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A Comprehensive Overview of the Current State of Development in Autonomous Vehicle Driving

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ABSTRACT

The 21st century has witnessed a rapid evolution in information technology, leading to significant transformations in the automotive industry. The focus has shifted from purely mechanical enhancements to the advent of a new generation of vehicles equipped with intelligent driving technology. These smart vehicles are capable of perceiving their surroundings and adapting to real-time conditions and traffic, enabling assisted or even fully autonomous driving. This advancement promises substantial improvements in safety, environmental sustainability, and comfort, enhancing the overall driving experience. This paper provides a comprehensive overview of the current state of autonomous vehicle technology, focusing on the fundamental principles of intelligent driving. It delves into three key areas: environmental perception, path planning, and the application of artificial intelligence in autonomous driving systems.

KEYWORDS

Intelligent Driving; Environmental Perception; Path Planning; Artificial Intelligence.

1. RESEARCH BACKGROUND

The inception of the automobile ignited a longstanding aspiration for autonomous driving, a dream that has flourished with the advancement of various technologies. The exponential growth in microelectronics, information technology, automatic control, and artificial intelligence has transformed this dream into reality, revolutionizing the conventional automotive industry. Autonomous driving is not just an observable trend; it's a transformative force reshaping traditional vehicle dynamics.

The benefits of intelligent driving are immense, ranging from enhancing safety by reducing traffic accidents to environmental considerations through emission reduction, and even to the pure pursuit of comfort by liberating individuals from the task of driving. Additionally, automotive manufacturers have been developing autonomous systems for specialized purposes like racing, beyond everyday driving applications. Intelligent driving represents a complex engineering challenge, encompassing multiple technologies and emerging as a prominent research area.

The origins of autonomous driving internationally date back to the 1980s. In 1984, the U.S. Defense Advanced Research Projects Agency (DARPA) in collaboration with the Army initiated the Autonomous Land Vehicle (ALV) project and organized several DARPA autonomous vehicle challenges. Prestigious universities like Carnegie Mellon, Stanford, and MIT actively participated in these challenges, with Carnegie Mellon's NavLab being a notable example as one of the world's first computer-driven vehicles.

In 2009, Google announced its foray into autonomous driving technology, led by Sebastian Thrun, former head of Stanford's Artificial Intelligence Laboratory and co-inventor of Google Street View. Google's strong mapping capabilities significantly bolstered their efforts in developing street-legal autonomous vehicles, as demonstrated by their extensive driving data.

Beyond research institutions, major automotive manufacturers also entered the realm of autonomous driving around 2010, with Tesla's introduction of the semi-autonomous Autopilot system in October 2015 being a notable commercial milestone.

In comparison, China's research in autonomous vehicles started slightly later, with the National University of Defense Technology pioneering the development of the vision-based CITAVT series intelligent vehicles since the late 1980s.

It is crucial to differentiate between the development of intelligent driving systems and autonomous vehicles. While autonomous vehicles and self-driving cars imply full autonomy in driving, intelligent driving focuses not only on autonomy but also on the progression towards smart, user-centric solutions. The key to intelligent driving lies in integrating artificial intelligence that resonates with human thinking, behavior, and habits. True intelligence in technology emerges when it aligns flexibly with human needs and preferences, prioritizing human-centered development.

2. ENVIRONMENTAL PERCEPTION

Autonomous operation of mechatronic systems fundamentally relies on the collection of external data, enabling an effective perception of the surrounding environment. In the context of automobiles, there are two primary aspects of environmental perception. Firstly, there is the perception of the external environment, which is crucial for planning and adjusting the vehicle's movement path. Secondly, it is essential to perceive the current state of the vehicle's movement, using this as a basis to compute and adjust subsequent movement states.

2.1. Sensors

In the realm of intelligent vehicles, sensors play a role analogous to human senses, serving as components that directly interact with the external environment. The limitations inherent in individual sensing methods prevent single sensors from providing a comprehensive global perception for the vehicle. Most automotive manufacturers employ a collaborative approach involving multiple types of sensors. Typically, vehicles equipped with intelligent driving capabilities incorporate an array of sensors including vision cameras, LiDAR, and supplementary sensors like ultrasonic radars. A key technical challenge in intelligent automobiles arises from this multi-sensor collaboration, particularly in efficiently fusing raw data from various sensors. Data fusion, requiring high precision and real-time processing, is crucial for ensuring the reliability of environmental perception and subsequently smoothing the path for decision-making in route planning.

