Intelligent Driving Algorithms Based on Varied Sensors: Technical Characteristics and Evolution

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Abstract. This paper conducts a review study on intelligent driving algorithms based on different sensors. Firstly, it outlines the working principles and characteristics of core sensors for intelligent driving, namely millimeter-wave radar, LIDAR, and cameras. Subsequently, it sorts out the key algorithms corresponding to each sensor: target detection and speed measurement algorithms for millimeter-wave radar, point cloud processing and target detection and tracking algorithms for LIDAR, and computer vision and deep learning algorithms for cameras. It also compares the performance of different algorithms from the dimensions of accuracy, reliability, real-time performance, and cost. Finally, it analyzes the current challenges of the algorithms in terms of complex environment adaptability, balance between real-time performance and accuracy, and multi-sensor collaboration, and looks forward to their development trends, providing a reference for the research and application of intelligent driving perception algorithms.

Keywords: Intelligent driving; environmental perception; multi-sensor; perception algorithms.

1. Introduction

In recent years, the global automotive industry has been undergoing profound changes. As a core direction of the new generation of automotive technology, intelligent driving has attracted great attention from academia, industry, and governments of various countries. According to relevant data, the global intelligent driving market size has grown from less than 50 billion US dollars in 2020 to more than 150 billion US dollars in 2024, and it is expected to maintain an average annual compound growth rate of over 25% in the next five years. Behind this rapid development is the urging of problems such as traffic congestion and frequent traffic accidents in the process of urbanization, as well as the inevitable result of continuous breakthroughs in multi-disciplinary technologies such as artificial intelligence, sensor technology, and communication technology. Intelligent driving is generally regarded as an important way to solve the problems of traffic safety and efficiency, and its commercialization has become a key indicator to measure the competitiveness of a country's automotive industry.

In the intelligent driving technology system, environmental perception is the premise for the system to realize "autonomous decision-making" and "safe control". Just like the "eyes" of the system, it needs to obtain real-time and accurate information such as the position, speed, category of targets around the vehicle and road scenes. The performance of environmental perception largely depends on the collaborative performance of sensors and adaptive algorithms. As the "acquisition interface" of environmental information, the performance of sensors directly determines the quality of original information at the perception layer; algorithms, as the "core of information processing", are responsible for extracting effective features from original data, identifying targets, and outputting key information required for decision-making. Both are indispensable.

At present, the widely used sensors in intelligent driving systems mainly include millimeter-wave radar, LIDAR, and cameras. Millimeter-wave radar can stably output information such as the distance and speed of targets in complex weather conditions due to its electromagnetic wave characteristics, but its ability to identify target categories is limited; LIDAR can generate high-precision three-dimensional point cloud data to achieve accurate target positioning and contour perception, however, it is difficult to process data and has high cost; cameras can provide two-dimensional images with rich information such as color and texture at a low cost, and perform well in the identification of fine target categories, but they are extremely sensitive to environmental factors such as light and weather. The research on algorithms based on different sensors is aimed at giving full play to the advantages of various sensors and making up for their shortcomings, so it has become a research focus in the field of intelligent driving.

In view of this, this paper focuses on intelligent driving algorithms based on different sensors. Firstly, it outlines the basic situation of the three core sensors, then deeply analyzes the principles and application scenarios of the key algorithms corresponding to each sensor, compares the performance of different algorithms from multiple dimensions, and finally summarizes the current challenges in the research and looks forward to the development trends, aiming to provide a comprehensive and valuable reference for the research and practice of intelligent driving perception technology.

2. Overview of Intelligent Driving Sensors

Sensors act as the "interface" for intelligent driving systems to acquire environmental information, and their performance directly determines the information quality of the perception layer. Environmental perception technology depends on multiple core elements, including hardware sensors like LIDAR, millimeter-wave radar, and cameras [1]. The following is an overview of the basic situation of three commonly used sensors.

2.1. Millimeter-Wave Radar

Millimeter-wave radar transmits millimeter waves (with a wavelength of 1-10 mm and a frequency of 24-77 GHz) and obtains target information by utilizing the reflection characteristics of electromagnetic waves. It can simultaneously output the target's distance, speed (based on the Doppler effect), and angle. Millimeter-wave radar mainly includes three types of signal waveforms: triangular wave signals, sine wave signals, and sawtooth wave signals [2]. After transmitting radio waves, it collects the target's scattered waves through a receiving antenna and performs a series of signal processing to obtain target information [3]. Millimeter-wave radar can not only obtain the precise distances of multiple targets but also measure the relative speed by using the Doppler frequency shift effect. It is widely applied in obstacle detection, pedestrian recognition and vehicle identification [4, 5].

