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A comparative study of state-of-the-art driving strategies for autonomous vehicles

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ABSTRACT

The autonomous vehicle is regarded as a promising technology with the potential to reshape mobility and solve many traffic issues, such as accessibility, efficiency, convenience, and especially safety. Many previous studies on driving strategies mainly focused on the low-level detailed driving behaviors or specific traffic scenarios but lacked the high-level driving strategy studies. Though researchers showed increasing interest in driving strategies, there still has no comprehensive answer on how to proactively implement safe driving. After analyzing several representative driving strategies, we propose three characteristic dimensions that are important to measure driving strategies: *preferred objective*, *risk appetite*, and *collaborative manner*. According to these three characteristic dimensions, we categorize existing driving strategies of autonomous vehicles into four kinds: *defensive driving strategies*, *competitive driving strategies*, *negotiated driving strategies,* and *cooperative driving strategies.* This paper provides a timely comparative review of these four strategies and highlights the possible directions for improving the high-level driving strategy design.

1. Introduction

With the development of transportation systems, traffic safety has become a major concern around the world in the last few decades. According to the statistics report from the World Health Organization's (WTO), the traffic accidents around the world bring more than 1.24 million fatalities and a huge loss of property per year. (NSC, 2017; NHTSA, 2017). However, road traffic is a complicated system and affected by a diversity of risk factors representing driver characteristics, vehicle performances, road geometric, and so on. Although various research struggled on traffic safety have been done, there is still no comprehensive solution that can take all factors into account.

Efforts devoted to traffic safety can be generally classified into two categories: (a) research about traffic environment and (b) research about vehicle. The first kind of research aims to provide a better driving environment for all kinds of traffic participants, e.g., better geometric designing and infrastructure (OECD and ECMT, 2006; FHWA, 2017), more reasonable speed limits and traffic regulations (van Nes et al., 2010), better-advanced traffic monitoring (Ahmed et al., 2016) and law-enforcing technologies (Smith, 2017), more accurate traffic evaluation and scheduling system (Hauer, 1982; Huang and Abdel-Aty, 2010; Abdel-Aty et al., 2011), etc. The second kind of research focuses on improving the capability of vehicle and drivers to reduce the accident rate (Li et al., 2012), e.g., driver fatigue detection based on image recognizing or biological information monitoring (Doshi and Trivedi, 2009; Murphy-Chutorian and Trivedi, 2010; Hansen and Ji, 2010; Huo et al., 2016; Mandal et al., 2016; Favarò et al., 2018; Matthews et al., 2019), Advanced Driving Assistant System (ADAS) based on perception enhancement (Horter et al., 2009; Halimeh and Roser, 2009; Gormer et al., 2009; Rubio et al., 2012) or risk assessment (Hillenbrand et al., 2006; Li et al., 2012; Staubach, 2009; Katrakazas et al., 2019), etc.

During the last decade, Autonomous Vehicles (AVs) have been proposed as a comprehensive approach, which combines the advantages of the above two kinds of research. On the one hand, AVs have the potential to obtain environmental information more efficiently than humans with the help of high-precision sensors. On the other hand, we hope AVs can avoid some mistakes common among human drivers such as tiredness, misoperation, and dangerous driving. Therefore, people believe AVs will provide an effective solution to every transportation-related issue, such as safety, efficiency, and energy consumption (De

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Winter et al., 2014; Merat et al., 2014; Mahmassani, 2016; Litman, 2017). With the joint efforts of researchers and vehicle manufacturers, AV has made some inspiring advances. For example, Waymo announced their test mileage on the public road had reached 10 million (Andrew, 2019); Nvidia had achieved billions of miles of virtual safety driving within their simulation environment called DRIVE Constellation (Freund, 2019).

However, Uber's self-driving accident happened in March 2018 (Pavia, 2018), and Tesla's fatal accident in May 2016 (Tesla, 2016) reminded people of a cruel fact: until now, the technological breakthroughs achieved are still not enough to ensure the safe driving. According to the annual report of the California Department of Motor Vehicles (DMV), there were 49 AVs accidents occurring in California during 2018, of which 57 % were due to rear-ended collisions; while the most of rest were caused by non-hardware reasons, such as faulty prediction or incorrect planning (California DMV, 2018). The investigations indicate that, in the absence of other traffic participants, the AV prototypes may ensure normal running only depended on accurate perception and location information. However, accidents may occur when AV prototypes interact with other traffic participants (Lv et al., 2017).