2.1.1. Vision Cameras

Vision cameras in intelligent vehicles capture image information that closely resembles what the human eye perceives, accurately gathering two-dimensional images with color, thereby offering a high degree of environmental fidelity. However, since these cameras capture images in two dimensions, they are almost incapable of making precise distance judgments. Thus, the analysis of images captured by vision cameras focuses on color and image features to identify lanes and obstacles. The performance of vision cameras is influenced by common imaging parameters, including resolution, frame rate, and exposure, which determine the clarity and fluidity of the images.

It's noteworthy that compared to the point cloud data generated by various radars, the usable data from vision camera images is quite limited. After image recognition and filtering, most of the data becomes redundant. While vision cameras provide necessary data with higher clarity, they also generate a substantial amount of superfluous data, leading to significant computational waste for limited storage solutions. Consequently, managing the role of visual information in vision-based or vision-integrated intelligent driving systems has been a continuous effort. Among numerous automotive manufacturers, Tesla in the United States has been persistently developing a purely vision-based intelligent driving system. Relying solely on vision cameras, Tesla has achieved considerable success in mass-produced vehicles, demonstrating effective performance even on less standardized rural roads.

The advantages of retaining only vision cameras are clear: the generation of a single type of data eliminates the complex process of data fusion, and omitting radar-type sensors helps control production costs. This approach necessitates extensive analysis and utilization of the available visual information. Achieving such effectiveness requires the development of corresponding visual neural networks and more accurate algorithms for image feature extraction, representing a substantial engineering effort at the software level.

2.1.2. LiDAR (Light Detection and Ranging)

LiDAR sensors operate by detecting the position of objects through the comparison of reflected laser beams with the emitted ones. [1] LiDAR systems can be categorized into single-line and multi-line types, based on the number of laser beams they can emit simultaneously. The ability to emit more laser lines at once translates to acquiring more target position data concurrently, significantly benefiting environmental perception, albeit at a substantially increased cost. Equipping vehicles with more advanced and numerous LiDAR units not only elevates costs but also introduces greater complexity in software development, garnering respect for automotive companies competing in this fiercely competitive field.

Current manufacturers, such as NIO in their ET7 model, have equipped LiDAR systems capable of up to 300 lines, with a horizontal field of view of 120° and a detection range of up to 500 meters, achieving highly satisfactory results. The primary data type produced by LiDAR is point cloud data, which represents the distribution of detected points in three-dimensional space, thereby simulating the external environment. As the field of view expands, the accompanying data volume grows exponentially, necessitating advanced algorithms and processors to handle the immense data.

Compared to other types of sensors, LiDAR offers unparalleled advantages, including rapid acquisition of target positions in extremely short times, wide detection ranges, and strong anti-interference capabilities. However, its functionality is significantly affected in specific environmental conditions like sandstorms and heavy fog, where laser penetration through the medium is hindered.

2.1.3. Ultrasonic Radar

Ultrasonic radar systems operate by emitting and receiving ultrasonic waves reflected from obstacles, determining the distance to these obstacles based on the time taken for the waves to travel. As an auxiliary sensor, in contrast to primary sensors that perceive environmental and road information, ultrasonic radars use sound waves that travel significantly slower than light, thus having a much smaller effective ranging capacity. They are primarily used for detecting obstacles in confined spaces, aiding drivers in avoiding collisions. Ultrasonic radars have a long history in automotive applications, pre-dating intelligent vehicles, and were initially installed at the rear of cars to assist drivers in gauging distances to obstacles while reversing. Luxury car models may even incorporate ultrasonic radars all around the vehicle for comprehensive monitoring of surrounding obstacles.

The data types sampled by ultrasonic radars are relatively simplistic and lack high precision, with a limited collection range. They are not integrated into the decision-making processes of intelligent driving systems but are used for assistance during precise maneuvers, helping adjust the vehicle's position by providing information about nearby obstacles.

2.2. Data Preprocessing

Data preprocessing refers to the initial treatment of raw data collected by sensors before its integration and analysis. The primary aim is to filter out irrelevant information and enhance pertinent data for clearer analysis. This involves steps like converting images captured by vision cameras into grayscale, applying filtering, edge enhancement, and binarization. For data from LiDAR and millimeter-wave radars, preprocessing includes noise reduction, filtering, and selection of areas of interest.[2]

Additionally, since sensors cannot be mounted at the same location, it's essential to calibrate the coordinates by selecting a common origin point for sensors positioned at different locations. [3] This calibration ensures that the collected data is processed in the same coordinate system, a prerequisite for effective data fusion. In the research "Vehicle Assistance Driving Technology Based on LiDAR and Camera" by Wang Shuai from Jilin University, methodologies for preprocessing and joint calibration of data derived from LiDAR and cameras are proposed.

