

Research prospect of autonomous driving decision technology under complex traffic scenarios

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Abstract. Decision-making system is the essential part of the autonomous vehicle "brain", which determines the safety and stability of vehicles, and is also the key to reflect the intelligent level of autonomous vehicles. Compared with simple scenarios such as expressway, urban traffic scenarios have the characteristics of complex and frequent interaction between traffic participants. Carrying out in-depth research on complex traffic scenarios and optimizing autonomous decision-making algorithms are the key methods for the purpose of promoting the application of autonomous driving technologies. In the future, we can further combine the artificial intelligence methods such as cognitive or knowledge map, behaviour prediction of traffic participants, and humanoid intelligence, so as to enhance the intelligent level of autonomous driving.

Keywords: Autonomous driving, Decision making, Complex traffic scenario.

1 Introduction

Autonomous vehicles have attracted worldwide attention in the past 10 years. As a carrier of various emerging technologies and a new generation of mobile terminals, the autonomous vehicles have become the strategic direction of the global automotive industry. Autonomous vehicles can play the role of freeing human from driving tasks in many fields. It is mainly reflected in the following aspects: improving the safety and efficiency of transportation system, effectively replacing human beings in dangerous and heavy work, and integrating various kinds of cutting-edge technologies.

Autonomous vehicles can provide verification platforms for emerging technologies such as artificial intelligence, advanced communications and information science. The related technologies can be fully verified and improved by the development and application of autonomous vehicles. After more than ten years of rapid development, the current autonomous vehicles have been applied gradually in mining, taxis, closed parks and other specific scenarios. Current technical level can basically satisfy the autonomous driving needs of the simple scenarios on open roads, such as expressways [1]. However, in most application scenarios, the related technologies are difficult to support broad applications.

Due to the complexity of urban traffic, autonomous vehicles are facing many unpredictable situations, such as the uncertainty of the surrounding environment perception information and that of the behaviour intention of traffic participants. Various environment elements and their frequent interactions, as well as the complex road patterns, bring challenges to the decision-making system of autonomous vehicles [1-3]. Decision-making system is the core of the autonomous driving system. It plays a decisive role in driving safety and behaviour rationality. The research on autonomous decision-making method in urban complex traffic scenarios is of great significance for promoting the rapid development and application of the related technology.

2 Recent research of decision-making methods

2.1 Technology framework of autonomous driving

The safety, comfort, economy and efficiency guarantee of autonomous vehicles under complex environment are derived from a complete and scalable technical framework^[1-4], as shown in Figure 1.

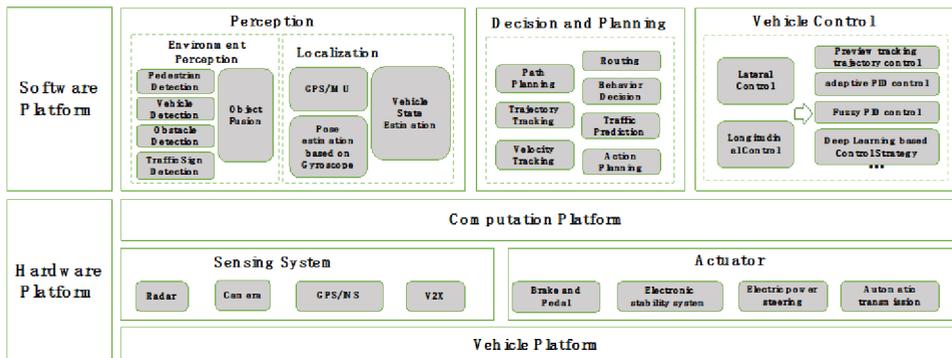


Fig. 1. Technology framework of autonomous driving.

The framework can be generally divided into the environment perception module, decision-making module and control module, in which decision-making is the core part. In addition to the above basic architecture, motion prediction, the component that dynamically predict the behaviour of surrounding traffic participants, can also help autonomous vehicles make better driving decisions.

2.2 Problems of realizing autonomous driving in complex traffic scenarios

2.2.1 Characteristics of urban complex traffic scenarios

Compared with expressways, rural roads and specific park scenarios, urban traffic scenarios have more complex environment, which is mainly reflected in the following aspects:

- Multiple traffic participants coexist in urban traffic environment.
- More complex and various road topologies.
- Complex interactions exist between diverse environment elements.

