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A review of decision-making frameworks for autonomous vehicles

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Abstract. This review has discussed framework of the decision making in automatic vehicles which is rarely adopted in current researches. Autonomous driving, a step forward in assisted driving technology and the rapid advancement of automotive electronics, has become an essential means to address traffic issues in the future. This area has been a major focus for research on technology worldwide. The history of human transportation has been significantly altered by autonomous driving in recent years. This paper will concisely outline the evolution of this technology and its associated components. On this basis, this paper also reviews the development in different sorts of decision making. It also analyses characteristics, as well as their advantages and disadvantages of some typical application among the different decision making. Summarizing the current predicaments of automated driving, this paper looks to what lies ahead for autonomous driving technology's future development.

Keywords: autonomous vehicles, decision-making, sequential planning, behavior-aware planing, end-to-end planning.

1. Introduction

Self-driving cars will reduce traffic deaths, give the independence to people in old age, and allow them to drive anywhere and anytime. Americans drive approximately 300 billion miles a year and spend much of their time in traffic. With more than 3,000 lives lost each day and most accidents caused by human error, time spent in traffic is potentially dangerous. Automated vehicles have great potential to improve the quality and efficiency of driving by making traffic safer, more efficient, and more easily accessible to all. This will require advances in many aspects of autonomous vehicles, from vehicle design to vehicle control, sensing, planning, coordination, and even human-computer interaction [1].

This review focuses on the framework in autonomous vehicle planning of decision making, particularly introducing distinguish leaded by sorts of decision making in different situation such as determining the next steps in its journey, taking advantage of sensor data to make short- and long-term decisions, the process of interactions with other vehicles can help itself learn to drive based on its history and experience, and the guarantee that ensuring multiple vehicles on the road are coordinated and controlled simultaneously to get people and goods to their destinations as efficiently as possible. The science and technology of autonomy, inspired by the possible future of transportation as a public service, has become an exciting field for academia and industry, and much work has been done to address these challenges. This paper discusses recent findings on various aspects of decision-making and design of autonomous vehicles. Figure 1 will show a visual representation of decision architecture [2].

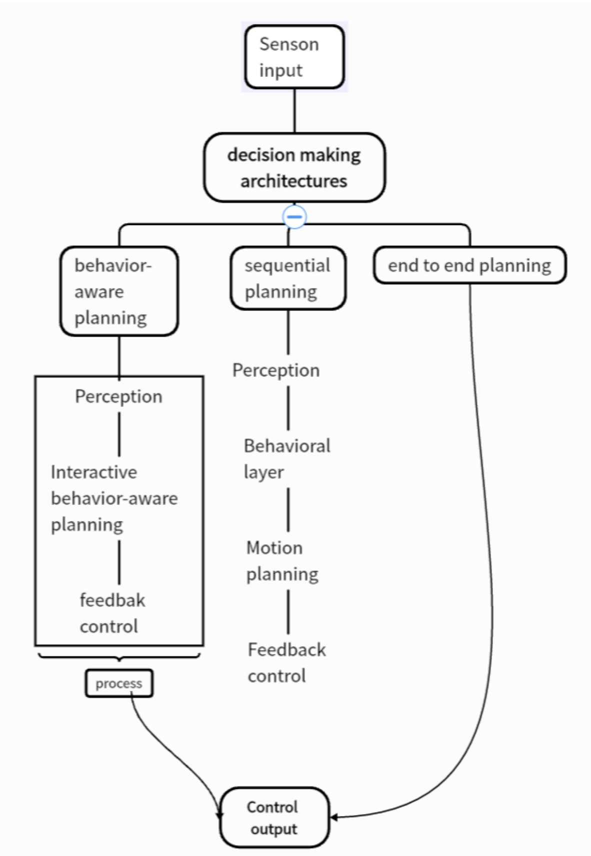

Figure 1. Architectures of decision-making for Autonomous Vehicles.

