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Research on Perception and Control System of Small Autonomous Driving Vehicles

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Abstract: With the continuous advancement of autonomous driving technology, the application of small autonomous vehicles in changing environments has gradually attracted attention. This article discusses the core technologies of perception and control systems for small autonomous vehicles. An analysis was conducted on the key issues faced by the perception system of small autonomous vehicles, including improving the accuracy of local and global positioning, as well as the application of multi-source sensor fusion technology. By integrating various sensing devices such as LiDAR and image sensors, the perception accuracy of the system has been enhanced. The improvement of the control system was also discussed, and the overall path planning method based on gridded maps and the improvement strategy of the motion control system were analyzed. With precise path design and efficient motion control algorithms, the driving stability and safety factor of the car are ensured in changing environments. Finally, the integration and testing of perception and control systems were discussed, and solutions for software hardware collaboration enhancement and comprehensive debugging and testing in complex scenarios were proposed.

Keywords: small autonomous vehicles; perception system; control system; path planning; sensor fusion

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1. Introduction

With the rapid advancement of autonomous driving technology, the application scope of small autonomous vehicles is gradually expanding. It is no longer limited to traditional passenger and freight vehicles, but gradually penetrates into multiple industries such as urban distribution, warehousing and logistics, and agricultural operations. In such vehicles, the perception system is the "brain" that integrates information from various sensors to perceive the surrounding environment in real time, achieving accurate position determination and obstacle recognition. The control system is based on these perception data to complete path planning and dynamic adjustment, ensuring the safety of vehicle operation. Despite this, how to efficiently and accurately perceive and control under complex and changing driving conditions remains a technical challenge that small autonomous vehicles need to overcome. This article aims to study the perception and control system of such vehicles, analyze their core technologies, and explore improvement solutions to promote their widespread deployment in practical applications.

2. Research on Perception System for Small Autonomous Driving Vehicles

2.1. Localization and Global Localization

Localization and global positioning are key technologies in the perception system of small autonomous vehicles, to ensure efficient and accurate operation in complex environments, as shown in Figure 1. Localization refers to the establishment of the relative coordinates of a vehicle in a dynamic scene, while global positioning involves the fusion of the vehicle's local position information with the global coordinate system to obtain its exact location. Localization mainly relies on accurate sensor data and map data, which are analyzed through specific algorithms to achieve accurate positioning of vehicles in specific environments. Common localized positioning methods include vision based positioning methods, LiDAR positioning methods, and visual inertial odometry. For such autonomous vehicles, the difficulty of local positioning lies in ensuring the accuracy and real-time processing capability of sensor data under dynamic and complex conditions. In narrow city streets or areas dense with complex obstacles, the localization system of vehicles must immediately refresh their coordinates and quickly handle sensor deviations and environmental changes [1].

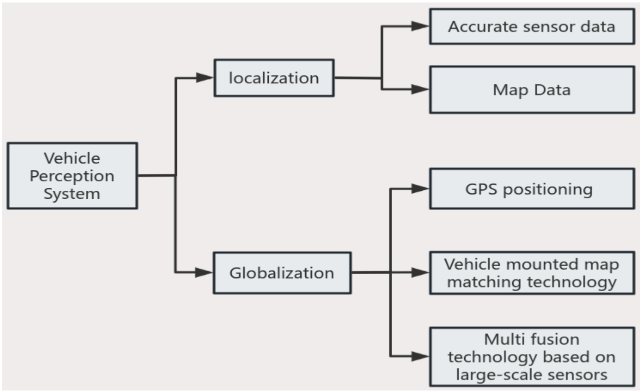

Figure 1. Vehicle Perception System.

Global positioning is based on high-precision digital maps or satellite navigation systems to calibrate the vehicle's position in a global coordinate system. Common global positioning technologies include GPS positioning, vehicle map matching technology, and multi fusion technology based on large-scale sensors. Global positioning technology provides a stable reference frame for vehicles, enabling them to clearly determine their own orientation in a wider area and effectively plan their driving path. The fusion of local positioning and global positioning is generally realized through the comprehensive processing of sensor information. The data collected by different sensors are combined, and Kalman filtering and other algorithms are used to further improve the positioning accuracy. For example, at a certain moment, the global positioning of the vehicle is provided by GPS with an accuracy error of ±5 meters, while the local positioning accuracy provided by the LiDAR sensor is ±0.1 meters. In this case, the final positioning of the vehicle can be fused through the weighted average method. The specific formula is:

$$x_{fused} = \frac{w_{gps} \cdot x_{gps} + w_{lidar} \cdot x_{lidar}}{w_{gps} + w_{lidar}} \quad (1)$$

