Automatic Driving Strategy based on Machine Vision: Review

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Abstract. With the growth of the number of automobiles, traffic safety problems are highlighted, and automatic driving technology becomes an important means of solution. Machine vision, as the key perception technology of automatic driving, acquires image data through vehicle-mounted cameras to provide a basis for decision-making. Its application in automatic driving is in environment perception and detection, path planning and decision making, and multi-sensor fusion. Among them, 3D object detection is the key technology in environment sensing. In path planning and decision making, uncertainty prediction and environment-aware motion planning are research hotspots. Multi-sensor fusion improves the accuracy and robustness of the perception system. However, machine vision still faces many challenges, such as lack of reliability in bad weather and light conditions, adaptability in complex traffic environments, and difficulties in multi-sensor data fusion. In the future, machine vision will increasingly emphasise interdisciplinary integration within the realm of autonomous driving. The amalgamation of deep learning, multi-sensor fusion, advancements in hardware technology, and the evolution of V2X communication technology will elevate the development of autonomous driving technology, thereby offering technical support for achieving safer and more convenient autonomous driving.

Keywords: Environment Sensing; Path Planning; Multi-Sensor Fusion

1 Introduction

The rapid increase in automobile numbers is exacerbating traffic safety issues, as the incidence of traffic accidents continues to rise. According to the China Statistical Yearbook 2020, China experienced 247,646 road traffic accidents in 2019, leading to 62,763 fatalities (an average of 172 daily), 256,101 injuries, and direct property damages amounting to 1.35 billion yuan. The data indicates that road traffic accidents represent a significant danger to life and property, necessitating immediate resolution of this issue.

Traffic safety problems are becoming increasingly serious, and driverless technology and assisted driving technology are important solutions to solve the current traffic safety problems. Automatic driving technology aims to realize safe,

A. J. Moshayedi (ed.), *Proceedings of the 2025 2nd International Conference on Electrical Engineering and Intelligent Control (EEIC 2025)*, Advances in Engineering Research 279,
https://doi.org/10.2991/978-94-6463-864-6_46

efficient and comfortable travel, and machine vision, as its key perception technology, acquires image data through the on-board camera, which is processed and analyzed to provide a basis for automatic driving decision-making [1]. Compared with LIDAR, RADAR and ultrasonic sensors, the measurement data from the camera is directly associated with physical quantities such as distance and speed, which could be directly used as a reference for vehicle control. Therefore, more intricate computational and algorithmic processing is needed to extract information from the bright intensity patterns that the camera captures that can be utilized for vehicle control. Applications of cameras in driver assistance systems in the automotive industry include lane-keeping assistance systems, traffic sign recognition systems, collision avoidance pedestrian protection systems, forward collision warning or mitigation systems, parking assistance systems with a monocular rearview camera or multiple surround-view cameras, and monocular night vision systems [2-4]. A single camera has even been used to implement conventional adaptive cruise control systems, which are typically controlled by radar or LIDAR sensors. Additionally, camera-based lateral control features have recently been added to longitudinal control systems. Several automakers have used these features for autonomous lane-keeping on highways.

Machine vision, as one of the core perception technologies for autonomous driving, has the advantages of low cost and rich information compared with other sensors such as LiDAR and millimeter wave radar [5, 6]. It can directly acquire image data of the road scene, provide intuitive visual information for vehicles, and help the automatic driving system better understand and perceive the surrounding environment. In recent years, the application of machine vision in the field of automatic driving has brought new opportunities and challenges. In particular, the rapid development of deep learning in machine learning has provided powerful algorithms for the application of machine vision in autonomous driving, which has driven the development of autonomous driving technology to a higher level [7]. In this paper, a systematic review of related recent research is provided, including challenges and future development direction of machine vision-based autonomous driving strategies.

2 Autonomous Driving with Machine Vision

The primary benefit of autonomous driving is the reduction in human involvement due to the separation of drivers and vehicles. Motion planning, vehicle positioning, automated parking, road markings, traffic signs, pedestrians, cybersecurity, and system troubleshooting are a few of these.

2.1 Environmental sensing and detection

Environmental perception is the foundation of autonomous driving, providing the necessary information about the surrounding scene for subsequent decision making and control. 2-D and 3-D object identification and segmentation comprise the perceptual exploration portion. As seen in Fig. 1, three-dimensional (3-D) object identification is crucial among them in order to assess the size and precise location of oriented items in the real world [8].