Autonomous vehicles operating in complex and dynamic environments need technologies that support comprehensive disaster analysis and rapid decision-making for reliability and safe human-level response in complex urban environments. With the increasing prevalence of machine learning and advanced planning and decision-making techniques, the validation and effectiveness of autonomous driving is an unsolved challenge. In recent years, research on autonomous driving has mainly used learning-based planning and decision-making methods, with good results in some specific scenarios [3]. These methods are directly dependent on driver training. These methods are directly dependent on the training phase and require large training datasets that reflect the vehicle's operating conditions. Furthermore, training-based methods have not yet been validated in terms of safety, reliability and comprehensibility. Deep learning methods for decision-making and planning have not yet been integrated into production systems.

Since an agent's behavior depends on the behavior of other agents, this increases the uncertainty of its future state and may cause the robot to stop. If the robot does not stop completely, it may take a very unique or random path through the problem space, which is often not only suboptimal but also potentially dangerous. This means that machine learning techniques must be developed, evaluated, and integrated into planning and decision-making processes [4].

Section I introduce the theme and the context of the article,;Section II describes three specific parts in the architectures of decision-making for autonomous vehicle; Section III introduce the application of different sort of decision making in autonomous vehicle; Section IV describes the challenges researchers face as they progress;and Section V summarizes the conclusions of this research and the trends in autonomous decision making [5].

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2. Core Principles

Depending on the architecture of the solution, design approaches can be divided into three different types: sequential design, behavioral design, or holistic design, depending on the architecture used in the design modules.

2.1. Sequential Planning

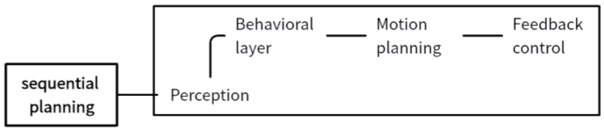

Figure 2. Framework of sequential decision making.

In sequential decision making (described in Figure 2), the control tasks are presented as separate elements to be performed in a temporal order: starting with the sensor input through the detection phase, followed by motion planning as the first element of the design phase, motion planning as the second element of the design phase and finally the control phase [6].

There are three common solutions to traditional path planning problems: Spatial discretization Collision detection: That is, the A* algorithm, the map is first discretized, and then relies on collision detection to search for a path inside. This is a very efficient method that has a lot of room for use in simple environments like highways. However, it is usually applicable to a relatively small environment and has relatively high requirements for observation. Stochastic programming method: That is, the genre of RRT, should also discretize obstacles to the map first, but through random scattering and optimization, it can achieve planning in a larger search space (although it does consume a lot of computing power, but it can still be engaged) [7]. Constraint optimization & rolling optimization method: The use of optimization for motion planning is far-fetched to put together with the first two, which are more used in path planning, and this method is usually used in path tracing (such as trajectory optimization during lane changes). At the same time, it should be pointed out that in automatic driving, "finding a way" does not necessarily mean that such a road can be taken, because there are also various traffic rules constraints. Therefore, how to integrate "traffic rules" into sports planning has become a problem that needs to be studied. At the same time, sometimes traffic rules are not necessarily followed, especially when other cars have already violated traffic rules and brought certain dangers, and minor violations of traffic rules to ensure safety are acceptable. Therefore, how to balance rules and security is also being studied. Most of the methods are studied in static or estimable dynamic environments, but in real road environments, dynamic objects are numerous and unpredictable, and crowded environments are a nightmare for autonomous driving, so the next chapter will focus on this problem through end-to-end methods [8].

2.2. Behavior-aware Planning

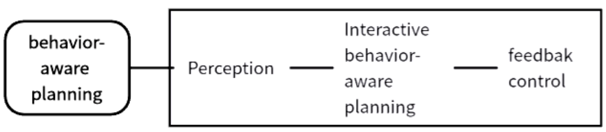

Figure 3. framework of behavior-aware decision making.

Behavior-aware or interaction-aware planning (described in Figure 3) considers both maneuver and motion planning tasks are done in the same stage.

Most methods need to avoid collision based on predicting the future trajectories of other road users, but actual traffic scenarios are often based on complex interactions between road users. Therefore, ensuring safety requires managing this complex chaos and modeling the behavior of other road users.