In formula (1), x_{fused} is the fused position, x_{gps} and x_{lidar} are the positioning data provided by GPS and LiDAR, respectively, and w_{gps} and w_{lidar} are the corresponding weights. By using a weighted fusion strategy, the inaccuracy of positioning can be reduced, and the credibility and accuracy of the system can be enhanced.

2.2. Multi Sensor Fusion Technology

With the increasing demand for perception accuracy and real-time performance in small autonomous vehicles, the limitations of a single sensor are gradually becoming apparent [2]. The technology of integrating multiple sensors has become the core solution for optimizing system performance. By fusing the information received by different sensors, this technology overcomes the shortcomings and deviations of a single sensor in perception, and enhances the stability and accuracy of the system. In the perception system of small autonomous vehicles, commonly used sensor types include laser radar, cameras, millimeter wave radar, and ultrasonic sensors. These sensors each have their own characteristics. Lidar has high accuracy in measuring distance and outstanding environmental modeling capabilities, but its performance is relatively inferior in harsh weather and complex lighting environments. The camera performs well in capturing image details, especially in target recognition and classification tasks, but is sensitive to changes in light and climate. Millimeter wave radar can still maintain stable operation under extreme weather conditions, although its resolution is not as good as cameras. In order to integrate the advantages of different sensors and overcome the limitations of single use, the strategy of integrating multiple sensor technologies is particularly critical. Common sensor fusion technologies include methods based on extended Kalman filtering, particle filtering, and deep learning. Among these technologies, extended Kalman filtering has become the preferred solution for handling nonlinear system state estimation due to its wide application in small autonomous vehicles. For example, there are two types of sensors S_1 and S_2 that provide measurement data Z_1 and Z_2, respectively, with corresponding error covariance P_1 and P_2. The fused state estimate $\hat{x}$ and covariance P can be calculated using the following formula:

$$\hat{x}_{\text{fused}}=\mathrm{P}\cdot\left(P_1^{-1}\cdot\hat{x}_1+\mathrm{P}_2^{-1}\cdot\hat{x}_2\right)$$
$$P_{\text{fused}}=(P_1^{-1}+\mathrm{P}_2^{-1})^{-1} \quad (2)$$

In formula (2), there are state estimates for sensors S_1 and S_2, and P_1 and P_2 are their respective error covariance matrices. By using weighted fusion methods, small autonomous vehicles can integrate information from various sensors to achieve higher stability and safety performance in changing environments. The fusion of multi-source sensor data can improve the accuracy of vehicle detection and enhance the robustness of the system in different environments. Thanks to the rapid development of deep learning, many autonomous driving systems have adopted multimodal sensor fusion schemes with neural networks at their core, accelerating the development of autopilot technology in terms of intelligence and efficiency.

3. Research on Control Systems for Small Autonomous Vehicles

3.1. Global Path Planning Based on Grid Maps

Global path planning plays a core role in the perception and navigation systems of small autonomous vehicles, with the aim of designing the optimal travel trajectory from the starting position to the destination for the vehicle. In the process of using gridded maps for path planning, the entire environment is subdivided into numerous grid cells, The entire environment is subdivided into numerous grid cells, each representing an independent space, where vehicles move between these cells. The implementation of global path planning generally adopts the A algorithm or Dijkstra algorithm. The A algorithm is widely recognized for its high efficiency and excellent path search ability. When applying grid maps, heuristic search strategies are often used to evaluate each grid cell. The A* algorithm selects the path with the lowest cost by comprehensively considering the real-time cost from the starting point to the current cell and the expected cost from the current cell to the target cell. The core process of Algorithm A is as follows:

1) Initialize open and closed lists, and include the starting point in the open list.
2) Select the node with the lowest cost from the open list for expansion.

Calculate the cost of neighboring squares according to the heuristic function, and include the adjacent squares that have not been expanded into the open list. If the target point is expanded in the open list, return the path; otherwise, continue expanding [3].

