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Application of Machine Learning and Big Data Analysis in Intelligent Driving

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Abstract. With the development of artificial intelligence, sensor technology, and computing power, intelligent driving has evolved from theory to application. However, it faces challenges such as poor reliability of human driving, insufficient reliability of sensors in complex environments, the need to improve the real - time performance of decision - making systems, and user privacy protection. This paper systematically analyzes the technical bottlenecks of intelligent driving, expounds on the concept definition, technical evolution, and core driving forces of intelligent driving. It proposes solutions to problems such as insufficient perception reliability, a gap in decision - making real - time performance, and user privacy risks. The application of machine learning in enhancing perception reliability and decision - making efficiency is explored, and the technology integration and benefits in typical scenarios are evaluated. By comparing the research status at home and abroad, the future technology development direction is prospected, aiming to provide feasible ideas for improving the safety, stability, and user trust of autonomous driving systems.

Keywords: Intelligent driving, Machine learning, Big data analysis, Decision - making efficiency, Privacy protection

1. Introduction

With the breakthroughs in artificial intelligence, sensor technology, and computing power, intelligent driving has gradually shifted from theoretical research to practical applications. In this technological evolution, the problem of the reliability of human driving has never been fundamentally solved. According to the World Health Organization, among approximately 1.35 million traffic accident fatalities globally each year, about 94% of the accidents are caused by driver errors [1]. This shocking data indicates that using intelligent driving to assist or replace human driving behavior is a necessary choice to improve road safety.

However, there are still significant challenges to the development of intelligent driving technology. Firstly, complex environments lead to insufficient reliability of sensors. Research by MIT shows that heavy rain can increase the false detection rate of vision systems to 35% [2]. Secondly, the real - time performance of decision - making systems needs to be improved. Studies have shown that the decision - making delay of current autonomous driving systems (0.5 - 1.0 seconds) is significantly higher than the reaction time of human drivers (0.25 - 0.3 seconds) [3, 4].

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This gap may pose a safety hazard in emergency situations. Thirdly, user privacy protection faces severe challenges. A survey by the China Academy of Information and Communications Technology shows that 67% of users are concerned about the data security of autonomous driving [5]. This research systematically examines core challenges in intelligent driving—including environmental perception reliability, decision-making real-time performance, and data privacy protection—to propose interdisciplinary solutions. The findings will enhance safety redundancy in complex scenarios, optimize algorithmic response time, and establish robust data encryption frameworks. These advancements can reduce accident rates, accelerate commercialization.

2. Development patterns and driving forces of intelligent driving

2.1. Standards and development of intelligent driving technology

2.1.1. SAE J3016 standard

The SAE J3016 standard was formulated by SAE International and is a globally recognized classification standard for autonomous driving technology [6]. Its grade division is shown in Figure 1.

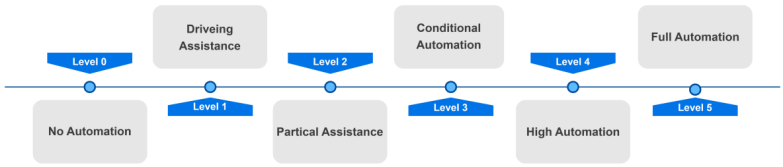

Figure 1: SAE J3016 standard

2.1.2. Comparative analysis of intelligent driving development: milestones, technical routes and regulatory frameworks

Milestones of Intelligent Driving in China (Fig.2): the policy foundation period (2010-2015), marking the initiation of industrial layout with "Made in China 2025" [7]; The period of technological explosion (2015-2020) was accompanied by the rise of new forces and breakthroughs in L3-L4 road tests. During the commercial implementation period (2020 to present), Robotaxi operations and a 40% penetration rate at L2 level have been achieved, forming a distinctive development path of "vehicle-road coordination". The specific time nodes are shown in Figure 2.

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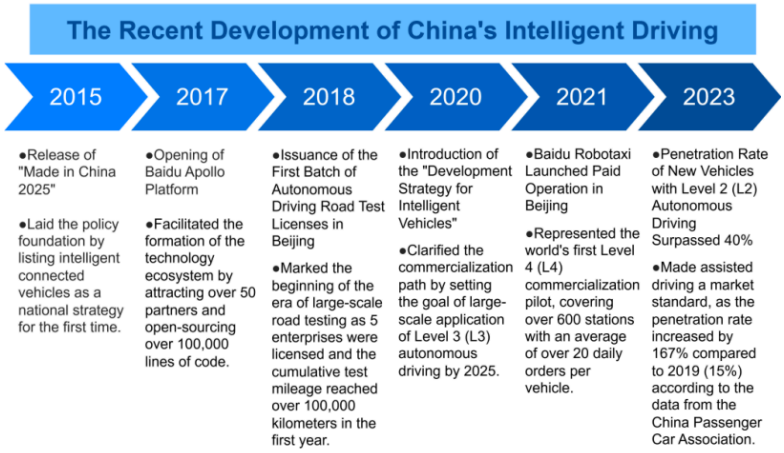

