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Risk Prediction and Safety Driving in Automated Driving: A Review from the Perspective of Embedded Systems

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Abstract: In recent years, automated driving technology is booming and reshaping the pattern of transportation, but its safety has attracted wide attention. In the embedded system, it is necessary to solve the security risks caused by sensor failures, complex road environments and emergencies. To enhance autonomous driving safety, risk detection, a crucial part, must accurately spot potential hazards. This review focuses on the risk detection and safe driving field of autonomous driving, and analyzes related cutting-edge technologies in depth. In terms of risk prediction, it explains the key technology paths based on multi-sensor fusion, deep learning, and data-driven, and realizes risk judgment and insight from comprehensive information capture, deep feature mining, and model optimization, respectively. Safety driving technology section, discusses lane keeping and departure warning, collision warning and automatic braking, blind area monitoring and obstacle avoidance technology. In the future, deep learning, edge calculation, multi-sensor fusion will promote autonomous driving to break through the dilemma, but challenges such as regulations, ethics, and network security will also follow.

Keywords: Automated driving , Risk prediction, Safety driving

1. Introduction

Autonomous driving was proposed in 1956, where vehicles are expected to drive without human involvement [1]. In the recent years, with the development of artificial intelligence (AI) and embedded systems, automated driving technology has been widely used worldwide. The emerging autonomous vehicles should be able to sense their surroundings through on-board cameras, sensors, and transceivers, understand the driving scenario, and then make appropriate control decisions to operate the engine, wheels, and brakes [1]. Due to the sharp rise in traffic problems such as sudden accidents and life-threatening cases, people's concern for automobile driving safety is also growing [2]. Autonomous driving vehicles still suffer from many safety hazards in practical applications, such as data loss, perception bias, and environmental interference (e.g., rain, snow, and fog leading to a decrease in LiDAR performance), which may lead to the vehicle making incorrect judgments about its surroundings, thus causing safety accidents. In addition, complex road environments (such as unstructured roads, construction areas, and sudden traffic control) and unexpected events (such as pedestrians suddenly crossing the road, sudden braking of the vehicle ahead, and falling road obstacles) all pose extremely high requirements for the real-time decision-making ability of intelligent driving systems. The study of safe driving technology for self-driving cars enhances the

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stability of the self-driving system thus providing safety measures for the car. In the research of automobile automatic driving safety-related fields, assessing driving risk as the key to ensuring the safety of intelligent vehicles has become a current research hotspot [3]. Comprehensive risk assessment models can predict potential risky events in advance and warn drivers in time to make adjustments to avoid collisions or enable the autonomous driving system to plan a safe driving trajectory [3]. Therefore, this review delves into a number of relevant technologies in the field of risk detection and safe driving, aiming to analyse the existing results and, through an understanding of the strengths and weaknesses, to further look into the future trends and challenges to be overcome. Through a comprehensive review of the technical landscape in this field, it is expected to provide useful references and guidance for promoting automated driving to a higher safety level and achieving a wider range of applications.

2. Risk prediction technology

Risk prediction technology in embedded intelligent driving utilises an embedded systems that integrates data from multiple sensors, such as cameras and radars, capturing complex and dynamic road conditions around vehicles in real-time, including vehicle spacing, pedestrian dynamics, road signs, and sudden obstacles. By leveraging AI algorithms and big data analytics, the system processes vast amounts of information at high speed to identify potential risks. For example, the intelligent driving system can predict the risk of a possible collision or skidding on a slippery road, and provide an early warning through the intelligent driving system to allow sufficient reaction time for the vehicle and driver, and then automatically take braking, avoidance, and other measures to ensure all-round driving safety.

2.1. Risk prediction technology based on multi-sensor fusion

2.1.1. Cross-modal data fusion

Wang fused the vision sensors and millimeter wave radar data to analyze the running state of the autonomous vehicle and the leading vehicle, and studied the forward collision warning system for autonomous driving based on sensor fusion [4]. The forward collision warning system is composed of three units: information acquisition unit, electronic control unit and human-computer interaction unit [4]. The structural representation of this system is shown in Figure 1. The information acquisition unit collects information by using a variety of sensors, the electronic control unit fuses information to assess collision risk, while the human-computer interaction unit issued warning information according to the command [4]. Based on the road information obtained from sensors and radar, the system accomplishes tracks such as tracking the obstacles ahead, measuring the distance, calculating the relative speed, determining the likelihood of a rear-end collision based on the alarm model, and issuing an alert in case of danger [4].

