autonomous vehicle is placed in a -30°C environment for a period of time to allow its sensors to reach thermal equilibrium. The thermal defocus of sensors like cameras and the vehicle's algorithm compensation are tested. Then, the temperature is gradually raised to 85°C, and the above tests are repeated to assess the thermal drift compensation accuracy at different temperatures.

Vibration Environment Robustness: The autonomous vehicle is placed on a vibration test bench and subjected to random vibration conditions in the range of 5-500Hz. During the vibration process, the functionality integrity of the vehicle's sensors and autonomous driving system is tested (e.g., whether data loss or functional anomalies occur).

6) Safety Redundancy Mechanism Test Method

Heterogeneous Algorithm Cross-Validation Consistency: In the test scenario, the autonomous vehicle simultaneously runs two or more heterogeneous algorithms for tasks like target detection, decision-making, and planning. The output results of the different algorithms are compared, and the proportion of times the results are consistent is calculated, to evaluate the consistency of heterogeneous algorithm cross-validation.

Spatiotemporal Synchronization Fault Tolerance Threshold: In the test environment, artificial clock offsets are set between different sensors and system modules, starting from a small offset and gradually increasing. When the autonomous driving system experiences a functional anomaly (e.g., target detection errors, decision-making mistakes), the corresponding clock offset is recorded. The system's ability to meet the fault tolerance requirement of clock offset <1ms is then validated.

Emergency State Degradation Strategy Effectiveness: In a simulated emergency state scenario (e.g., severe sensor failure, system malfunction), the autonomous vehicle triggers its degradation strategy from L3 autonomous driving to L2 autonomous driving. The success of the degradation process is recorded (e.g., whether the driver can successfully take control, whether the vehicle maintains a safe state, etc.), and the proportion of successful L3→L2 transitions is calculated relative to the total number of tests.

7) Explainability Measurement Test Method

Visual Decision Confidence Visualization: Multiple experienced drivers are involved in the test. During the autonomous vehicle's drive, the vehicle's visual decision results (such as target detection boxes, decision paths, etc.) are shown to the drivers. After the test, through surveys or on-site questioning, the level of understanding of the visual results by the drivers is measured, and the understanding ratio is calculated.

Risk Estimation Lead Time: In simulated dangerous scenarios (e.g., sudden braking of a vehicle ahead, a pedestrian suddenly crossing), the autonomous vehicle monitors and estimates the risk in real-time. The time from when the vehicle detects the potential hazard to when the warning is issued is recorded, verifying whether the early warning time for dangerous scenarios meets the requirement of ≥2.5 seconds.

Takeover Request Clarity: In scenarios where a driver takeover is required, the autonomous vehicle issues a takeover request to the driver using multimodal methods, such as sound, images, and vibrations. Multiple drivers are invited to participate in the test, and the number of misinterpretations of the multimodal prompts by the drivers is recorded to calculate the misreading rate.

Full Lifecycle Testing Process

Based on the evaluation index system in Table 2, a corresponding system testing process is constructed. The specific steps are shown in the table below.