2.2. LIDAR

LIDAR, as a sensor capable of obtaining the spatial position of objects, essentially achieves environmental perception through laser detection and ranging [6]. Its working principle involves emitting laser beams (mostly near-infrared light), using the round-trip time or phase difference of the beams to calculate the distance to the target, and ultimately generating "point cloud" data centered on three-dimensional coordinates (x, y, z). Based on this, LIDAR’s environmental perception method mainly focuses on three-dimensional target detection algorithms. The core lies in identifying the collected point cloud data through three-dimensional target recognition algorithms. In point cloud target recognition, there are mainly three-point cloud processing methods: indirect processing, direct processing, and fusion processing. Owing to its outstanding performance in target contour measurement, angle measurement, distance measurement, and general obstacle detection, LIDAR has gradually become the core equipment for L4 and above level autonomous vehicles [7].

2.3. Camera

Benefiting from its low-cost advantage, the vehicle-mounted camera has become a basic sensor in the perception system of intelligent vehicles and a mainstream choice in both industry and academia. The primary classification categories of on-vehicle cameras in intelligent driving perception systems encompass monocular cameras, binocular stereo cameras, RGB-D (Red, Green, Blue-Depth) cameras, and panoramic cameras. In terms of functionality, vehicle-mounted cameras can handle multiple core tasks such as multi-target detection, tracking, semantic segmentation, and lane line detection. The cameras can capture rich information about targets in the surrounding environment, such as color, texture, and shape, and can effectively identify various targets in non-extreme environments. Compared with millimeter-wave radars and LIDAR, cameras have significant advantages of dense data and high resolution. However, the limitations of vehicle-mounted cameras are also very prominent: their perception performance is easily affected by weather conditions and will drop sharply in scenarios such as rainy and foggy days or at night. At the same time, they are extremely sensitive to scenes with sudden changes in light. For example, when an intelligent vehicle enters or exits a tunnel, or when an oncoming vehicle suddenly turns on its high beams, the perception effect will be adversely affected.

3. Intelligent Driving Algorithms Based on Different Sensors

3.1. Algorithms Based on Millimeter-Wave Radar

The core output of a millimeter-wave radar is a "target list" (containing information such as distance, speed, and angle). Algorithms need to solve the problems of "target detection accuracy" and "data association", with a focus on target detection and speed measurement algorithms. The target detection and speed measurement algorithm of millimeter-wave radar achieves target judgment, positioning, and speed measurement by processing electromagnetic wave signals, and its core is divided into four links: signal transmission and reception, distance extraction, speed extraction, and target determination. Firstly, in the functional phase of signal transmission and reception within the operating mechanism of automotive radar, the radar system emits millimeter-wave signals, which then undergo reflection upon interacting with surrounding target objects, thereby generating echo signals. After being received, the echo signals are converted into digital signals. The frequency-modulated continuous wave (FMCW) signal system is usually adopted, whose frequency changes linearly with time, and the distance and speed information of the target can be related through the frequency difference between the transmitted signal and the echo signal. Based on this information, the distance is measured using the "frequency difference" between the transmitted and echo signals. There is a time delay in the propagation of the echo, which makes the frequency difference between the two have a linear relationship with the target distance. The distance of the target can be obtained by extracting the frequency difference from the frequency domain through Fast Fourier Transform (FFT). Then, relying on the Doppler effect, the movement of the target causes a frequency shift of the echo (Doppler frequency shift), and the shift amount is related to the radial speed. By continuously transmitting chirp signals to form a sequence, performing a second Fourier transform (Doppler FFT) on the echo to extract the frequency shift, the target speed can be inferred inversely, with an accuracy of ±0.1m/s, which can meet the needs of dynamic target perception. Finally, the Constant False Alarm Rate (CFAR) algorithm is used to distinguish between target and noise signals, and the threshold is dynamically set by counting the noise level. The commonly used ones are CA-CFAR (suitable for scenarios with uniform noise) and GO-CFAR (suitable for scenarios with multiple targets or non-uniform noise). When the signal power exceeds the threshold, it is determined that a target exists, and its distance and speed are output.