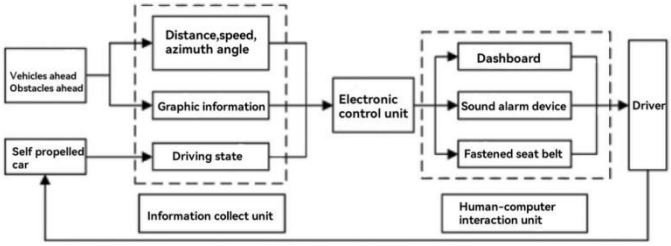


Figure 1: The composition of the forward collision warning system[4]

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In addition, Leng et al. developed a multi-sensor fusion framework integrating LiDAR data with vision-based object detection algorithms and an enhanced clustering method for robust environmental perception and state estimation, enabling reliable collision avoidance in unmanned vehicles [5]. Figure 2 shows the schematic diagram of the hardware system interface of anti-collision warning system based on multi-sensor fusion. Detailed designs include hardware connections using UDP for efficient data transmission and a direct step-down power distribution scheme [5]. The software stack, built on the Robot Operating System (ROS), adopts a modular architecture comprising four functional layers: human-machine interface (HMI), data acquisition, sensing, and collision warning strategy decision-making. Shared memory optimizes sensor data transmission, and Virtual Network Computing (VNC) ensures real-time monitoring and control [5].



Figure 2: Schematic diagram of hardware system interface of anti-collision warning system based on multi-sensor fusion[5]

2.1.2.3D scene reconstruction

Hao et al. fused multi-modal sensor data, such as RGB cameras and LiDAR, to design a multi-modal multi-view sensor fusion model. The overall model architecture consists of a backbone network, a Transformer encoder, a Transformer decoder, and a safety controller, as it shown in Figure 3. The backbone network extracts features from different multimodal and multiview sensor data using a convolutional neural network (CNN) backbone. The encoder performs multimodal feature fusion of feature tokens from different sensors. The decoder is responsible for predicting waypoints, generating object density maps and interpreting traffic rules after introducing three different types of queries. The traffic scenario is reconstructed based on the predicted object density map and a tracking system is used to predict the future movement of other objects. The safety controller constrains the low-level control by means of safety-focused interpretable features, thus improving driving safety and efficiency in complex traffic scenarios [6].

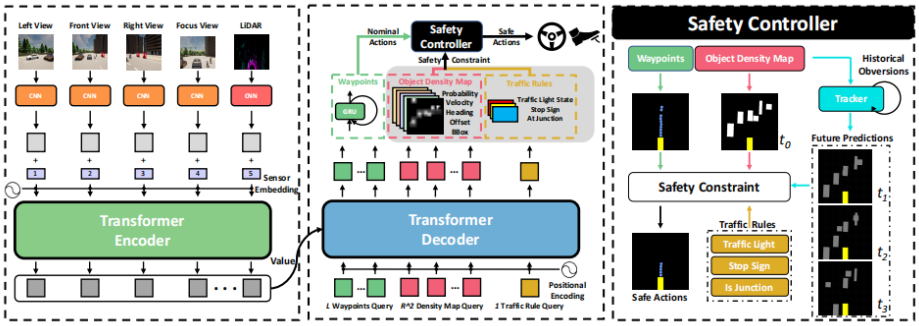


Figure 3: Detailed structure diagram of an autonomous driving system based on multi-modal sensor fusion[6]

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2.2. Risk prediction technology based on deep learning

There are many methods based on deep learning, such as risk prediction based on convolutional neural network, risk identification based on multi-source data fusion, trajectory prediction based on long short-term memory network (LSTM), and so on.

2.2.1. Spatial feature analysis

Feth et al. proposed a new method based on deep learning for dynamic risk assessment of driving scenes using forward-looking stereo camera images, aiming to create situational awareness for vehicles with higher levels of automation. There are currently two main approaches to achieve higher vehicle automation: robotics and deep learning, and the new method proposed by Feth et al. can be used in both paradigms[7]. Compared with related work, this method uses quantitative and objective risk indicators to solve the regression problem, and the data are more systematic. The data for the research was generated by the simulation environment, the stereo camera and the SGM algorithm were used to obtain the disparity map[7]. Taking the inverse time interval as the risk indicator, the CNN network including convolutional layer and fully connected layer was trained under the TensorFlow framework[7]. The experimental results show that the average error of the final test is 0.01470, and the accuracy is 72.87%[7]. Although the classification is based on objective indicators, the performance improvement is not obvious, mainly because the camera Angle does not match the calculation area and the reliability of this method is challenged, and it can only be used as a redundant system[7].

