

Key Technologies for Automatic Driving Function Implementation

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Abstract: Along with the application of electronic cars and advanced technology, the rapid development of intelligent driving and automatic driving as an important auxiliary driving technology is a more advanced stage, will be the future of transport is an important mode of transportation, the autopilot has now become the country and extremely and hot research topic in the world. Especially in recent years, autonomous driving has made great progress through technological innovation. This article provides an overview of the history and key technologies of autonomous driving, which today promises a safe, comfortable and efficient driving experience. In recent years, the field of artificial intelligence has made great strides in computer vision, machine learning and self-driving cars. As with any fast-moving field, it's getting harder and harder for a beginner to keep up with technology or get into it.

Keywords: Automatic Drive; Artificial Intelligence; Computer Vision.

1. Introduction

Since the mid-1980s, many universities, research centers, automotive companies, and companies in other industries around the world have been researching and developing autonomous vehicles (also known as self-driving cars and driverless cars). Important examples of autonomous vehicle research platforms over the last two decades are Navlab's mobility platform (Thorpe et al., 1991), the automotive ARGO of the Universities of Pavia and Parma (Broggi et al., 1999), and UBM's vehicles VaMoRs and VaMP (Gregor et al., 1999). 2002). To promote the technological development of autonomous vehicles, the Defense Advanced Research Projects Agency (DARPA) has organized three competitions over the past decade. The first Challenge, called the DARPA Grand Challenge, was achieved in the Mojave Desert in the United States in 2004 and required a self-driving car to traverse a 142-mile desert route in 10 hours. All the competing cars failed within the first few miles.

Since the first successful demonstrations in the 1980s, the field of self-driving cars has made great progress. However, despite these advances and ambitious commercial goals, fully autonomous navigation in the general environment has not been achieved so far. The reasons are twofold: First, autonomous systems operating in complex dynamic environments require models that can be generalized to unpredictable situations and reason in a timely manner. Second, intelligent decision making requires accurate perception, yet most existing computer vision models are still inferior to human perception and reasoning.

Existing approaches to autonomous driving can be broadly divided into modular pipelines and monolithic end-to-end learning approaches. Modular assembly lines are the standard approach to autonomous driving and are followed by most in the industry. The core idea is to decompose complex mapping functions from high-dimensional inputs to low-dimensional control variables into modules that can be independently developed, trained, and tested. These modules include low-level awareness, scene analysis, path planning, and vehicle control. However, this is only one specific example of

modularization of the self-driving stack, and other or more fine-grained modularization is possible. Existing methods often utilize machine learning (e.g., deep neural networks) to extract low-level features or parse a scene into individual components. In contrast, path planning and vehicle control are dominated by classical state machines, search algorithms, and control models.

An alternative to a modular pipeline is an end-to-end learning-based model that attempts to learn a strategy that uses a function from observation to action using a generic model such as a deep neural network. Network parameters can be learned by mimicking a teacher's behavior, or reinforcement learning can be used by exploring the world and taking actions that are likely to produce high user-specified rewards. However, reinforcement learning methods have problems with point allocation and reward shaping, are generally slow, and can only be applied in non-safety-critical simulation environments. Imitation learning, on the other hand, suffers from over-fitting and is not easy to generalize to new scenarios. Furthermore, methods based on global neural networks are often difficult to interpret because they present themselves as a "black box" for the user and cannot reveal why a certain error occurred.

2. The History of Autonomous Driving

Similar to Carl Benz's invention of the automobile in 1886, autonomous driving technology promises to profoundly affect our mobility. In this chapter, we briefly review the history of driverless and autonomous vehicles from 1925 to 2019.

In 1925, Houdina Radio Controls demonstrated the "American Wonder," a remote-controlled car that drove down Broadway in New York City, followed by the driver of another vehicle. In 1986, the first prototype of a self-driving car that did not rely on dedicated infrastructure began hitting the road. This pioneering work was led by the Navlab team at CMU in the United States and the Ernst dickmann team at the Bundeswehr University in Munich, Germany. While fully autonomous driving remains unsolved to this day, driver assistance systems have been commercially successful,

improving the comfort and safety of driving. In 1995, Mitsubishi proposed the first LiDAR based range control, and in 1999 Mercedes-Benz implemented radar-assisted adaptive cruise control.

In 2000, navigation systems and digital road maps were introduced. Today, differential GPS, combined with an inertial measurement Unit (IMU), can position with 5cm accuracy under good conditions, enabling the use of detailed lane-level road maps (HD maps) and providing redundancy for vision-based noise positioning. In 2019, Bosch and Daimler announced the formation of a fleet of autonomous vehicles to provide automated vehicle transfers to customers on selected routes in California.