Figure 2: Key development nodes of modern intelligent driving in China

Milestones of Intelligent Driving in Foreign (Fig.3): The early exploration period (1920-1930), starting with the concepts of Houdina radio-controlled cars and electronic highways, laying the technical prototype [9,10]; During the introduction period of computer vision (1960-1980), the Shakey robot in the United States and the camera-driven self-driving car in Japan emerged successively [11,12]; During the period of technological breakthroughs and cooperation (1980-1990), the prototype vehicles of the NavLab series completed the historic test of crossing the United States [13]; During the leading period of technology companies (from 2000 to the present), Waymo, Tesla and other enterprises have driven commercial breakthroughs in intelligent driving. The specific time nodes are shown in Figure 3.

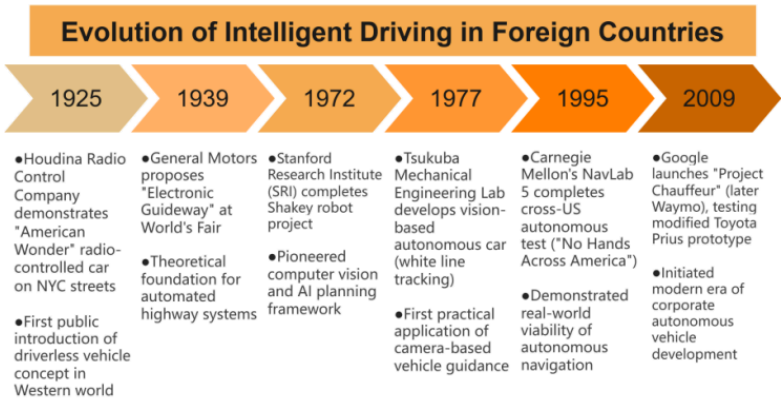

Figure 3: Key development nodes of intelligent driving in foreign countries

Technical Routes (Fig.4): International leaders like Waymo prioritize LiDAR-dominant perception and end-to-end deep learning, leveraging over 10 million miles of real-world testing for Robotaxi deployment [14]. Chinese counterparts (Baidu/Pony.ai) adopt multi-sensor fusion and modular hybrid architectures, focusing on simulation-based validation and V2X pilot projects. [15]

Autonomous Driving Research Comparsion

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Dimension	International(Waymo/Cruise)	China(Baidu/Pony.ai)
Perception Focus	LiDAR-dominat	Multi-sensor fusoin
Decision Architecture	End-to-end DL	Modular hybrid
Data Scale	10M+ miles road testing	Simulation/closed-course dominant
Deployment Model	Rabotaxi commercialization	V2X pilot projects

Figure 4: Comparison of intelligent driving research: domestic vs international

Regulatory Frameworks (Fig.5): The U.S. follows voluntary guidelines (NHTSA AV 4.0), while the EU enforces mandatory certification (UN-R157) [16,17]. China implements strict approval processes, requiring 3,000km closed testing under its 2023 ICLV rules [18].

International Comparison of Technical Regulation for Autonomous Driving

Category	US	EU	China
Key Regulation	NHTSA"AV 4.0" Framework	UN Regulation No.157	ICLV Access Administration
Regulatory Approach	Voluntary Guidelines	Mandatory Certification	Mandatory Approval
Testing Requirements	State-level Administration	Euro NCAP Certification	3,000km Closed Testing
Effective Data	2022	2021	2023

Figure 5: Comparative analysis of autonomous driving regulations in three jurisdictions

2.2. Core driving forces analysis

First, policy thrust. The United Nations' UN-R157 regulation represents a global milestone by establishing clear liability frameworks for L3 systems [19]. The second factor is market pull. Research from the MIT Times Lab shows that L2+ systems can reduce driver fatigue by more than 40%, which directly translates into a greater willingness of consumers to adopt and pay for these technologies[20]. Last, technological catalysis. in the recent computer vision benchmark test, through an innovative architecture that combines the bird 's-eye view perspective and the attention mechanism, the perception system achieved a significant accuracy rate of over 98% in complex scenes[21]. Meanwhile, the advancement of hardware has greatly accelerated the development cycle. The next-generation computing platform offers exascale performance (1.1 EFLOPS), reducing the typical model training time by 80%[22].

3. Key technical bottlenecks and demand analysis for intelligent driving

3.1. Challenges in extreme scenarios with insufficient perception reliability

Current intelligent driving systems face significant limitations in perception capabilities under complex environmental conditions. According to Waymo's test data, heavy precipitation can reduce lidar's effective point cloud collection rate by over 50%[1], while optical cameras exhibit a one-third probability of false target recognition in low-light backlit scenarios[23]. Notably, although such edge cases represent less than 2% of actual driving mileage, studies indicate they account for up to 60% of potential risk incidents[24]. This discrepancy highlights three critical extreme scenarios: severe weather interference (e.g., heavy rain), adverse lighting conditions (e.g., backlighting), and sensor performance degradation in edge cases – all of which remain unresolved challenges for perception reliability.