2.3. Data Fusion

Current approaches to multi-sensor data fusion for object recognition typically integrate traditional vision processing with 2D LiDAR point cloud techniques within a single system, as seen in VeloFCN, Vote3D, and others. A pioneering perception fusion framework, MV3D (Multi-View 3D Object Detection Network), innovatively combines 2D LiDAR point cloud data with RGB imagery. It utilizes 2D LiDAR processing techniques, representing three-dimensional information through both frontal views and bird's-eye views, and fuses them with RGB images to predict oriented 3D bounding boxes.[2]

The combination of LiDAR and vision camera data effectively compensates for each other's limitations and mitigates occlusion issues. However, since frontal and bird's-eye views are generated from point cloud projections, they retain a level of sparseness. Thus, enhancing the resolution of point cloud projection information is key to future developments. Additionally, a major challenge in data fusion lies in sensor synchronization, including precise temporal and spatial alignment.

Addressing these shortcomings, Chen Zhiyu from Nanjing University of Posts and Telecommunications conducted research on multi-sensor fusion algorithms for environmental perception in autonomous driving. Leveraging the AVOD framework and the GIOU algorithm concept, this study improved the efficiency and accuracy of 3D object detection post-data fusion, reducing the occurrence of overlapping phenomena in environmental perception.

3. PATH PLANNING

Path planning in intelligent driving is divided into global and local path planning. Global path planning involves calculating the optimal route between two points on a map, where optimality is typically gauged by the shortest distance, supplemented by various evaluative factors such as avoiding congestion and considering user preferences. Current major mapping and navigation software providers are capable of rapidly executing global path planning. Intelligent vehicles, by integrating with these providers, can meet travel needs by following their global routing plans.

In contrast, the focus for intelligent vehicles should be more on the development of local path planning. Local path planning entails choosing the optimal driving path in short-term cycles, typically requiring lane maintenance, sensitive obstacle avoidance, and, when necessary, rational lane changing. This type of planning demands high short-term consideration of multiple needs and cannot rely on cloud computing. It requires the vehicle's sensors to be highly sensitive and capable of processing information efficiently, with algorithms that are reliable, make rational decisions, and exhibit robustness.

Effective local path planning is what makes a car truly intelligent, and it is a continual pursuit in the development of intelligent vehicles.

3.1. Path Planning Algorithms

The execution of diverse tasks by computers fundamentally relies on the support of algorithms. For the same objective, multiple algorithms can be employed, each with its own merits and demerits. The selection of the optimal algorithm is contingent upon the specific context and requirements. Engineers continually strive to optimize algorithms within the same category, employing various methods to enhance their effectiveness and achieve superior outcomes.

3.1.1. Global Path Planning Algorithms

In the realm of computing the shortest distance between two points on a map, prevalent algorithms include Dijkstra's algorithm and the A* algorithm. The A* algorithm employs an evaluation function that considers two key aspects: the cost from the search point to the current point, essentially the depth of the node in the search tree, and the design of a heuristic search function. These elements collectively determine a path. This algorithm is utilized to find the shortest paths from one vertex to all other vertices in a weighted graph.

Dijkstra's algorithm is characterized by its method of outward expansion from the starting point in concentric layers until it reaches the destination. This approach is instrumental in solving shortest path problems in weighted graphs.

3.1.2. Local Path Planning Algorithms

In obstacle avoidance, common path planning algorithms include the Dynamic Window Approach (DWA) based on path vector clusters and the Vector Field Histogram (VFH) method. The DWA algorithm generates a dynamic vector window based on the vehicle's real-time dynamics and selects the optimal local path through an evaluation function that assesses each direction's merits within this window. On the other hand, the VFH algorithm is developed from the artificial potential field method. This method views the effects of targets and obstacles on vehicles or mobile robots as forces in a field, with targets exerting an attractive force and obstacles a repulsive force. By establishing corresponding force fields and analyzing the force field model, a rational path is planned. The VFH algorithm abstracts this force field into a histogram grid that computers can easily recognize, planning paths by collecting sensor data in these areas. Both algorithms have their strengths and weaknesses in practical application; DWA offers higher smoothness due to its consideration of real-time velocity changes, while VFH excels in precision.

Addressing the shortcomings of existing algorithms, Zhang Hui from Taiyuan University of Technology introduced a new smoothing factor for DWA in their research on campus intelligent vehicle path planning and tracking control based on a hybrid algorithm. This adaptation effectively resolves DWA's tendency to fall into local optima.