The above characteristics and uncertainties require that the autonomous decision-making system can accurately model and predict the heterogeneous information from the

surrounding environment. Besides, the ability to make full use of the prior driving knowledge is also vital to make efficient and safe driving decisions.

2.3 Related works of motion prediction

Among all the environment components, the surrounding vehicles are the most important factor affecting the safety of autonomous driving and their dynamic positions and speeds increase the uncertainty of traffic flow characteristics [3]. For the autonomous vehicle itself, usually called the host vehicle, to drive safely in such a dynamic environment it is very important to accurately predict the driving behaviours of the adjacent vehicles. Moreover, the longer the prediction time and the higher the accuracy, the decided driving behaviours and planned trajectories of the host vehicle can be safer.

The common behaviours of a driving vehicle mainly include car following, lane change, turning and reversing [4]. Lane change is the most frequently occurring driving behaviour and is also the behaviour that is most likely to disturb the driving order and lead to dangerous situations. When the real-time lane change intention and motion trajectory of surrounding vehicles are unknown, autonomous vehicles are likely to collide with surrounding vehicles due to improper driving behaviour and unreasonable path planning [5].

The research on lane change behaviour prediction mainly includes three topics: the acquisition of characteristic variables related to the lane change features, the research on the factors affecting lane change process, and the research on the model construction for effectively characterizing the lane change mechanism. It is usually analysed in previous research that the lane change characteristics to optimize the global traffic flow efficiency [6-9]. Different from this, the goal of researching lane change mechanism in the field of autonomous driving is to optimize the driving efficiency and safety of a single vehicle. Due to the richer scenarios and diverse information input, an autonomous vehicle needs to explore more detailed features and more microscopic model expression to accurately grasp the future motion intention and trajectory of surrounding vehicles.

2.3.1 Lane change driving characteristic variables

Similar to human driver's lane change behaviour, information about current lane, position and relative speed between the host vehicle and surrounding vehicle is usually used to infer whether there is enough space to change lane and whether safety can be ensured at the same time [10-12]. There must be a series of characteristic variables that can be used to describe the specific process of lane change. Leonhardt et al. analysed the driving characteristic variables from the three aspects of vehicle driving scenario description, vehicle lane change preparation and host vehicle motion information [13].

2.3.2 Methods of lane change prediction

Methods of vehicle lane change prediction is mainly divided into classical prediction methods, sequence prediction based on recurrent neural network and trajectory prediction based on long-distance communication.

Classical prediction methods usually consist of Bayesian network, Monte Carlo simulation, hidden Markov model (HMM), Kalman filter, Gaussian process regression. These methods analyze the internal motion rules according to the historical motion of moving targets. They are often used in simple traffic scenes with less interaction between vehicles, and their long-term prediction ability is weak.

Sequence prediction method based on recurrent neural network. In recent years, deep neural network (DNN) has received great attention in sequence prediction [15-17]. Recurrent

neural network (RNN) is a subclass of DNN. It is widely used in sequence generation research in many research fields, including speech recognition, machine translation, image semantic capture [18-20]. Various network models based on different branches of ordinary RNN networks are applied to research topics such as behaviour classification, trajectory prediction.

Trajectory prediction method based on long-distance communication. The process of collecting information by on-board sensors is usually blocked by surrounding vehicles. It can improve the driving safety and reliability by capturing the interaction information based on on-board vehicle communication devices to predict lane change behaviour. This method not only retains the ability of vehicle autonomous perception, but also introduces the concept of V2X remote communication.

2.4 Related works of decision-making methods

The decision-making methods of an autonomous vehicle can be usually divided into two categories: rule-based methods and learning based methods [18].

2.4.1 Rule based autonomous decision-making

Rule based methods usually group the autonomous vehicles behaviours according to driving rules or driving knowledge. Finite state machine is the typical method, which has the advantages of clear logical relationship, strong practicability [19]. The finite state machine method has strong applicability and stable structure. It has been popularized in complex autonomous driving decision making system.

2.4.2 Learning based autonomous decision-making

The typical learning-based decision-making methods include deep learning method and decision tree method. Deep learning method has good flexibility and has been widely used in the decision-making system [20]. NVIDIA applies the end-to-end convolutional neural network to the decision-making system by taking the obtained image as the input directly and outputting the steering wheel angle of convolutional neural networks (CNN) as the result. The decision tree model is used more frequently in early research. However, due to the increased number of attributes, the decision tree model cannot scale flexibly, and cannot realize incremental rule updating.