2.2.2. Decision optimization level

Furthermore, Chen et al. proposed an autonomous driving strategy based on hierarchical deep reinforcement learning that takes vehicle weight into account for risk prediction. Existing automatic driving decision-making strategies do not pay sufficient attention to the influence of vehicle weight, and human error is considered to be the main cause of current traffic accidents. The study adopted a hierarchical actor-critic framework, developed the HPPO algorithm, incorporated an attention mechanism, and proposed the ADR index for use in the reward function to optimize autonomous driving decisions[8]. Experimental results on the SUMO simulator and the HighD dataset show that this strategy can effectively reduce the possibility and severity of accidents, improve driving efficiency, and demonstrate good performance in different traffic densities and real-world scenarios, providing a new direction for autonomous driving control[8].

In the field of autonomous driving, trajectory prediction is a key link to achieve advanced autonomous driving, and it is essential for assessing potential collision risk. Thus, Wang et al. focused on the problem of trajectory prediction in safety-critical scenarios and explored the application of various models in this scenario, including the long short-term memory (LSTM) model. As a classical machine learning model, LSTM can learn the time series features in the historical trajectory of vehicles, capture the movement trend of vehicles through the analysis of past motion states, and thus predict the position of vehicles at future moments. When assessing the potential collision risk, the LSTM model uses the predicted future trajectory, combined with other relevant information, to judge the likelihood of collision. However, due to the relatively simple structure of the LSTM model, its prediction performance is much worse than some recently proposed models in the face of complex vehicle dynamics and driver intention changes in safety critical scenarios [9]. For example, there is a large gap in the prediction accuracy and risk assessment ability, which makes it difficult to accurately evaluate the potential collision risk in complex safety-critical scenarios, and cannot meet the high requirements for trajectory prediction and risk assessment of autonomous driving in this scenario [9].

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2.3. Risk prediction technology based on data-driven

2.3.1. Scene knowledge graph construction

Yu et al. proposed a data-driven method based on scene graph enhancement to solve the risk assessment problem of autonomous driving system in complex road scenarios. In this method, the scene graph is used as the intermediate representation, and the multi-relational graph convolutional network, long short-term memory network and attention layer are fused to transform the subjective risk assessment into a supervised scene classification problem training model [10]. Experiments show that this method has higher classification accuracy on synthetic datasets of different sizes, strong learning ability on small datasets, and better knowledge transfer ability in real-world datasets [10]. The spatial and temporal attention layers also improve the performance and interpretability of the model, which effectively solves the limitations of existing deep learning methods[10].

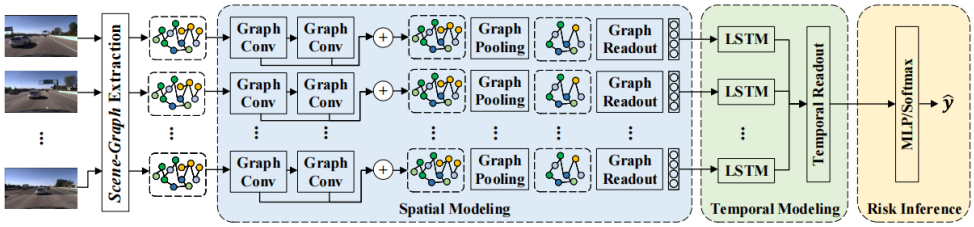


Figure 4: An illustration of Yu model's architecture

According to Figure 4, firstly, each image belonging to the set is converted into a scene graph through the scene graph extraction pipeline. Then, using the spatial modeling layer, each scene graph is transformed into the corresponding scene graph embedding. Subsequently, these scene graph embeddings are temporally modeled to obtain a spatiotemporal representation of the scene graph sequence. Finally, with the help of a multi-layer perceptron (MLP) with Softmax activation function, the risk inference results of video clips were calculated according to the spatio-temporal representation.