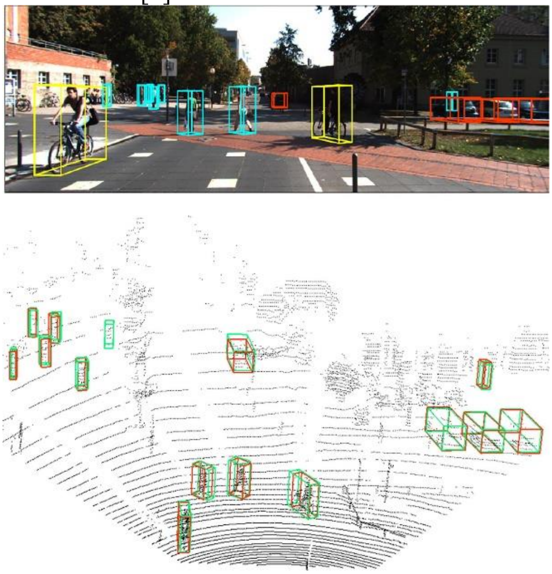

Fig. 1. Three-dimensional (3-D) object detection [8]

3D object detection is a key technology in autonomous driving and robot navigation for recognizing and estimating the spatial state of objects in the environment. Dong et al. proposed an algorithm that maps a random graph to a network of probabilistic timed automata to achieve environment sensing through four phases: learning, modeling, quantitative analysis, and decision making, as shown in Fig. 2 [9]. Contemporary predominant research emphasises deep learning, multimodal integration, and real-time robust optimisation. Research methodologies encompass data-driven approaches, transfer learning, reinforcement learning, and simulated environment training, with the objective of enhancing detection accuracy and adaptability to fulfil the requirements of applications like autonomous driving. Gu et al. proposed a hybrid control architecture for vision-based lateral control in autonomous driving, integrating Robust Linear Quadratic Regulator (RLQR) and Deep Reinforcement Learning (DRL) to enhance vehicle stability [10].

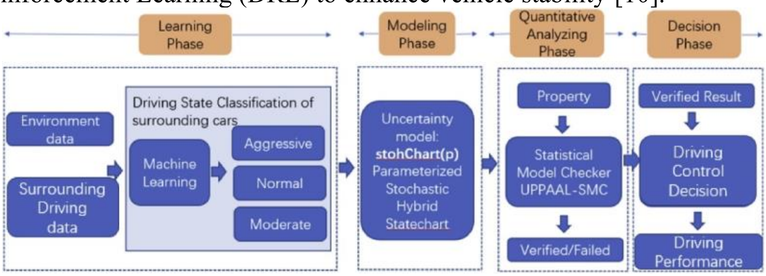

Fig. 2. Probabilistic timed automata network framework [9]

Sun et al. proposed a new network model for 3D object detection for in-vehicle applications-CenterPoint-SAE. The model modifies the architecture of CenterPoint, a well-known anchorless 3D object detection algorithm, as shown in Fig. 3. In order to improve feature representation and extraction, an effective SSDCM backbone is suggested right away in light of the restricted distribution of computational resources and the performance snag brought on by pillar encoders [11]. The upgrade achieves a 1.2% NDS and 1.6% mAP performance gain at a cheaper cost when compared to the benchmark.

For the field of lane line detection, Gurghian et al. developed a neural network through a program to achieve further classification of images with reduced pre-processing and post-processing [12]. This method can directly output the location information of lane lines with an error control of less than 5 pixels. Davy et al. proposed a new detection method, which is innovative and integrates two network models, H-Net and LaneNet [13]. The cooperative operation of these two models can efficiently perform the segmentation and classification tasks of lane line images, effectively reduce the processing steps and simplifying the overall process of lane line detection. These deep learning-based approaches not only improve the accuracy and processing speed of lane line recognition, but also significantly reduce the reliance on human intervention. This improvement provides a more reliable and efficient solution for application scenarios such as autonomous driving and intelligent navigation.

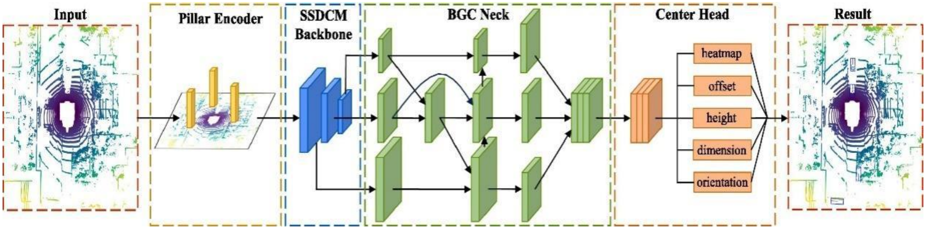

Fig. 3. Overall network architecture of CenterPoint-SAE [11]

These researches provide important technical support for the environment sensing and control of automatic driving.3D object detection, as the core technology of environment sensing, is evolving, from single modality to multimodal fusion, and from complex computational models to efficient knowledge distillation methods, which are all driving the progress of automatic driving technology. In the future, with the further maturation of the technology and the reduction of the cost, the environment sensing technology will play a greater role in the field of automatic driving, and bring a safer, more convenient and comfortable experience for people's traveling.