The DARPA Urban Challenge project proposed several solutions for tactical planning, but these solutions were designed for specific challenge requirements. Most methods rely on state mechanisms to switch between predefined behaviors, but this rule-based approach has limitations in dealing with unknown situations and handling uncertainty.

Automatic control requires the ability to interact and cooperate with human behavior to make decisions. Autonomous vehicles must be able to understand the intentions of other drivers and integrate those intentions into the planning system to achieve intelligent decision coordination without inter-vehicle communication.

At the same time, autonomous vehicles must also be able to ensure that other road users can reasonably understand their intentions. This mutual understanding is based on visible and perceivable behaviors that do not involve explicit communication.

In the following sections, we will further explore more general interaction planning, including interaction with other participants and the environment, as well as actively modeling or reducing uncertainty caused by incomplete images and sensor information. This planning approach aims to achieve intelligent coordination with various traffic participants to address a complex and changing traffic environment [9].

2.3. End-to-Ending Planning

End-to-end planning (shown as the black route in Figure 1) represents all learning-based methods, which can be divided into four types: end-to-end, end-to-middle, middle-to-end, and middle-to-middle. In the autonomous driving framework, there is a clear boundary between perception and planning control. However, with the development of deep learning and neural networks, the field of image recognition has become increasingly popular, and more and more researchers have entered the field of planning control. In the past two years, some end-to-end planning learning works have emerged, such as end-to-end trajectory prediction using driving trajectories in the driving data set as ground truth for weak supervision learning in ITSC2017, and a group of weak supervision learning methods using automatic labeling and annotation assumptions during data collection and labeling, which all have similar appeal.

At the same time, these original image researchers are often unwilling to participate in end-to-end planning and learning, but instead attach some "auxiliary tasks" to the learning networks, such as "scene semantic segmentation, assisting driving behavior prediction," "localization and depth estimation, assisting navigation decision," and so on. However, this method is usually meaningful through analysis, and the results symbolically improve a little.

Further discussing the black-box end-to-end method, which is called the "behavioral reflection method" in decision-making problems, this method was originated by neural networks in 1996 (ALVINN). With the continuous strengthening of GPU computing capabilities, the image field felt that they could not only predict simple classification problems but also solve the problem of directly predicting driving behavior. However, people can indeed think of some things, and NVIDIA's work in 2016 was almost a summary of similar works over the years, using images and control commands as data inputs for the model, and then optimizing it can indeed be used, but people indeed have some of their own things, not just throwing the driving image data in front of the camera into the network, but also setting up a camera on the left and right, which is equivalent to generating some data in the reverse direction, equivalent to generating a large number of correction samples near the operation point, which is very important.

3. Applications

3.1. Sequential Planning

Sequential planning is the most traditional method, and according to the Figure 4, the three parts of perception, decision-making and control are relatively clear [10].

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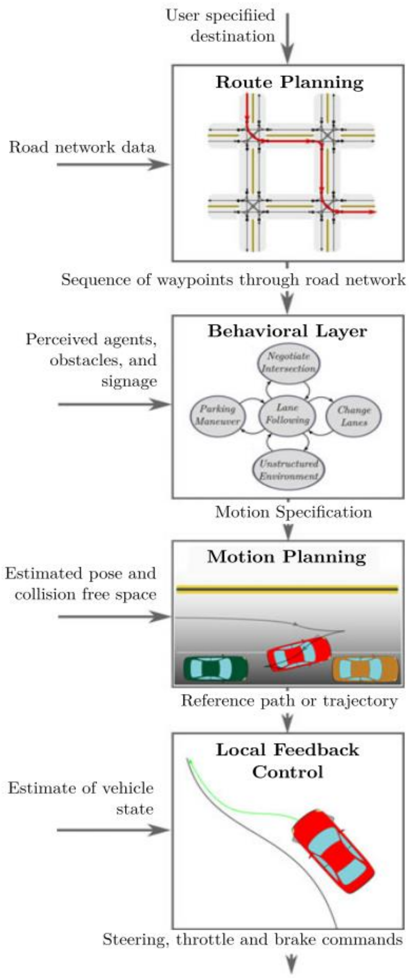

Figure 4. Illustration of the hierarchy of decision-making processes.