2.3.2. Breakthrough in personalized modeling

Cui et al. proposed a data-driven risk map construction method for personalized scenarios of intelligent vehicles as shown in Figure 5. They used two key technologies: the driving scene modeling based on graph representation and the dangerous scene recognition model based on graph kernel. Graph representation-based driving scenario modeling defines the driving scene graph model as an undirected node labeling graph [11]. Node positions are determined by the dynamic element (vehicle), the node labels are generated by dividing the grid with the static element (lane line), and the edges are defined according to the potential collision relationship and represented by the adjacency matrix[11]. In contrast, the dangerous scene recognition model based on graph kernel use graph kernel methods (such as shortest path graph kernel and neighborhood hash graph kernel) to measure the similarity of graph data, as well as personalized evaluation labels generated by constructing kernel matrices combined with clustering of driver operation data through the inner product of the projected graph. Meanwhile, the hazardous scene recognition model based on graph kernel is trained to construct a hazardous scene classification model by linear SVM model [11]. The results show that the accuracy of the driver personalized danger scene recognition model based on the scene risk map can reach 95.8%, which is 38.2% higher than that of the feature vector representation method, and can effectively evaluate the risk degree of personalized scenes[11].

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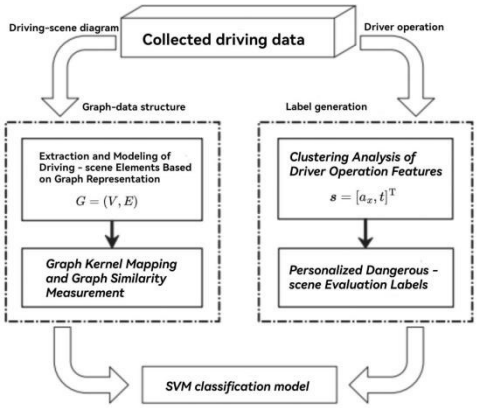


Figure 5: Data-driven personalized scene risk map construction method of intelligent car[11]

2.4. Comparison of risk prediction techniques

Technical Dimension	Sensor Fusion	Deep Learning	Data-Driven
Core Advantage	Real-time perception reliability	Complex pattern recognition	Scenario knowledge mining
Data Requirement	High-frequency streaming data	Quality of labeled samples	Large-scale scenario databases
Processing Latency	50-200ms	100-500ms	Offline modeling + Online inference
Typical Application	Collision warning	Trajectory prediction	Driving strategy optimization

Figure 6: Three types of technologies show significant differences and complementarity

In practical systems, these technologies form a complementary architecture: the sensor fusion layer feeds target detection results into the deep learning trajectory prediction module, which in turn guides the data-driven risk-aware planner. Current research and development efforts are focused on breaking through technical bottlenecks - developing FPGA-accelerated sensor fusion networks to handle 1000Hz lidar data, using semi-supervised learning to reduce the labeling cost of deep learning, and leveraging generative AI to synthesize rare accident scenarios to enhance data-driven training (Figure 6).

3. Safety driving technology

The safe driving technology in embedded intelligent driving, based on the embedded hardware architecture, integrates all kinds of vehicle resources in an all-round way. It not only accurately gathers the visual picture captured by the camera and the range data detected by the radar, but also includes high-precision map information and the operating parameters of the vehicle itself. On the one hand, intelligent algorithms are used to continuously monitor the real-time status of vehicles to ensure the stable operation of power, steering, braking and other systems. On the other hand, real-time analysis of the surrounding traffic situation can accurately control the safe following distance in the high-speed traffic flow or the priority passing decision at complex intersections of urban roads. Once an abnormality is detected, it will immediately cooperate with the intelligent driving system to accurately adjust the speed and plan the optimal avoidance path. From active

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prevention to immediate response, it will systematically ensure the safety of the whole driving process, so that drivers and passengers can enjoy a carefree journey.

3.1. Lane keeping and departure warning, collision warning and automatic braking

Shen et al. comprehensively reviewed the driving risk assessment methods of intelligent vehicles, analyzed the advantages and disadvantages of various methods, and pointed out that the integration of multiple methods is the future development trend by analyzing the advantages and disadvantages of various methods (Figure 7).

Based on the deterministic method, the threat metrics such as collision time (TTC) and braking time (TTB) are used to provide basic risk judgment basis for lane keeping systems and collision warning systems. In the evaluation of automatic emergency braking system (AEB), the TTC concept was first proposed and integrated into the threat assessment algorithm to estimate the operation of the vehicle driver to avoid collisions, and to determine the criteria for activating driver assistance systems such as collision avoidance system (CAS) to prevent rear-end collisions [12]. The probability-based method can deal with uncertain information and comprehensively considers multiple factors for risk assessment, which provides support for safety technology in managing complex and dynamic driving environments. By using a Bayesian network, the influencing factors of driving environment risk can be integrated into the model to monitor the overall risk during driving in real time, so as enhancing collision warning accuracy and providing more reliable decision-making basis for automatic braking [12]. Machine learning-based methods automatically extract patterns from large-scale datasets, handle nonlinear and complex data, and achieve high-precision risk assessment. Deep learning model can precisely predict collision risk, trigger timely warning and braking interventions, and improve the detection of lane boundaries and vehicle motion states for lane-keeping assistance. These capabilities significantly boost the reliability of collision alerts and lane-keeping performance [12].