2.2 Route planning and decision-making

In the domain of autonomous vehicles, secure motion planning in dynamic environments has garnered significant attention. Despite the efficacy of predicting surrounding vehicles for optimal motion planning strategies, reachability prediction is hindered by the erratic control behaviours of adjacent vehicles and the environmental factors of driving scenarios. The resultant motion planner will exhibit enhanced performance if environmental parameters are integrated into reachability prediction. The research centres on three aspects of autonomous driving: 1. Motion and uncertainty forecasting with environmental considerations 2. Ambiguity in motion planning Fig 4 depicts environment-aware motion planning [14].

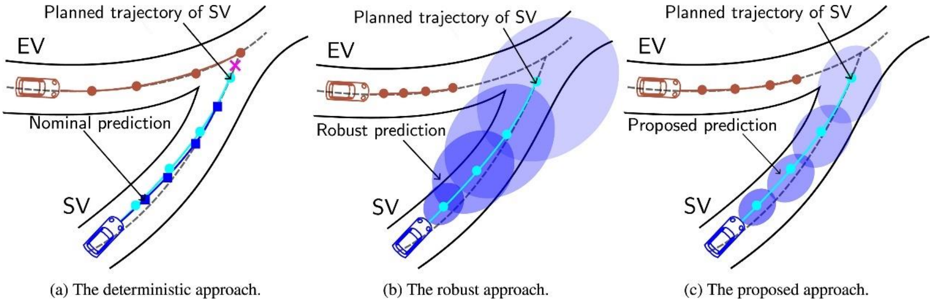

Fig. 4. Research on three related aspects of autonomous driving [14]

By outlining the range of possible states for the vehicle, uncertainty prediction increases the prediction findings' resilience. In order to forecast a more realistic collection of states, environment-aware uncertainty prediction additionally takes into account the impact of environmental factors [15]. Both learning-based and model-based methods can be used to forecast this set. In order to calculate the set of forward reachable general traffic players, Althoff et al. suggested an abstraction-based method that takes into account the road network's limitations as well as the projected objects' worst-case control capabilities [16]. Assuming that the potential factors satisfy the treatable distribution, Lee et al. present a sequentially trained environment-aware prediction approach to forecast the probabilistic drivable zone of an agent [17]. A learning-based multimodal motion prediction technique that can capture the features of intelligent body interaction with the roadway network was proposed by Varadarajan et al. [18]. The output displays several projected pathways along with their corresponding likelihood and covariance. To mitigate off-road prediction, Hallgarten et al. devised an environment-aware motion prediction methodology that can be integrated with various learning-based approaches. The prediction output comprises several distinct trajectories, each corresponding to the road network and associated with a specific probability [19].

For self-driving electric vehicles, robust, stochastic, and scenario-based approaches can be used to provide uncertainty-aware motion planning based on obstacle prediction and uncertainty assessment. Taking into account the worst-case motion uncertainty, Seo et al. used forward reachability analysis of barriers to create a robust planner based on model predictive control (MPC) [20]. Assuming the leading vehicle adheres to the Super Martin, Gao et al. investigated a risk-aware optimal controller for non-conservative robust motion planning in overtaking situations [21]. An uncertainty-aware scenario MPC is presented by Zhang et al. for electric vehicle motion planning subject to multiple collision avoidance requirements utilizing SV; the more scenarios that are incorporated, the more restrictions there are [22].