The most traditional method is sequential planning, which consists of three relatively independent parts: detection, decision-making and control. The destination is sent to the route planner, which creates a route on the road network. At the behavioral level, the environmental reasons are described and a behavioral specification for following the chosen route is generated. The traffic planner examines the possible traffic options to achieve this specification. The feedback control modifies the traffic variables to correct errors that occurred during the reference route [11]. This article describes recent applications and advances in movement planning, using partial movement planning (PMP) as an example. Partial motion planning (PMP) is not always effective for learning complete programs; therefore, to simplify the computational process, local motion planning can be used instead of searching the entire spatial domain. Local search methods use the behavioral space of the vehicle space, such as geometric curves (splines, buffers, etc.) and lateral movements. The work of Benenson et al. used PMP and RRT to study unavoidable collision situations (ICS). In addition, as point overlap, line overlap, and undecided overlap. They used A* search and quadratic programming (QP) to obtain the advantages of long-term longitudinal motion and short-term trajectory based on search and optimization methods. However, due to the longitudinal discrete actions, their search method may not cover the optimal solution.

In the research of MR.Althoff et al , they used PMP and probability collision state (PCS) concept, which guarantees no collision. Collisions between objects and the main robot, as well as any object collision, were considered in cost optimization. In this method, the objective function is based on target direction and trajectory smoothness. However, the requirement for full knowledge of the area around the vehicle is the main drawback of this method. The steps of PMP include: finding the nearest node to the application control and trajectory generation, removing ICS, keeping collision-free trajectory end nodes, selecting the optimal trajectory, and adding it to the tree initial planning [12].

3.2. Behavior-aware Planning

Behavior-Aware Planning is characterized by upgrading the decision-making planning process to an interactive process, including driver-driven vehicle and driver-driven vehicle-external environment. The purpose of this approach is to incorporate the uncertainty of the external environment into decision-making planning, thereby improving the driving safety of autonomous vehicles. When autonomous driving is faced with complex and detailed situations, such as pedestrians crossing the street, we will see that behavior-aware planning plays a very good job in this condition. In this passage we will evident an efficient behavior-aware control of automated vehicles at crosswalks using minimal information pedestrian Prediction Model.

Mr. Kumaar has proposed an optimization framework for intersection autonomous control based on MPC. Unlike existing research, they do not rely on the assumption of future pedestrian information, but adopt a previously developed pedestrian crossing model that predicts pedestrian crossing behavior. This model treats crossing behavior as a mixed system, which includes a simple gap acceptance model that only requires the most basic information of pedestrian position and speed. By integrating this crossing model into the controller, we can demonstrate the effectiveness of the controller in intersections with waiting and approaching pedestrians. In comparison, existing research often assumes that pedestrians are already waiting to cross the intersection. However, the B-MPC we have implemented can handle various situations in simulations with a wide range of acceptable gaps for pedestrians without collisions. This indicates that the controller has good adaptability and robustness. Furthermore, this framework can provide safe and efficient solutions for long-term planning while maintaining real-time performance. This provides strong support for the safe operation of autonomous vehicles in complex urban environments, and is expected to play an important role in the future of autonomous driving.

The models and controllers we have developed have certain limitations. Among them, the model assumes that the speed is constant in every discrete state, which may lead to an oversimplification of the real situation. In addition, the model assumes that all pedestrians have the intention to cross the street, but this is not always true in real life. Currently, the controller is implemented only in simple simulation environments for simple scenarios and simple autonomous driving motion models. To further improve the performance and adaptability of the model, future work will focus on implementing the complete model and controller in more complex situations, such as curved roads, intersections, and scenes with multiple pedestrians. In addition, we will also explore methods for using pedestrian data in real scenarios to develop and evaluate the model, in order to better understand the interaction between autonomous vehicles and pedestrians.