Technical Dimension	Deterministic Method	Probabilistic Method	Machine Learning Method
Theoretical Basis	Classical control theory	Bayesian inference	Data-driven modeling
Core Indicators	TTC (with an error of ±0.2 s)	Risk probability distribution	Feature embedding space
Response Mechanism	Threshold triggering (e.g., braking when TTC < 2.5 s)	Probability-weighted decision	End-to-end control
Advantageous Scenarios	Following vehicles on structured roads	Adverse weather with poor visibility	Complex urban intersections
Limitations	Inability to handle interactive games	Strong dependence on prior knowledge	Poor interpretability of black boxes

Figure 7: Comparison of methods based on three different dimensions

3.2. Blind area monitoring and obstacle avoidance system

Lin et al. proposed a blind spot warning system based on in-car wireless sensor networks (IVWSN) to solve the problems of high cost and false positives of traditional radar-based blind spot warning systems (Figure 8). The system utilizes the idle time of the low duty cycle sensor in IVWSN, based on BLE technology to determines whether the vehicle is in the blind zone by detecting the received signal strength of the beacon packet broadcast by the sensor of the target vehicle, and adopts NP classifier to determine the decision graph and evaluate the system detection rate and false positive rate[13]. Through the parking and driving scene experiments, the system detection rate can reach

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95%-99%, and the false alarm rate is less than 15%[13]. Compared with other schemes, the system has low cost, simple implementation and broad application prospects [13].

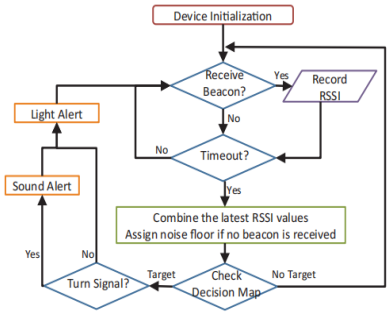


Figure 8: Flowchart of the Side Blind Zone Alert System(SBZA) based on IVWSNs[13]

Horgan et al. 's vision-based driver assistance system first classifies the systems from multiple dimensions, such as interaction degree, camera field of view, and working mode, in order to clearly define and understand various systems[14]. Simultaneously, a series of algorithms such as image acquisition, preprocessing, segmentation, motion and depth estimation, state tracking and object detection/classification are used to build modules to process image data[14]. In terms of applications, there are mature applications such as surround view system and adaptive cruise control, and emerging applications such as automatic parking and traffic congestion assistance are also being developed[14] which embody its existing practicability and value, show its development potential, and comprehensively present the overall situation of the system from classification, image data processing to practical application. At the same time, facing the challenge of moving towards automatic driving, a general and extensible algorithm framework which is shown in Figure 9 is proposed, which is constructed by top-down modeling method[14]. Therefore, the system can improve the processing ability of complex scenarios and enhance the adaptability and functional scalability of the system.

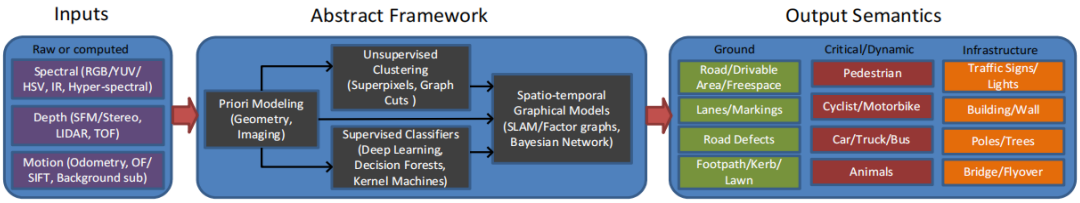


Figure 9: Generic scalable model for vision Advanced Driver Assistance Systems(ADAS)[14]

In the autonomous driving technology of intelligent networked vehicles, obstacle recognition is very important. He et al. constructed a deep learning framework based on CNN and integrated multi-sensor data to develop an obstacle detection system[15]. Figure 10 gives an outline of obstacle detection algorithm.The model is optimized by hollow convolution and regularization, and trained by batch gradient descent. The experimental results show that the system has high detection accuracy of different types of obstacles in a variety of road environments, and has obvious advantages in complex scenarios, and its performance exceeds that of traditional methods[15]. However, there is still room for improvement in the recognition accuracy and real-time performance of special obstacles. This study provides support for the development of unmanned driving technology and makes prospects for future research directions[15].