Environment-aware motion planning for autonomous vehicles refers to the utilisation of state variables (SVs) for motion prediction in electric vehicle navigation, incorporating environmental parameters to regulate the vehicle's movement. Zeinali proposed an energy-efficient Model Predictive Control (MPC) planner for autonomous electric vehicles that considers environmental factors such as traffic regulations and generates deterministic forecasts for the state variable (SV) [23]. Kabzan et al. developed a learning-based Model Predictive Control (MPC) for motion control of racing autonomous vehicles, utilising a Gaussian process to address the vehicle's modelling uncertainty, based on track geometry [24]. Given an uncertainty distribution of dynamic obstacles for the motion planning of a mobile robot system, De Groot, Brito, Ferranti, Gavrila, and Alonso-Mora (2021) formulate a scenario optimisation problem that leverages the geometry of the workspace to reduce the number of scenarios. Given the known trajectory of the SV, road geometry is employed to linearize the EV's dynamic model to predict the forward reachable set in a robust motion planning scenario. The decision and motion planning problem can be articulated as a nonlinear estimation problem by incorporating road network data alongside optimisation techniques. This issue is addressed through hindcasting particle filtering, wherein a lateral controller forecasts the state variable (SV). Forecasting the offline backwards reachable set of state variables by classifying their driving patterns through road geometry data results in a less conservative approach to collision avoidance for electric vehicles.

2.3 Sensor Data Fusion

The precise and instantaneous recognition of environmental objectives in intricate traffic situations, utilising visual sensors, remains a significant research challenge in the realm of autonomous driving technology. To accurately perceive environmental information in a traffic scene in real-time, various sensors, such as millimeter-wave radar, LiDAR, and cameras, are utilised to capture target features. In assessing these sensor applications, metrics of precision and efficacy are essential [25]. Cameras exhibit significant potential; however, their sensing technologies remain in the developmental phase and are not sufficiently advanced for practical application. In intricate traffic scenarios, including varying locations, weather conditions, and times of day, the colour and texture of target images may fluctuate considerably due to substantial noise interference. Consequently, visual sensor-based techniques for road environment detection encounter considerable obstacles. The significant rise in computational demand concurrently elevates the stability requirements of the hardware platform [26].

The AdaBoost method was used by Y et al. to increase the classifier's accuracy [27]. The sensitivity of Haar's algorithm to variations in illumination, angle, and scale may result in missed and erroneous detections, despite the fact that this technique can successfully identify numerous distinct targets (such as pedestrians and cars) in an image. Teoh et al. presented a symmetry-analysis based vehicle detection technique that employs a machine learning classifier for vehicle classification and local symmetry features to describe the texture and shape of vehicles [28]. In complicated background situations, it is prone to misdetection despite its excellent accuracy and real-time performance. By combining two target detection techniques, Viola-Jones and HOG + SVM, Xu et al. were able to overcome the vehicle detection problem and increase detection efficiency and accuracy through candidate target identification and picture screening [29]. But in complicated scenarios, this approach fails. The aforementioned research makes it clear that traditional procedures are expensive since they need specialized equipment and a significant investment in labor. Furthermore, when detecting cars in complex scenes—that is, vehicles with multiple targets, occlusion, or inadequate illumination, these systems exhibit mistakes.

In recent years, the development of deep learning theory has led to a major breakthrough in target detection algorithms based on convolutional neural networks (CNNs.) CNNs surpass conventional computer vision techniques by automatically learning the fundamental characteristics of targets, hence increasing detection accuracy [30]. This step not only promotes the development of environmental sensing and detection technology but also provides new perspectives and methods for multi-sensor data fusion.

3 Technical challenges

The present state of research in machine vision for autonomous driving indicates that, despite considerable advancements in visual perception abilities, numerous challenges remain to be addressed. Pal et al. identified deficiencies at the technical level; the reliability of sensors in adverse weather conditions (e.g., rain, snow, and fog) and varying lighting conditions requires enhancement, while algorithms remain inadequate regarding their adaptability in complex traffic environments and their predictive capacity concerning human behaviours [31]. Researchers have analysed survey papers on specific sub-problems; however, a comprehensive review of computer vision challenges, datasets, and methodologies for autonomous vehicles remains absent. Janai et al. address this deficiency by providing a comprehensive overview of advanced datasets and methodologies [32].

Object identification and recognition accuracy can be adversely affected by adverse weather and lighting conditions, including rain, snow, fog, and extreme brightness or dimness. Currently, machine vision operates erratically in complex traffic situations. Zhao et al. investigated the integration of virtual simulation with decision-making algorithms to enhance system intelligence and performance [33]. Nonetheless, the potential hazards associated with extreme weather are often overlooked. Despite the potential of multi-sensor fusion technology to enhance the accuracy and robustness of sensing systems, challenges persist in the management of conflicting data from various sensors and in the execution of real-time data fusion. Conversely, autonomous driving necessitates an urgent implementation of a corresponding safety assessment system to address the limitations inherent in the current data-driven approach for evaluating the safety of reliable autonomous vehicles. Kang et al. introduced an interpretable scenario based on eXplainable AI (XAI) that utilises LiDAR data to encompass a broader array of environments and parameters, emphasising scenario representativeness, coverage, extensibility, and compatibility with black box models [34].