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3.2. Causes and optimization of the real-time gap in decision-making

The current autonomous driving system is confronted with three key bottlenecks: perception data transmission, behavioral prediction computing load, and motion planning complexity.

Firstly, the perception data transmission is limited by the existing vehicle Ethernet architecture, introducing a fixed 15-20ms delay in cross-domain sensor data transmission[25]. Secondly, due to the complex modeling of social norms, the computational load for behavior prediction requires 50-80ms[26]. Finally, in a dense urban environment, the complexity of motion planning increases exponentially, and non-convex trajectory optimization becomes computationally intensive[27].

To address these challenges, edge computing acceleration (for example, the NVIDIA Thor platform) reduces the local path planning latency to approximately 25ms[28]. Meanwhile, crowdsourced data updates (for example, Mobileye's REM system) can achieve near-real-time road network updates at a refresh rate of 10Hz[29]. Furthermore, distributed training optimizations (such as Tesla's Dojo supercomputer) have increased the training efficiency of the decision model by 8 times and accelerated the algorithm iteration[30].

3.3. Response plans for user privacy risks

Tesla's data breach in 2023 indicated that the in-vehicle vision system could expose sensitive user locations (with an accuracy of less than 30m) through environmental image analysis. To mitigate such risks, three key privacy protection strategies have emerged: differential privacy optimization, distributed learning architecture, and blockchain-based auditing.

Firstly, differential privacy optimization (for example, the Laplacian noise injection ε=0.3 of Uber ATG) balances data utility (<5% loss) and location anonymization[31]. Secondly, the distributed learning architecture utilizes parameter servers to achieve collaborative model training without the need to centrally collect raw data. Finally, blockchain auditing systems (for example, IBM AutoChain on Hyperledger Fabric) ensure tamper-proof transaction logging of over 200 requests per second[32].

4. Machine learning enhances perception reliability and decision-making efficiency

Multimodal data fusion: the latest research shows that integrating liDAR and visual data through the cross-modal attention mechanism can significantly improve the perception performance [33]. The evaluation results on the standard test set show that this method achieves an average detection accuracy of 78.9%, which is significantly improved compared with the traditional scheme [34]. Hierarchical decision-making framework: existing literature has confirmed that graph neural networks have advantages in the interaction modeling of traffic participants [35]. In terms of real-time control, the computational efficiency of the optimized predictive control algorithm has been significantly improved [37]. Control accuracy: the latest control algorithm has achieved sub-degree steering accuracy [38], and the braking response time has been shortened to the millisecond level.

5. Technology integration and benefit assessment in typical scenarios

First, in terms of expressway construction zones, the integration of dynamic high-precision mapping (Mobileye REM crowdsourcing) with 5G NR-V2X transmission enables real-time updates (<5s delay)[39] and doubles construction cone detection range to 300m compared to traditional visual methods (150m)[40]. Second, it’s about extreme weather conditions. A multi-redundant sensor suite combines anti-freezing cameras (-40 ℃ operation) and 1550nm LiDAR with rain/snow

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compensation algorithms[41,42]. When perception degrades, the system activates radar-dominant mode (<0.3m positioning error)[43] and leverages high-precision map prediction during communication outages. Last, when mentioning geosensitive areas, privacy-aware navigation employs geohashing with differential privacy (50m location blur) [44]and implements selective data erasure for sensitive locations (e.g., schools, government buildings), ensuring compliance without compromising core functionality[45].

6. Conclusion

This article conducts research on intelligent driving, systematically analyzes various key issues in the development of intelligent driving and proposes solutions, and also looks forward to its future development. Future technological development directions in the field of intelligent driving will present the following important features: Firstly, sensor technology will witness a major breakthrough. The teamwork of new 4D imaging radars and high-resolution solid-state laser detection devices, along with advanced scene reconstruction algorithms, is expected to greatly improve the accuracy of understanding in complicated settings. Secondly, the architecture of the decision-making system will evolve towards brain-like intelligence. The multimodal fusion model based on the attention mechanism will significantly enhance the system's adaptability in sudden situations, while the improvement of the distributed learning framework will promote cross-platform knowledge sharing.

In terms of vehicle control, the combination of the new generation of by-wire control systems and modular drive units will achieve unprecedented control accuracy and response speed. In the field of infrastructure, the construction of vehicle-road coordination systems will enter a new stage. The combination of high-speed communication networks and edge computing nodes provides a broader development space for autonomous driving. According to the prediction of the Institute of Automata Engineers International, within the next five to ten years, the application of highly autonomous driving technology in specific scenarios will achieve substantial breakthroughs.

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