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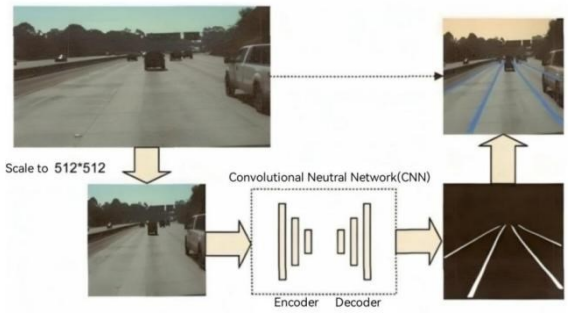


Figure 10: Flowchart of obstacle detection algorithm [15]

3.3. Comparison

The above content aims to explain the lane keeping and departure warning, collision warning and automatic braking, blind area monitoring and obstacle avoidance system in intelligent driving assistance technology, so as to show the multiple means and advantages of intelligent driving assistance technology to ensure driving safety (Figure 11).

Technical Path	Detection Range	Angle Coverage	Response Delay	Applicability in Typical Scenarios
Ultrasonic Array	0.2-2.5 m	120°	50 ms	Low-speed parking
Millimeter-wave Radar	1-150 m	60°	20 ms	High-speed following
LiDAR + CNN	0.5-200 m	360°	80 ms	Complex urban road conditions
Event Camera	0.1-50 m	140°	5 ms	Extreme lighting conditions

Figure 11: Comparison of obstacle avoidance technologies

4. Applications

At present, the field of automatic driving has blossomed and achieved remarkable results. In China, Tesla launched the "Advanced Intelligent Summoning (ASS)" function, which is suitable for models equipped with EAP and FSD (full autonomous driving capability), which can allow vehicles to park automatically from a variety of parking Spaces, and owners can remotely "summon" their cars only through mobile phone apps[16]. At the same time, Xpeng Automobile's XNGP intelligent driving system is the industry leader, one to two years ahead, and its hardware is luxurious, with two liDAR, dual NVIDIA DRIVE Orin supercomputing platform, 13 cameras, 12 ultrasonic radars and 5 millimeter wave radars working together[17]. It provides strong support for vehicles to accurately collect surrounding environment data and realize integrated perception[17]. Moreover, Waymo has deployed self-driving taxi services in Phoenix, according to its public road safety performance data report, Waymo's autonomous driving system has traveled more than 6.1 million miles on public roads in the Phoenix area[18]. In short, whether it is the innovation of car giants Tesla and Xiaopeng in functions and hardware, or the data accumulation of Waymo in commercial operation, it highlights the vigorous development vitality and great potential in the field of autonomous driving.

5. Challenges and future development trends

5.1. Main challenge

The computing capacity limitations in embedded intelligent driving encounter numerous challenges, including hardware performance bottlenecks. For example, NVIDIA Drive PX Pegasus has high

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power consumption and more expensive hardware costs. In addition, the amount of data generated by various sensors is huge, and it is difficult for computing platforms to process large amounts of data in real time. As well, complex neural network models are computationally intensive, and current hardware cannot meet the demands of algorithm execution. Meanwhile, the poor system compatibility caused by the non-openness of the in-vehicle CAN protocol hinders the development of a unified in-vehicle operating system [19].

Futhermore, in embedded intelligent driving, data privacy also faces severe challenges. A large number of images and other data collected by autonomous vehicles contain private information. If directly uploaded to the edge server for processing, it is easy to lead to user privacy leakage, and data privacy problems may appear in the model training and reasoning stage[20]. In addition, under the limited bandwidth of distributed model training, the model exchange between vehicles and server parameters will produce high communication cost, data samples also increases the difficulty of data privacy protection, and the vehicle from the base station coverage, car workshop collaboration cache and calculation can solve some problem, but V2V communication delay will have new influence on data privacy protection[20].

In terms of regulations and ethics, there is not yet a car on sale that can be recognized as fully “self-driving”, so there is the issue of companies' marketing priorities not matching the reality of their products. For example, Tesla advertised Autopilot and the system as fully autonomous driving ability, but in reality, the vehicle does not have the ability to drive fully autonomously, in which false advertising is contrary to the relevant legislation and regulations [21]. At the ethical level, the definition of corporate responsibility in accidents is becoming blurred, and when an accident occurs, it is difficult to determine whether the responsible party for the accident is the driver or the automaker or the design of the vehicle [21]. From the perspective of software testing, it is difficult to fully test the software in complex scenarios, but some enterprises will still bring the undertested software to the market, increasing the security risks[21]. In terms of information accuracy, companies may make misleading publicity and hide their software limitations. In addition, if enterprises do not actively cooperate with the investigation, timely errors and express concerns, they will also cause ethical disputes, and these challenges need to be solved urgently.