Table 3. Autonomous Driving Full Lifecycle Safety Coefficient

Step	Test Stage	Test Content	Test Procedure
1	Virtual simulation testing	Scenario library construction	1. Import OpenScenario standard format scenarios
			2. Create a matrix of 1000+ typical- edge- extreme scenarios
			3. Inject adversarial test samples (hallucination targets, optical attacks, etc.)
		Digital twin verification	4. Construct sensor physical models in CARLA/ESmini
			5. Perform Monte Carlo random testing
			6. Execute Fault Tree Analysis (FTA) and Failure Mode Analysis (FMEA)
2	Closed-Course testing	Dedicated test site verification	7. Deploy at CATARC/MIRA proving grounds
			8. Dynamic lighting corridor (flashing/gradient/glare)
			9. Multi-phase roads (dry/wet/ice surface alternation)
			10.Moving target system (variable speed/size/ trajectory)
		Real vehicle calibration test	11. Install high-precision RTK reference system
			12. Perform ISO 3888-2 double lane change test
			13. Conduct ECE R79 steering correction rate verification
3	Open road testing	Progressive road verification	14. Accumulate 100,000 kilometers of natural driving data collection
			15. Cover 10 climate zones (tropical rainforest-polar environment)
			16. Include 50+ special areas (schools/construction zones/tunnel groups)
		Shadow mode verification	17. Deploy non-intrusive data recording system
			18. Compare differences between human driver and system decisions
			19. Build a closed loop for scenario automatic mining, labeling, and regression testing
4	Certification and iteration	Safety certification preparation	20. Generate a SOTIF report compliant with the ISO/PAS 21448 standard
			21. Complete ASIL level (B-D) safety demonstration
			22. Prepare UNECE R157 type approval materials
		Continuous learning iteration	23. Establish an OTA data return channel
			24. Deploy federated learning update mechanism
			25. Implement dynamic risk assessment based on Bayesian networks

Key Innovations

Innovation 1: Extend traditional MIL/SIL/HIL testing to a "Digital Twin-Physical Domain-Real World" three-dimensional validation framework, constructing a multi-level verification model.

Innovation 2: Introduce GANs (Generative Adversarial Networks) to build an optical attack scenario library, establishing an adversarial testing mechanism.

Innovation 3: Real-time mapping of system capability boundaries based on deep reinforcement learning, creating a dynamic risk assessment model.

Innovation 4: Establish a mapping model between driver cognitive load and system explainability, quantifying human factors engineering relationships.

6 Conclusion

This paper provides a comprehensive analysis of the limitations of existing safety testing methods. While traditional simulation testing and real vehicle testing each have their advantages and disadvantages, neither can fully assess the safety of autonomous driving systems in complex scenarios.

Therefore, a comprehensive testing framework based on a hybrid testing strategy is proposed to more accurately evaluate the reliability and adaptability of autonomous driving vision systems. Additionally, by combining big data analysis and artificial intelligence technologies, a data-driven testing framework is established that can continuously optimize and improve safety testing methods to address the ever-changing traffic environment and technological challenges. Effective safety testing can significantly reduce accident rates and increase public trust and acceptance of autonomous driving technology, thus accelerating the application and widespread promotion of new technologies.

Additionally, this paper also delves into the safety testing technology framework based on vision systems, explaining how to improve the effectiveness of the vision system through comprehensive evaluation metrics under different environmental conditions. At the same time, the importance of diverse testing scenarios and evaluation standards is emphasized in the discussion of testing processes, particularly how advanced signal monitoring technologies and image recognition algorithms can be used for detection and recognition in dynamic scenarios. Ensuring the accuracy and credibility of the testing results will lay a solid foundation for the future safety of autonomous driving systems. By establishing an iteratively optimized feedback mechanism, dynamic adjustments to testing strategies and parameters can better adapt to technological advancements and changes in market demands.

Conflicts of Interest

The authors declare no conflicts of interest.

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基於車路協同與視覺識別融合的自動駕駛系統在復雜城市路況下的安全性評估測試方法研究

郭展威　　溫宇峰

摘要：隨著自動駕駛技術的迅猛發展，其安全性問題日益受到重視。通過對自動駕駛技術進行深入分析，重點梳理了自動駕駛系統架構中的視覺系統（Vision System）作用，指出其在信息感知、環境建模和決策規劃中的關鍵性地位。對現有安全性測試方法進行了系統的評估，並識別其在快速變化的駕駛環境中難以適應的局限性。針對視覺系統的特定需求，提出了一種新型的安全性測試方法框架，涵蓋了測試數據準備（Data Preparation）、測試流程（Testing Process）和評估指標（Evaluation Metrics）等多個方面。為視覺系統輔助下的自動駕駛安全性測試提供了新的理論基礎和實踐指導，推動了這一領域的進一步發展。

關鍵詞：自動駕駛；安全性；測試方法；指標體系