2.4.3 Comparison of the above mentioned methods

In terms of functional complexity, the finite state machine method can process several scenarios in parallel and is good at making split decisions for a given scenario. Besides, this method can also make decisions for slightly complex combined scenarios like intersection or finish long distance autonomous driving [21]. Current learning-based algorithms rely heavily on the integrity of the training set and can perform well in a given scene, but it is difficult to adapt to the collaborative decision-making of multi-scene and multi-task. NVIDIA trained the decision system by CNN and obtained real-time response to small change of environment [22]. In terms of the correctness of decision results, both rule-based algorithm and learning-based algorithm can complete accurate driving tasks in appropriate scenarios and give correct decision results. In complex scenarios, rule-based algorithm has the problem of unclear sub state boundaries, and learning-based algorithm has the problem of insufficient data support. In terms of system complexity, rule-based algorithm faces

redundant algorithm scale problem in complex scenarios, which is caused by the limitation of logical structure. Learning-based algorithm has a simple system structure and can be well extended. However, limited by the basic principles, current learning-based decision algorithms still have poor adaptability and robustness under complex urban scenarios.

2.4.4 Decision making based on man-machine hybrid intelligence

Simple accumulation and combination of algorithms or models cannot realize autonomous driving in all scenarios and satisfying broad application needs. To surpass human intelligence, the first step is imitation. We can integrate human intelligence into the existing technical framework to obtain a higher level of artificial intelligence. This kind of concept can be called man-machine hybrid intelligence.

Man-machine hybrid intelligence system establishes human environment perception, memory, reasoning and learning ability, as well as the information integration, search and computing ability of machine agents. It not only integrates biology and machinal engineering, but also integrates electronics, information and more other fields. We can transfer and generalize human expert knowledge by applying man-machine hybrid intelligence to the decision-making system. The expression forms of expert knowledge usually include mathematics, graphics, algorithms, data, structure and various mixed forms. The expert knowledge related to driving scenarios includes traffic rules, driving knowledge and accumulated driving experience.

- Driving experience extraction based on traffic rules

Traffic rules based decision-making model relies on accurate and complete expression of the prior knowledge of traffic regulations. Traffic rules in different scenarios can be used as the source for constructing the knowledge map of basic driving rules.

- Driving experience extraction based on Internet data

Data on the Internet support the summary and refinement of driving experience. Knowledge map is composed of nodes and edges and exists as a symbolic form of network connection between various entities. Semantics, text, rules and other complex information can be transformed into the knowledge map, the structure of which can also be visually displayed.

Building a knowledge-based decision-making model usually use the driving cognitive map for knowledge expression and reasoning. It can not only classify and manage a large amount of knowledge, but also save the time spent on traditional rule-case matching process, so as to improve the real-time performance of knowledge retrieval. The knowledge unit integrates symbol based and connection based knowledge, which can solve the combinatorial explosion problem. There is a good application prospect for the reasoning and decision-making of traffic knowledge in complex scenarios. The way to apply knowledge map on decision-making of autonomous vehicles is an important research topic worthy of in-depth research in the future. Reinforcement learning based method is a solution worth exploring. Successfully integrating the knowledge map and reinforcement learning model can make the decision-making system adaptable to different scenarios and sensitive to the change of task. In the future, various information in the knowledge map can be transferred to the target decision-making task of reinforcement learning for reuse, so as to realize the application of prior knowledge and the imitation of human learning.

3 Conclusions

City complex scenarios bring many "long tail problems" to the decision process of autonomous vehicles. These problems must be solved to promote the broad application of autonomous driving technology. Firstly, it is necessary to further analyse the complexity

and difficulties faced by behaviour prediction in complex urban traffic scenarios and consider time-space interaction relationship in the process of lane change, so as to make more effective predictions of lane change intention and trajectory. Secondly, based on the current development of artificial intelligence, it is possible to further explore the possibility of applying knowledge or cognitive maps to the decision-making system. The goal is to develop decision-making methods based on man-machine intelligence. Applying the theory of brain edge calculation on the decision-making system is another feasible way to improve the flexibility and effectiveness. We can also take the safety performance evaluation into consideration to improve the safety of the decision-making process.

This work is supported by the National Key R&D Program of China (No. 2018YFB0105200).
Acknowledgments

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