5.2. Future directions

5.2.1. Application of deep learning in risk prediction

The application of embedded intelligent driving deep learning in risk prediction will focus on enhancing the robustness and adaptability of the system, and further improve the performance of the system by exploring and applying new model technologies such as pre-trained vision model and diffusion model[22]. At the same time, the environment perception module is continuously optimized to handle more complex scenarios, optimize the decision support system, and improve the accuracy and real-time of decisions, so as to predict risks more accurately and promote the development of intelligent driving technology to higher safety, efficiency and reliability[22].

5.2.2. Real-time risk prediction based on the edge calculation

The real-time risk prediction of embedded intelligent driving based on edge computing has three main development directions in the future: first, to use historical and real-time data and new learning methods to solve the problem of limited marker training data and explore sensor integration combined. Second is to optimize the distributed model training with V2V communication to reduce the communication cost of wireless bandwidth limitation. And third is to rely on vehicle assembly team assisted reasoning, realizing reasoning through V2V communication when the vehicle leaves the base station coverage, and studying the influence of formation dynamics[20].

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5.2.3. Multi-sensor data fusion optimizes security

Embedded intelligent driving has multiple future development directions in the safety optimization of multi-sensor data fusion. First, a comprehensive large-scale data set needs to be collected, covering different scenarios, to provide more completeness for algorithm design, testing and validation face data support[23]. Secondly, the application of mobile edge computing technology to extend cloud services to the edge of the network, reduce the burden of on-board computing, and realize data for rapid processing[23]. Moreover, the development of real-time and lightweight CNNs can improve the sensing accuracy while reducing the need for memory and energy to improve the safety and robustness of autonomous driving[23]. Finally, risk assessment algorithms are developed to identify potential hazardous events in real time and reduce no the risks of predictable behavior can comprehensively improve the safety of autonomous driving[23].

6. Conclusion

Embedded intelligent driving is reshaping mobility through safe driving and risk prediction technologies. The current technology breaks through the single perception limitation through sensor data fusion, combines the autonomous decision-making ability of deep learning and big data risk prediction, and collaboratively improves the reliability of the system and promotes its application.

Future research focuses mainly on the structure of algorithms for optimising computational efficiency HO, which requires the development of high-performance, low-power chips. In addition, data security needs to be strengthened to protect privacy through encryption technology and permission management, while improving relevant regulations and standards, and coordinating multiple parties to develop technical specifications and security accountability.

Current research exists with some shortcomings within the analyses, including the fact that some leading-edge results are not included in the analyses and the lack of empirical verification. In the future, the authors plan to conduct in-depth research on the integration of multiple technologies, explore the intersection of disciplines, and carry out multi-scenario empirical research relying on enterprise platforms. In the future, the author plans to conduct in-depth research on multi-technology integration, explore cross-disciplinary intersections, and carry out multi-scenario empirical research relying on the enterprise platform to verify theories..

References

[1] *Zhang, S., Chen, J., Lyu, F., Cheng, N., Shi, W., & Shen, X. (2018). Vehicular communication networks in the automated driving era. IEEE Communications Magazine, 56(9), 26-32.*

[2] *Zhang, J., Cao, J., Chang, J., Li, X., Liu, H., & Li, Z. (2024). Research on the Application of Computer Vision Based on Deep Learning in Autonomous Driving Technology. arXiv preprint arXiv:2406.00490.*

[3] *Shen, Chuanliang, Xiao, Xiao, Tong, Yan & Hu, Hongyu. (2024). A Review of Driving Risk Assessment for Intelligent Vehicles. Automobile Digest, (08), 1-8. doi: 10.19822/j.cnki.1671-6329.20230104.*

[4] *Wang, Lei. (2022). Research on Forward Collision Warning System for Autonomous Driving Based on Sensor Fusion. Journal of Anhui Vocational and Technical College, (03), 15-19.*

[5] *Leng, Z. X. (2021). Design of an Anti-Collision Warning System for Self-Driving Vehicles Based on Multi-Sensor Fusion (Master's Thesis, Jilin University). Master. doi:10.27162/d.cnki.gjlin.2021.006968.*