3.2. Algorithms of LIDAR

3.2.1 The point cloud processing algorithm

The point cloud processing method for LIDAR is a technical process of processing and analyzing the three-dimensional point cloud data generated by the LIDAR to extract useful information. The core is to convert the original unordered point set into structured information that can be used for positioning, target detection, etc. In the preprocessing stage, noise points caused by sensor errors or environmental interference are removed through statistical filtering, radius filtering, etc., and multi-frame point cloud registration is completed using the ICP algorithm to unify the coordinate system [8]. Then, through voxel filtering and other downsampling methods, redundant data is reduced and key structures are retained to solve the problem of data availability; subsequently, point cloud segmentation is used to split the target and the area, and the RANSAC algorithm is used to segment the ground and non-ground to distinguish the drivable area from obstacles [9]. The non-ground points are segmented into distinct target clusters using the DBSCAN clustering algorithm, or alternatively, deep learning models such as PointNet are employed to perform semantic segmentation and classify target categories. Geometric features—such as bounding boxes—are extracted to infer target types based on their dimensions, while descriptors like FPFH are computed for target matching and identification, enabling the extraction of key attributes. Finally, the processed point cloud data can generate outputs including target lists, drivable area maps, and 3D environmental maps, which support environmental perception in applications such as autonomous driving, robot navigation, and mapping tasks.

3.2.2 The target detection and tracking algorithm

The LIDAR target detection and tracking algorithm is a technology that realizes target recognition, positioning, and motion trajectory tracking in the environment based on point cloud data, and it is a core application of LIDAR environmental perception. In the detection stage, targets need to be identified from the point cloud first through algorithms such as PointPillars and SECOND. These algorithms extract features through methods such as cylindrical projection and sparse convolution, generating 3D detection boxes for targets and outputting information such as position and size, solving the recognition difficulties caused by the sparsity of point clouds. The accuracy in the detection of common targets such as vehicles and pedestrians can reach over 85%. The core of the tracking stage is to associate target trajectories. Usually, it combines detection results with filtering algorithms. First, the detection algorithm is used to obtain the target state in the current frame, and then the Kalman filter is used to predict the target's position in the next frame [10]. By calculating the matching degree between the detection box and the historical trajectory, trajectory association is achieved, which can improve tracking stability in scenarios such as target occlusion.

3.3. Algorithms for Cameras

Cameras are among the most important and widely used sensors in autonomous vehicles [11]. Their core output is "2D images", and related algorithms need to achieve environmental perception through "image understanding".

3.3.1 Computer vision algorithms

Traditional computer vision algorithms serve as the foundation for environmental perception in camera systems, relying on manually designed features and rules for image interpretation. For instance, algorithms such as SIFT and HOG are employed to extract key features, including edges and textures, which are then combined with sliding window techniques and classifiers like SVM for object detection. Image segmentation is achieved through methods such as threshold segmentation and the Canny operator to distinguish background from foreground. Additionally, depth information of scenes is obtained by calculating disparity from stereo camera images, thereby compensating for the limitations of monocular cameras.

3.3.2 Application of deep learning algorithms in visual perception

Deep learning, with its powerful ability of automatic feature learning, has become the core technology for camera visual perception. In the field of object detection, algorithms such as YOLO series and Faster R-CNN extract deep features through CNN to achieve efficient localization and classification of multiple types of objects [12]. In semantic segmentation, models like FCN and DeepLab series label pixels with categories, providing detailed environmental semantic information; instance segmentation combines the advantages of detection and segmentation to distinguish individual targets of the same type; single-camera depth estimation models can infer depth from a single image, reducing system costs. In visual SLAM, deep learning optimizes feature extraction, loop closure detection, etc., improving the positioning and mapping accuracy in dynamic or weak-texture environments, providing key support for autonomous driving decision-making and control.