Observing the data in Table 1, it can be observed that as the complexity of the environment increases, both the length and time of path planning show an upward trend. The selection of optimization algorithms is particularly crucial when dealing with path planning tasks in complex environments.

Table 1. Data Analysis of Grid Map Path Planning.

Environmental complexity	Distance from starting point to target point (m)	Planned path length (m)	Path planning time (ms)	A * algorithm optimal path
simple	50	52	120	YES
secondary	50	55	200	YES
complex	50	70	350	NO

3.2. Optimization of Motion Control System

It is crucial to optimize the motion control system of small autonomous vehicles in order to ensure their stability and accuracy during operation [4]. The system generally covers multiple subsystems such as path planning, speed adjustment, and vehicle attitude maintenance, and precise optimization design of these subsystems is particularly crucial. The optimization process aims to enhance the accuracy and response speed of the control system, and prevent vehicle body deviation caused by dynamic constraints or trajectory deviations. When building the motion control system, the model is usually established according to the vehicle dynamics characteristics, which involves the core parameters such as speed, acceleration and deceleration, steering angle, etc. For example, the motion of a vehicle can be described by the following dynamic equation:

$$\dot{x} = \mathrm{v}\cos(\theta),\ \dot{\mathrm{y}} = \mathrm{v}\sin(\theta),\ \dot{\theta} = \frac{v}{L}tan(\delta) \quad (3)$$

In formula (3), X and Y are the current position coordinates of the vehicle, θ is the orientation angle of the vehicle body, V is the linear velocity of the vehicle, δ is the steering angle, and L is the wheelbase of the vehicle. In order to improve the performance of the control system, it is essential to fine tune the parameters of the dynamic model, especially the precise setting of speed and rudder angle. Although conventional PID controllers can achieve smooth control in most situations, they may have drawbacks such as overshoot or slow response when facing changing and complex operating environments. Adopting adaptive control strategies or model predictive control (MPC) techniques can enhance control performance. The MPC algorithm dynamically adjusts path planning to reduce trajectory deviation and energy consumption, achieving higher precision motion control in variable environments. When implementing optimization strategies, comprehensive consideration should be given to vehicle dynamics limitations and environmental changes. For example, the vehicle's steering and speed can be corrected based on tire models to prevent control errors caused by rapid acceleration or oversteering. The specific optimization objective can be represented by the following performance function:

$$J = \int_0^T (w_1(\dot{\mathrm{x}}(t) - v_{des}(t))^2 + w_2(\delta(t) - \delta_{des}(t))^2)\mathrm{dt} \quad (4)$$

In formula (4), $v_{des}(t)$ and $\delta_{des}(t)$ represent the expected speed and steering angle, respectively. w_1 and w_2 are weighting coefficients used to balance the relative importance of speed control and steering control. After thorough optimization of the above performance indicators, the motion control system can achieve more stable and efficient operation in various driving environments. The upgrade and transformation of the system not only involve adjusting control parameters but also adopting advanced algorithms and real-time response mechanisms. These improvements comprehensively consider the vehicle's dynamic properties and surrounding environmental factors, enabling high-precision control of autonomous vehicles.

4. List and Testing of Perception and Control Systems

4.1. System List Architecture

The core of perception and control in small autonomous vehicles relies on a refined architecture system to ensure smooth coordination between various functional units. This architecture system covers multiple key parts such as sensing components, data processing units, decision-making and command units, and execution units. The sensing components include laser radar, cameras, ultrasonic sensors, and GPS, which are responsible for detecting the surrounding environment and the dynamics of the vehicle itself. These sensing components use data fusion technology to construct a real-time digital model of the vehicle's surrounding environment, providing information support for decision-making and control processes. The main task of the data processing unit is to perform preliminary processing, filtering, fusion, and in-depth analysis on the data collected by the sensing components. At this stage, advanced signal processing techniques such as Kalman filtering and particle filtering will be applied to optimize the accuracy and reliability of sensor data [5].