[6] *Shao, H., Wang, L., Chen, R., Li, H., & Liu, Y. (2023, March). Safety-enhanced autonomous driving using interpretable sensor fusion transformer. In Conference on Robot Learning (pp. 726-737). PMLR.*

[7] *Feth, P., Akram, M. N., Schuster, R., & Wasenmüller, O. (2018). Dynamic risk assessment for vehicles of higher automation levels by deep learning. In Computer Safety, Reliability, and Security: SAFECOMP 2018 Workshops, ASSURE, DECSoS, SASSUR, STRIVE, and WAISE, Västerås, Sweden, September 18, 2018, Proceedings 37 (pp. 535-547). Springer International Publishing.*

[8] *Chen, D., Li, H., Jin, Z., Tu, H., & Zhu, M. (2024). Risk-Anticipatory Autonomous Driving Strategies Considering Vehicles' Weights Based on Hierarchical Deep Reinforcement Learning. IEEE Transactions on Intelligent Transportation Systems.*

DOI: 10.54254/2755-2721/2025.KL22728

[9] Wang, Q., Xu, D., Kuang, G., Lv, C., Li, S. E., & Nie, B. (2025). Risk-Aware Vehicle Trajectory Prediction Under Safety-Critical Scenarios. IEEE Transactions on Intelligent Transportation Systems.

[10] Yu, S. Y., Malawade, A. V., Muthirayan, D., Khargonekar, P. P., & Al Faruque, M. A. (2021). Scene-graph augmented data-driven risk assessment of autonomous vehicle decisions. IEEE Transactions on Intelligent Transportation Systems, 23(7), 7941-7951.

[11] Cui, G., Lü, C., Li, J., Zhang, Z., Xiong, G., & Gong, J. (2023). Construction of personalized scene risk ma ps for intelligent vehicles driven by data. Automotive Engineering, 02, 231-242. doi:10.19562/j.chinasae.qcgc. 2023.02.008.

[12] Shen, C. L., Xiao, X., Tong, Y., & Hu, H. Y. (2024). Review of Risk Assessment for Intelligent Vehicle Driving. Automobile Digest (08), 1 - 8. doi:10.19822/j.cnki.1671 - 6329.20230104

[13] Lin, J. R., Talty, T., & Tonguz, O. K. (2015). A blind zone alert system based on intra-vehicular wireless sensor networks. IEEE Transactions on Industrial Informatics, 11(2), 476-484.

[14] Horgan, J., Hughes, C., McDonald, J., & Yogamani, S. (2015, September). Vision-based driver assistance systems: Survey, taxonomy and advances. In 2015 IEEE 18th International Conference on Intelligent Transportation Systems (pp. 2032-2039). IEEE.

[15] Zhang, Zhixiang & Wu, Jizhang. (2024). Research on Obstacle Detection for Autonomous Driving of Intelligent Connected Vehicles Based on Deep Learning. Auto Time, (23), 27 - 29.

[16] Tesla. (2023). Tesla FSD (Full Self-Driving) and "Advanced Smart Summon" feature launched in China. Tesla. https://www.tesla.com

[17] Waymo. (2020). Waymo autonomous taxi service operation and safety performance report in Phoenix. Waymo. https://www.waymo.com

[18] XPeng Motors. (2023). XPeng Motors XNGP smart driving system technology and hardware configuration. XPeng Motors. https://www.xpeng.com

[19] Liu, L., Lu, S., Zhong, R., Wu, B., Yao, Y., Zhang, Q., & Shi, W. (2020). Computing systems for autonomous driving: State of the art and challenges. IEEE Internet of Things Journal, 8(8), 6469-6486.

[20] Yang, B., Cao, X., **ong, K., Yuen, C., Guan, Y. L., Leng, S., ... & Han, Z. (2021). Edge intelligence for autonomous driving in 6G wireless system: Design challenges and solutions. IEEE Wireless Communications, 28(2), 40-47.

[21] Vincent, K. (2018). Ethical Implications: The ACM/IEEE-CS Software Engineering Code applied to Tesla's" Autopilot" System. arxiv preprint arxiv:1901.06244.

[22] Zhang, J., Cao, J., Chang, J., Li, X., Liu, H., & Li, Z. (2024). Research on the application of computer vision based on deep learning in autonomous driving technology. arXiv preprint arXiv:2406.00490.

[23] Dong, X., & Cappuccio, M. L. (2023). Applications of computer vision in autonomous vehicles: Methods, challenges and future directions. arXiv preprint arXiv:2311.09093.