Interaction usually refers to mutual or reciprocal action or influence. In road traffic, "interaction" occurs between two (or more) traffic participants. When the maneuvering behavior of vehicle A influences vehicle B, this impact will be reflected in the maneuvering behavior of B and reversely influence on A. The essence of "interaction" is a comprehensive process between both traffic participants, composed by perceiving, understanding, forecasting, cooperating with each other (Lay, 1992; Weingroff, 2017). There are various interactions in different driving scenarios. For example, in a vehicle-following scenario, the following vehicle needs to maintain a certain safety distance according to the speed of the preceding vehicle. In the lane-changing scenario, the merging vehicle needs to confirm the appropriate timing and speed, through the interaction with vehicles of the target lane. In the intersection scenario, the ego vehicle needs to interact with multiple vehicles coming from multiple directions to determine the passage sequence; otherwise, congestion or collision may be caused.

To deal with other participants on the road, AVs need to establish a set of regulations to prescribe and direct the interaction process, which is called as "driving strategy". After abstraction and simplification, we define driving strategy as: **a set of explainable and descriptive driving mechanisms developed by AVs based on the collected environmental and other traffic participant information, with the objective of directing ego to interact with others to determine next action so as to ensure the safety and efficiency.** Obviously, a successful driving strategy can prescribe AVs to interact efficiently and reasonably and make full use of limited road resources on the basis of safety; and a failed driving strategy may result in unreasonable scramble or congestion could have been avoided.

To highlight the core of driving strategy, we can divide the decision-making process of AVs into two levels based on the type of tasks and duration time scale (Michon, 1985; FHWA, 2004; SAE, 2016), by analogy with the human driving model proposed in (Fuller, 2005). According to (Li et al., 2012), the low-level decision-making process (i.e., behavior and control) focuses on generating controlled action patterns within 0.1 s to several seconds; and the high level, i.e., tactical and strategic, focuses on long-term driving planning. Analyses indicated that driving strategy majorly relates to the high-level decision-making process. The low-level strategy research is from bottom (requirements) to top (strategy), aiming to generate a driving strategy for a specific scenario; while the high-level strategy research is from top to bottom, aiming to generate a general driving strategy based on the hardware conditions and algorithm logic. However, the low-level decision-making process received far more attention in the past two decades.

The low-level decision-making studies are multiple and diverse, with publications dating back to the 1980s. More precisely, those methods mainly include (a) rule-based driving decision-making, such as logical reasoning (Gipps, 1986; Niehaus and Stengel, 1991), state machines (Montemerlo et al., 2008; Kurt and Özgüner, 2013) and decision trees (Olsson, 2016); (b) utility-based driving decision-making, such as behavior evaluation (Furda and Vlacic, 2011; Talebpour et al., 2015; Yu et al., 2018), path evaluation (Duering and Pascheka, 2014; Wei et al., 2014; Gu et al., 2016); (c) AI-based driving decision making, end to end learning (Hecker et al., 2018; Codevilla et al., 2018), imitation learning (Bansal et al., 2018).

However, these studies mainly focus on particular driving scenarios or detailed driving behaviors, and thus cannot be easily generalized. To fix this problem, many researchers kept trying to test the AV prototypes in well-designed experiments and "patch and upgrade" the AV prototypes to make it work in all the scenarios that had been tested. The investigations show that road tests can tackle the problem from the algorithm or execution layer by improving their risk identification and response capabilities (Broggi et al., 2013; Li et al., 2016; Favarò et al., 2018; Li et al., 2019a,b). Although these methods improve the performance of AVs, they were usually costly in time and economical, and heavily relied on human knowledge to design testing scenarios properly. Moreover, they are mainly designed for individual AVs and fail to model interactions between multiple traffic participates (Hu et al., 2019).