The real-time exchange of information between the information processing unit and the decision-making command unit relies on efficient data transmission channels to ensure the smooth operation of the system and data synchronization. The decision-making command unit completes route planning, obstacle identification, and the formulation of avoidance strategies based on the collected perception data. This unit integrates multiple intelligent algorithms, including deep learning, reinforcement learning, and fuzzy logic control, to enable fast response and accurate judgment under changing driving conditions. The control commands generated by this unit are then transmitted to the execution unit, which is composed of a motor controller and a drive mechanism, responsible for adjusting the speed and direction according to the instructions. The overall architecture design of the system needs to balance hardware resource allocation, computational efficiency, and real-time requirements. The modular design concept and standardized interfaces are adopted to ensure collaborative operation, as well as the scalability and upgradability of the system components.

4.2. Collaborative Optimization of Software and Hardware

For small autonomous vehicles, achieving efficient operation of perception and control modules requires highly coordinated optimization of software and hardware. In terms of hardware configuration, advanced laser radar and camera equipment are used in combination to achieve precise perception effects, while powerful embedded systems with GPU acceleration are employed to ensure adequate computational throughput. The optimization of hardware structure not only emphasizes the integration of high-precision sensing devices, but also emphasizes low energy consumption and stability to meet the requirements of long-term operation of automatic navigation vehicles [6].

At the software level, its optimization relies on efficient algorithms and powerful parallel processing techniques. Ensuring vehicle safety requires real-time processing of perception data and timely feedback from decision-making algorithms. At the algorithmic level, the use of deep learning networks and image recognition techniques has enhanced the recognition accuracy of road obstacles. Considering the limitations of hardware resources, methods such as model compression and computational quantization are applied to reduce resource consumption and accelerate inference. In order to comprehensively improve the overall performance of the system, collaborative optimization of software and hardware is indispensable, including adjustments to communication interfaces and data transmission rates to ensure smooth real-time exchange of data between processing units and control units. For example, using fast CAN bus and Ethernet to achieve data transmission, further reducing latency.

4.3. Integrated Debugging and Testing in Complex Environments

A comprehensive testing plan covering multiple environmental factors was designed to thoroughly examine the system performance of small autonomous vehicles in terms of perception and control [7]. The testing is divided into the following stages: Collecting and analyzing perceptual information, conducting effectiveness testing of trajectory planning, and evaluating dynamic control performance. During the experiment, the vehicle travels along the designated route at a predetermined speed, and the performance indicators of each testing stage are recorded in detail Multiple sensors were utilized to achieve synchronous collection of environmental data, allowing verification of the system's perception accuracy and response speed under changing environmental conditions. For example, in an environment where static obstacles and dynamic interference coexist, statistical analysis is conducted on the accuracy of vehicle detection of obstacle positions Apply the A * algorithm for path planning, measure the path planning time and length of vehicles facing different environmental complexities, and confirm the effectiveness and safety of the planned path By monitoring the vehicle's steering, acceleration, and braking response speed in real-time through the control system, evaluate the responsiveness of the motion control system to unexpected scenarios. The relevant test data is shown in Table 2.

Table 2. Partial Test Data.

Scene type	Perception accuracy (%)	Path planning time (ms)	Path deviation (m)	Control response time (ms)
Simple straight path	98	150	0.1	120
Dynamic intersection	95	250	0.2	180
Narrow road complex scene	92	300	0.3	200
Dynamic interference scenario	90	250	0.4	250

After verification, relying on multi-sensor integration and real-time trajectory planning, vehicles can effectively identify obstacles and construct reliable driving trajectories. In a constantly changing and complex environment, the detection accuracy is reduced and the time required for trajectory planning is significantly extended. The response speed of the drive control unit generally meets the driving requirements, and there is still room for improvement in its performance when encountering strong disturbances. This experiment has empirically validated the operational efficiency and environmental adaptability of the system, and future development needs to focus on enhancing its real-time response capability and stability in changing environments.

5. Conclusion

This article studies the perception and control system of small autonomous vehicles. By optimizing the strategies of local and global positioning, integrating information from multiple sensors, the reliability and accuracy of the perception process are enhanced. In terms of control strategy, the overall path design method based on gridded maps was adopted, and the dynamic control algorithm was finely adjusted to ensure that the vehicle can navigate stably and accurately in high difficulty environments. During the system construction and testing phase, comprehensive debugging was carried out in a changing environment by integrating software and hardware resources and conducting deep optimization, ensuring the system's operational efficiency and stability. Subsequent research will focus on improving the intelligence level of the system, exploring its potential applications in variable and extreme environments, and promoting the wider adoption of autonomous driving technology in the small vehicle industry.

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