Additionally, local path planning has seen the development of numerous emerging algorithms based on established functions. Peng Xiaoyan and colleagues from Hunan University proposed a discrete optimization-based method in their research on local path planning algorithms for autonomous vehicles, deriving the optimal local path through the weighted average of various cost functions.

Modern obstacle avoidance algorithms are relatively mature in pure avoidance, effectively responding to sensor data to achieve desired effects. However, continuous optimization is required in terms of safety and smoothness, ensuring that the vehicle's path and dynamics are smooth and that the planned path provides passenger comfort. Continuous algorithmic adjustments are essential not just for intelligent vehicles to learn local path planning, but to deliver a comfortable passenger experience. To achieve a human-like vehicular dynamic, Guo Yingshi and others from Changan University researched the anthropomorphic comfort of path tracking control methods in autonomous vehicles. They adjusted local path planning details and vehicle tracking posture based on parameters like lateral acceleration and steering angle to enhance passenger comfort.[4]

3.2. Path Planning Strategies

Local path planning strategies involve not only sensor-based obstacle avoidance reactions but also reasonable planning during maneuvers such as turning and overtaking. The act of changing lanes necessitates the incorporation of game-theoretic considerations and analysis of the driver's habits, setting higher demands on local path planning.[5]

In situations where lane changing is explicitly required, such as to exit the current lane or upon driver-initiated lane change commands, vehicles still rely on obstacle avoidance algorithms. They utilize data from various sensors to choose obstacle-free paths and follow pre-programmed lane-changing procedures, including actions like activating turn signals and smoothly changing lanes.

To emulate driver habits in pursuit of higher travel speeds under stable driving conditions, such as overtaking, it requires adherence to obstacle avoidance algorithms while learning the driver's driving style through artificial intelligence neural networks. After a period of training, the vehicle can then determine the timing for lane changes based on the learned results, executing local path planning and lane changing accordingly.

4. APPLICATION OF ARTIFICIAL INTELLIGENCE IN INTELLIGENT DRIVING

The essence of artificial intelligence (AI) technology lies in constructing neural networks for computers, endowing them with the capacity for learning and training. [6] This is achieved through reinforcement learning based on training materials, enabling computers to autonomously respond to given inputs with appropriate actions. AI technology has found widespread application across various fields, including activities traditionally associated with human intellect such as simulating outcomes in intellectual games and writing articles. Fundamentally, the intelligence of AI technology enables computers to develop proficiency in a specific domain through training, progressively improving performance. In the field of intelligent driving, AI undoubtedly presents a vast potential for application, leveraging its ability to enhance and refine vehicular decision-making and operational processes through continuous learning.

4.1. Environmental Recognition

The mentioned environmental recognition solutions involve computers mechanically processing sensor-acquired environmental data to identify conditions. [7] The integration of reinforcement learning allows computers to easily recognize road conditions and elements through distinct features, with recognition accuracy improving as the training dataset expands.

4.2. Driving Style

In future local path planning scenarios, vehicles could adapt to specific drivers by fitting their driving habits based on daily training, thereby taking over control in a familiar manner. [8] Even complex maneuvers could be autonomously executed by intelligent vehicles. With the aid of artificial intelligence, vehicles can safely perform a series of overtaking actions to expedite the journey. For instance, Toyota, a Japanese automotive manufacturer, has utilized such technologies to train racing cars, achieving feats like unmanned drifting.

4.3. Global Traffic Management

In the near future, as various systems become interconnected through the Internet of Things (IoT) and cloud-based control, artificial intelligence could leverage vast amounts of daily driving data and real-world traffic management experience to enhance the understanding of overall traffic conditions and autonomously regulate traffic flow.

5. CONCLUSION

The development trajectory of intelligent vehicles is a quintessential example of the evolution of mechatronic devices. This progression spans from manual operation to automated task execution and, ultimately, to intelligent dynamic control. However, vehicular travel differs from typical mechatronic systems due to the complexity of road conditions and the variability of road infrastructure, contributing to significant environmental uncertainty. Consequently, developing intelligent driving systems is an intricate process that necessitates a multitude of strategies. The advancement of sophisticated intelligent driving relies on high-precision sensors, ingenious data fusion techniques, powerful computing hardware, seamless data flow, a variety of path planning algorithms, and the integration of machine reinforcement learning. Only through a well-coordinated, multifaceted approach can a vehicle truly become intelligent, embodying the capabilities of an autonomous car as envisioned.

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