3. Key Technologies for Autonomous Driving

3.1. Perception

Perception refers to the process by which an autonomous driving system collects information from the environment and extracts relevant knowledge from it. It is responsible for estimating the state of the vehicle and using the data acquired by the onboard sensors to interact with the vehicle control system and decision-making unit. At the same time, the prior information of road network, traffic rules and vehicle dynamics is used to plan and control vehicles. It usually consists of two parts: environment awareness and localization. Among them, Environmental Perception (EP) is the ability to understand the environmental scene, such as the type of obstacles, road signs and routes, pedestrian and vehicle detection, semantic classification of traffic signals and other data. Localization is the post-processing of perceptual results. Localization can help autonomous cars understand their position relative to the environment through localization. The camera is a kind of environment sensing device closest to the human eye. Common vehicle-mounted cameras include monocular cameras, binocular cameras, and round-view cameras. The monocular camera is generally the top of the car, which is responsible for monitoring the roadblocks ahead, but is less sensitive to distance perception. The binocular camera can use the difference of visual distance to obtain the distance between the obstacle and the vehicle through the triangulation technology. For example, P1 and P2 are two cameras, and P is an obstacle. The distance from P to the vehicle can be obtained by triangulation.

And LiDAR, also known as LIDAR, his core principle is to send a light, the light will bounce back when it encounters an obstacle, and judge the distance by the time difference between the two. Through LiDAR data acquisition, point cloud map can be drawn, so as to achieve the shape, size and distance of obstacles. One of the main problems with lidar is that it is easily affected by the weather, for example, in rainy weather, water droplets can easily affect the effect of Lidar.

Environmental perception technology mainly helps vehicles to obtain road condition information, and positioning service can help vehicles to obtain the specific coordinates of the vehicle, providing a basis for vehicle decision-making and planning. Common positioning systems include satellite positioning, differential positioning and inertial navigation positioning. The basic principle of satellite positioning is that through the triangulation scheme, at least 3 satellites are connected with the ground vehicle at the same time, and the accurate vehicle coordinates can be calculated.

3.2. Planning

Planning is the process of making decisions and planning in order to achieve goals. For self-driving cars, this process typically involves getting from origin to destination, avoiding obstacles, and constantly optimizing routes and behaviors to keep you safe and comfortable. The planning layer is usually divided into three layers: task planning (MP), behavior planning (BP) and motion planning (MP). The layered structure design originated from the DAPRA Urban Challenge held in the United States in 2007. According to the papers published by the participating teams, most of the participating teams divided the autonomous vehicle planning module into the above three layers. Path planning is actually a technique in the field of high precision mapping. In the traditional human driving mode, if there is a mistake in the map navigation, it can actually be corrected by human flesh. In the era of autonomous driving, the accuracy of maps and the accuracy of navigation will be directly related to safety, so the high-precision map technology in the era of autonomous driving is very important. Because the vehicle autonomous driving problem is not a single variable problem, the vehicle in the formal process includes not only the behavior of the car itself, but also the behavior of other pedestrians and cars on the road. Therefore, behavioral decision mainly includes two aspects, one is the formal decision of the vehicle itself, and the other is the prediction of the behavior of other driving vehicles.

3.3. Execution Control

Control is the execution process of transforming the plan into action, mainly providing the necessary input to the hardware to execute the plan information and produce the desired action. Typically, controllers map real-world interactions based on hardware torque and energy. Feedback control is one of the most common control structures in the control field. It refers to measuring the system response and actively compensating for any deviation from the desired behavior. The most common form of classical feedback control is the proportional-integral-differential controller (PID). PID controller is the most widely used controller in process control industry. The concept of PID control is relatively simple. The method does not require a system model and the control law is based on error signals. Model control prediction refers to the method of using the vehicle motion model to predict the future motion of a certain period of time, and fitting a series of motions by optimizing the control parameters continuously. In general, the period of model prediction is relatively short. Model predictive control has achieved great success in industrial process control applications, mainly due to its simple concept and ability to handle complex process models with input constraints and nonlinearities. Model predictive control has also been widely used in the automotive field. The operation of the entire vehicle system must be optimal across the entire operating range to improve fuel economy, emissions and safety performance. However, the challenges of applying model predictive controllers to automotive systems are different from those faced by the process control industry. Processes inside the car are sampled in milliseconds, and the amount of available computing resources is limited by space. Therefore, advances in processor speed and memory, as well as the development of new algorithms, are important in driving MPC adoption in the automotive industry, and therefore have a profound impact on the use of traction control, braking and

steering, lane keeping, and more.

4. Conclusion

Driverless car is an important application of outdoor wheeled mobile robot in the field of transportation. It fundamentally changes the traditional vehicle control mode and can greatly improve the efficiency and safety of the transportation system. In addition, with the continuous expansion of the system scale and the increase in the number of driverless vehicles, how to effectively use workshop communication and multi-vehicle coordination, reduce the incidence of traffic accidents, and improve the efficiency of traffic systems is also an important topic of future driverless research. In the future life, people will travel directly with autonomous vehicles, without manually controlling the vehicle. But because the technology is not yet mature, it will take a lot of time to explore and experiment in the future,

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