4. Analysis of Performance Comparison Among Different Algorithms

In terms of accuracy, the point cloud processing algorithms of LIDAR excel in the 3D positioning accuracy of targets. For instance, the PointPillars algorithm can achieve a detection accuracy of over 85% for targets such as vehicles, which is significantly higher than that of a single millimeter-wave radar algorithm. The deep learning algorithms for cameras have greater advantages in target category recognition; the YOLO series algorithms can accurately distinguish fine categories like pedestrians and traffic signs, while millimeter-wave radar has a weak capability in judging target categories. In terms of reliability, millimeter-wave radar algorithms are less affected by weather and can stably output target distance and speed information in scenarios such as rain, fog, and night. Camera algorithms, however, are prone to interference from light and weather. The reliability of LIDAR algorithms in extreme weather is between the two, but when facing complex occlusion scenarios, the stability of their tracking algorithms will decrease. In terms of real-time performance, the target detection and speed measurement algorithms of millimeter-wave radar have the fastest response speed due to the relatively simple signal processing, which can meet the millisecond-level real-time requirements. The deep learning algorithms for cameras are slightly weaker in real-time performance due to the influence of model complexity and need to be optimized through model lightweighting. The point cloud processing algorithms of LIDAR face greater challenges in real-time performance because of the large amount of data and the time-consuming preprocessing and segmentation links. Nevertheless, the application of technologies such as sparse convolution is gradually improving this issue. The multi-sensor fusion algorithm can integrate the advantages of various single-sensor algorithms, and it is superior to single algorithms in both accuracy and reliability. However, the complexity of the algorithm increases, which puts higher demands on hardware computing power. Table 1. reflects the performance comparison of the three algorithms for LIDAR, camera, and millimeter-wave radar.

Table 1. Performance comparison of the three algorithms

Algorithm Type	Accuracy (Target Detection mAP)	Reliability (Accuracy in Severe Weather)	Real-time Performance (Frame Rate / FPS)	Cost (Sensor + Algorithm Deployment)
LIDAR Single Algorithm	85%-90% (Vehicle Detection)	70%-80% (Heavy Rain Scenario)	30-100	High (LIDAR accounts for 80% of the cost)
Camera Single Algorithm	75%-85% (Vehicle Detection)	30%-50% (Heavy Rain / Night Scenario)	50-200	Low (Camera cost only)
Millimeter-Wave Radar Single Algorithm	60%-70% (Vehicle Detection)	85%-95% (Heavy Rain Scenario)	10-30	Medium (Moderate radar cost)

5. Challenges

The current intelligent driving algorithms are faced with multiple challenges. In terms of adaptability to complex environments, the performance of existing algorithms is still insufficient under extreme weather conditions (such as heavy rain and heavy snow) and complex dynamic scenarios (such as sudden crossing pedestrians and continuous lane changes of multiple vehicles). The camera algorithm is prone to false detection due to sudden changes in light; LIDAR may suffer from point cloud loss in dense occlusion scenarios; and the millimeter-wave radar has low detection accuracy for small targets. The dilemma of balancing real-time performance and accuracy of algorithms is prominent. High-precision deep learning algorithms and point cloud processing algorithms often require strong computing power support, making it difficult to operate efficiently on ordinary on-board hardware. However, reducing the algorithm complexity will lead to a decrease in accuracy. The synergy of multi-sensor fusion algorithms needs to be improved. There are temporal and spatial synchronization errors in the data from different sensors, and information conflicts are likely to occur during data fusion. How to achieve efficient temporal and spatial calibration and information complementarity remains a difficult problem. In addition, the generalization ability of algorithms is insufficient. In new scenarios not covered by the training dataset (such as special road signs and rare vehicle models), the performance of algorithms will decline significantly.

6. Conclusion

To sum up, as the core sensors for environmental perception in intelligent driving, millimeter-wave radar, LIDAR, and cameras, and the algorithms based on them play an irreplaceable role in intelligent driving systems, each with distinct characteristics and applicable scenarios. The target detection and speed measurement algorithms of millimeter-wave radar have the prominent advantage of strong anti-interference ability and can work stably in harsh weather such as rain and fog, but their target recognition accuracy is relatively low; the point cloud processing and target detection and tracking algorithms of LIDAR have leading accuracy in target positioning and contour perception relying on the advantage of three-dimensional point cloud data, however, affected by the large amount of data, they face great challenges in real-time performance and have high cost; the computer vision and deep learning algorithms of cameras can achieve accurate identification of fine target categories with the help of rich visual information, and have low cost, but they are extremely sensitive to environmental light and weather conditions. The multi-sensor fusion algorithm has comprehensively improved accuracy and reliability by integrating the advantages of various sensors, and it is an important development direction in the future, but it also faces complex problems such as data spatio-temporal synchronization and information collaboration.

At present, intelligent driving algorithms based on different sensors still have shortcomings in terms of complex environment adaptability, balance between real-time performance and accuracy, multi-sensor collaboration, and generalization ability. In the future, it is necessary to further carry out research on algorithm lightweight, optimization of multi-sensor fusion strategies, and enhancement of complex environment perception ability, continuously break through technical bottlenecks, and promote the development of intelligent driving algorithms towards a more accurate, reliable, and efficient direction, so as to lay a solid technical foundation for the commercialization of intelligent driving technology.

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