Machine vision faces many challenges in the field of autonomous driving, especially in bad weather and complex traffic scenarios. Issues such as detection of partially occluded or moving objects, complexity and cost of data labeling, and lack of dataset diversity limit the development of the technology. Researchers are attempting to overcome these obstacles by creating sensors and algorithms that are tailored to severe weather, detecting moving objects more accurately, lowering the cost of data labeling, and strengthening models' capacity to generalize by gathering a variety of datasets. Furthermore, the advancement of autonomous driving technology depends on algorithm improvement and technological innovation. To create more accurate and dependable autonomous driving systems, multidisciplinary cooperation combining computer vision, machine learning, and sensor technologies is necessary.

4 Development Trends and Prospects

The development trend of machine vision in the field of autonomous driving will focus more on interdisciplinary integration. Enhancing the combination of deep learning and multi-sensor fusion will further improve the efficiency of environment sensing and path planning [35]. Multi-sensor fusion technology can significantly improve the accuracy and robustness of target detection by combining data from different sensors, such as LiDAR, radar and camera. In addition, the path planning and decision-making module will rely more on advanced machine learning algorithms, such as deep reinforcement learning, to realize real-time dynamic path planning. The researchers propose a deep learning-based dynamic path planning algorithm that can predict and respond to environmental changes in real time to ensure safe and efficient navigation.

With the advancement of hardware technology and optimization of algorithms, autonomous driving systems will be able to achieve higher safety and reliability in more complex environments. The development of high-resolution LiDAR technology provides self-driving cars with more accurate environment mapping and obstacle detection capabilities [36]. In addition, the development of vehicle-to-everything (V2X) communication technologies will enable self-driving cars to communicate with surrounding vehicles and infrastructure in real-time, leading to enhanced situational awareness and coordination. Researchers will also explore ways to reduce the computational complexity of systems through more efficient algorithms and hardware design, leading to wider commercialization. For example, end-to-end learning approaches simplify the architecture of autonomous driving systems and improve processing efficiency by training a single neural network to map raw sensor inputs to driving actions.

In addition, with the maturity of quantum computing technology, it is expected to solve complex problems that cannot be solved by current classical computers, further promoting the development of automatic driving technology. The research of machine vision in the field of autonomous driving is developing in the direction of smarter and more efficient, providing a solid technical foundation for the popularization of autonomous driving technology in the future. Through the continuous promotion of technological innovation and interdisciplinary cooperation, self-driving cars are expected to realize a wider range of applications in the near future, bringing a safer and more convenient travel experience to society.

5 Conclusion

This paper provides a systematic overview of the current status of machine vision application in the field of autonomous driving, the challenges it faces, and the future development direction. Machine vision, as one of the key technologies for autonomous driving, acquires environmental image data through on-board cameras and other devices to provide intuitive visual information for vehicles and help the system better understand and perceive the surrounding environment. Although machine vision has made significant progress in target detection and environment perception in recent years, its stability and accuracy in bad weather and complex traffic scenarios still need to be improved. In addition, the complexity and cost of data labeling and the lack of dataset diversity also limit the development of the technology. To address these challenges, researchers are working on developing sensors and algorithms adapted to severe weather, improving the detection of dynamic objects, reducing the cost of data labeling, and enhancing the generalization ability of the model by collecting diverse datasets. Meanwhile, technological innovation and algorithm optimization are key to advancing autonomous driving technology, requiring interdisciplinary collaboration that combines computer vision, machine learning, and sensor technologies to achieve more accurate and reliable autonomous driving systems.

In the future, machine vision in autonomous driving will focus more on interdisciplinary integration. Enhancing the combination of deep learning and multi-sensor fusion will further improve the efficiency of environment perception and path planning. With the advancement of hardware technology and the optimization of algorithms, the automatic driving system will be able to achieve higher safety and reliability in more complex environments. The development of high-resolution LiDAR technology, the application of vehicle-to-everything (V2X) communication technology, and the exploration of end-to-end learning methods will support the commercial application of autonomous driving technology. In addition, as quantum computing technology matures, it is expected to solve complex problems that cannot be solved by current classical computers, further promoting the development of autonomous driving technology. By continuously promoting technological innovation and interdisciplinary cooperation, self-driving cars are expected to realize wider applications soon, bringing a safer and more convenient travel experience to society.

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