Recently, some researchers proposed another way to attack this problem from the upper level. They tried to develop a systematic, specific, and practical high-level driving scheme applying for the whole decision process and all traffic scenarios (Shalev-Shwartz et al., 2017; (NHTSA, 2017). Generally Speaking, high-level strategies can be further specified and applied for each scenario. In the real world, the road conditions and risks are often unknown or uncertain, which requires AVs to have an adaptive long-term high-level strategy and the ability to adjust flexibly through interaction. During the process of designing high-level strategy, researchers need to consider not only the behavior itself, but also the logic model, prediction and planning behind the behavior, as well as the underlying hardware foundation and cooperation mode. For example, Responsibility Sensitive Safety (RSS) proposed by Mobileye and Safety Force Field (SFF) proposed by NVidia are representative works. They both commit to ensuring the whole-process safety of AVs, but along the different technical routes.

However, most researchers only take account of the interaction logic between the same kind of AVs and ignore the compatibility between different strategies. As a result, these kinds of studies may have implicit differences in their objectives setting, assumptions setting, or collaborative manner. This may result in AVs with different strategies incompatible with each other, and become a huge potential hazard to traffic safety. Apparently, it is difficult to unify various technologies in a short period of time, but we can try to find the greatest common divisor of these strategies and develop on the basis of a peaceful and safe coexistence.

Therefore, it is imperative to establish a set of standards to synthetically study those high-level driving strategies, maximizing the convergence, and minimizing the divergence among them. After reviewing existing studies, we propose three characteristic dimensions to measure and categorize high-level driving strategies: *preferred objective* (whether it has a reasonable tradeoff between rapidity and safety), *risk appetite* (whether it has a conservative appetite towards risk), and *collaborative manner* (whether it has an efficient collaborative manner compatible with human-driving vehicles and other AVs). If researchers can reach an agreement on these three characteristics, the compatibility and coexistence of different AVs will have a good foundation. According to these dimensions, we categorize existing strategies into four kinds: *defensive driving strategies*, *competitive driving strategies*, *negotiated driving strategies,* and *cooperative driving strategies*. We provide a timely review, including their formation process, core task, interaction logic, decision mechanism, and hardware foundation, to identify possible opportunities to improve their performance.

This paper sets out to gain insight into both their strengths and limitations. We highlight the feasible directions for improving the performance of high-level driving strategies, which is of great significance for integrating research resources and improving research efficiency. We hope that this paper can promote various manufacturers and technology vendors to reach a consensus on how to drive autonomous vehicles safely, efficiently, and harmoniously.

The rest of this paper is arranged as follows: in *Section II*, we propose three characteristic dimensions of driving strategies and explain why characteristics are important to driving strategy design; *Section III* categorizes the strategies into four kinds with respect to these three characteristics, aiming at a comprehensive inspection of these driving strategies used in mixed traffic flow. Section IV briefly discuss the relationship between autonomous vehicle design and the traffic efficiency of mixed traffic consists of human-driven vehicle and autonomous vehicles. In *Section V*, we summarize the whole study and propose several problems that await to be further explored.

2. Categorization about driving strategies

2.1. Some assumptions

In order to describe the characteristics of high-level driving strategies intuitively, we need to make simplification and define the environment before formal categorization.

First, limited by length, this paper only focuses on the interaction between two vehicles. However, since the high-level driving strategies studied in this paper have sufficient versatility and universality, they are easily applied to the interaction with other kinds of traffic elements with a few modifications, such as the interaction between vehicles and pedestrian/traffic environment (Obeid et al., 2017; Gupta et al., 2019).

Second, a practical driving strategy must consider the mixed traffic, because AVs will share road resources with human-driven vehicles in the foreseeable future. Moreover, we still lack a powerful and convictive model that can describe human actions adequately and accurately until now. This problem makes manufacturers such as Waymo struggle with "how to predict and react to human driver behavior" (Efrati, 2018). Besides, some ethicists worry AVs will inevitably fall into moral dilemmas during the process of interaction with people (Bonnefon et al., 2016; Di Fabio et al., 2017; Conitzer et al., 2017; Awad et al., 2018). Accordingly, it is necessary to require AVs to possess the ability to deal with human-driven vehicles and consider this as an important evaluation criterion (Wei et al., 2013; Müller et al., 2016a,b; Jeong et al., 2017; Yang et al., 2018; Crandall et al., 2018; Rahwan et al., 2019; Schwarting et al., 2019; de Melo et al., 2019).