Another research direction worthy of attention is to include the function of communicating the intention of autonomous vehicles and pedestrians in the MPC framework, enabling autonomous vehicles to decide whether to yield or to cross the intersection according to the wishes of pedestrians. This will help to improve the safety and efficiency of autonomous vehicles and pave the way for more advanced autonomous driving.

3.3. End-to-Ending Planning

In traditional autonomous driving systems, various functions are explicitly encapsulated in modules with clear and observable interfaces. This method is called mediated perception, which can detect and fuse interested objects, generate scene descriptions, and calculate driving commands. Next, I will demonstrate an example of an autonomous driving application based on a deep learning spatial-temporal end-to-end perception.

In this study, Mr. Huch proposes a deep learning spatial-temporal end-to-end perception process currently under development, named DeepSTEP [13]. This concept provides a new approach to realizing autonomous driving technology and is expected to play a significant role in the future of autonomous driving. With DeepSTEP, we aim to achieve more efficient and safer driving experiences, opening up new possibilities for the development of autonomous driving technology.

DeepSTEP integrates individual sensor characteristics through a spatial-temporal deep fusion network, achieving a unified abstraction of sensor data at the same feature level. This processing method makes it more convenient to add or remove sensor modalities and helps deepen understanding of their contributions to perceptual performance. By utilizing a shared latent space, we can apply perceptual heads for specific tasks, such as using detection heads to identify objects and traffic participants and acquiring road-level information from local mapping heads.

Currently, DeepSTEP is in the conceptual and proof stages, but it is expected to demonstrate the advantages of this end-to-end perceptual structure in the future. Our long-term plan is to apply this technology to public roads using new research vehicles, for which we plan to release a comprehensive dataset. Unifying the encoding of all sensor data to the same level will also help draw conclusions about the optimal sensor settings for autonomous vehicles [14]. In this way, DeepSTEP is expected to play an important role in the field of autonomous driving, bringing people a more efficient and safer driving experience.

4. Challenges

In the future, in addition to the efficiency of the ever-existing algorithm and the completeness of the modeling, there are also issues for driving safety which are still unfathomed, as follows:

4.1. Unreliable simulation of the model

The established vehicle operation model should be closer to reality, and most of the existing model only simplifies it to a 2-degree-of-freedom bicycle model, and comfort constraints should be gradually added [15].

4.2. High promotion costs

The biggest problem with the production of self-driving cars is expense. For instance, the cost of CPU is expensive, the maintenance costs of the wastage in the later stages of operation, and there is large. Therefore, the popularization of self-driving cars among the general public also needs to be considered in terms of funding.

4.3. Slow data processing

When the self-driving car is driving at a high speed of 100 km/h, the time left for the central processing unit to process the data is extremely short, which requires the central processing unit to have extremely high performance, and the current lidar has not yet matured mass production products, which will make the autonomous driving car unable to respond quickly in the event of danger [16], and there is a probability of causing accidents.

4.4. Immature provisions of resulting legal

With the popularization of self-driving cars on the road, the definition of accident liability is an important problem, and the existing laws around the world do not explicitly stipulate this issue. If we want self-driving cars to really drive on the road, we need the Ministry of Public Security, the Ministry of Transportation and other departments to work together and continuously improve the resulting legal provisions.

5. Conclusion

This review has discussed framework of the decision making in automatic vehicles which is rarely adopted in current researches. The definition and the development process of the three sort of the decision,the sequential planning, behavior-aware planning, and end-to-end planning has been summarized in the paper, absolutely we can also witness the applications and challenges in the cutting-age. Although autonomous driving is now the focus of the current development of the automotive industry, it is also a hot area that the whole society is concerned about. Once autonomous driving technology is popularized, it will greatly improve traffic safety, improve traffic efficiency, reduce energy consumption and emissions, and profoundly change our future transportation and social patterns. But the development of autonomous driving will not happen overnight, and we need to give this technology a little more time.

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