Third, we assume that there exists the possibility of an error during perception and prediction. As the prerequisite of decision-making, the purpose of perception and prediction is to collect information about the surrounding environment. In fact, predicting the intentions of other vehicles in a reasonable and effective way is likely to be a necessary function in the future. However, the current foundation of both hardware and software cannot guarantee the absolute accuracy of this process; otherwise, all accidents will not happen. Therefore, we highlight the importance of interaction, which is the key component to the efficiency and safety of traffic. The more accurate information of the space-time environment collected through interaction, the less inaccurate information (e.g., intent, expected trajectory) needs to be predicted. The existence of the communication process actually reduces the workload and difficulty of the prediction and planning shared with each individual.

2.2. Three typical characteristics dimensions

After analyzing several representative high-level driving strategies, we summarize that they can be measured from the following three characteristic dimensions:

2.2.1. Preferred objectives

Autonomous driving has multiple objectives (Li and Wang, 2007), e.g., safety, accessibility, efficiency, rapidity (duration of a journey), convenience, fuel consumption. The performance of AVs depends on dynamic programming among these objectives. Hence, determining the weights of different objectives and reaching a reasonable tradeoff is quite critical (Wu et al., 2017; Zimmermann et al., 2018).

In this paper, we denote the objectives related to AV itself as *self-interested objectives*, including security, safety, rapidity, comfort, visual field, fuel consumption, etc., and denote the objectives related to other traffic participants or regional traffic flows as *overall-interested objectives*, including congestion distance, traffic flow, and avoidance cost. Obviously, if all AVs only pursue self-interested objectives selfishly, road traffic will become a zero-sum game filled with congestion and accidents. Reversely, if the vehicle focuses too much on overall-interested objectives, the resulting terrible driving experience (i.e., slow driving, being overtaken frequently) is also intolerable. Three-traffic Phase ACC (TPACC) is a theory in which part of self-interested objectives is given up properly to achieve better overall-interested objectives. It has been proved through simulation experiments that when AV does not pursue the optimal following distance, the stability of traffic flow can be improved, and more detail will be discussed in Section 4. In sum, the different preferences between these two types of objectives will greatly influence the style of driving strategies, and more information will be provided in Section 2.3.

2.2.2. Risk appetite

Among a range of decisions about objectives needs to make, AVs need to first handle the risk from traffic environment or other vehicles (Arbis et al., 2016; Dixit et al., 2019). We interpret the risk appetite of AVs as the basic attitude and tolerance capacity in the face of potential risks from other traffic participants. Under the same software and hardware foundation, the difference in risk appetite will greatly influence the driving behaviors.

For traditional human-driven vehicles, this property to risk is commonly known as "driving style", divided into aggressive, normal, calm and so on (Bolovinou et al., 2014; Sagberg et al., 2015; Meiring and Myburgh, 2015; Deng et al., 2017; Li et al., 2017). In this paper, we use a more intrinsic way to classify. Similar to aggressive human drivers, risk-preference driving strategies tend to choose driving behaviors with high potential benefits as well as high risks, such as overtaking, short-distance merging, and so on. Reversely, risk-averse driving strategies regard safety as the key principle, so under their prescription, AVs prefer to reserve a conservative distance and speed rather than be involved in potential conflicts. Risk-neutral AVs would like to make decisions based on specific scenarios, to seek the balance of expected benefits and potential risks. It is worth emphasizing that risk appetite is an abstract feature of driving strategies reflected by the performance in real road traffic, rather than a specific numerical setting.

2.2.3. Collaborative manner

The above two dimensions are about the characteristics of AV itself, while the collaborative manner is about the characteristics of interaction with other vehicles. We position it as the essential means to accomplish a reasonable risk appetite, as well as a trade-off among driving objectives. The importance of interaction in a multi-individual road environment has been emphasized above. The main function of interaction is assisting AVs to complete the assignment process of right-of-way, and the efficiency of this process is determined by the collaboration manner. Historically, the term "right-of-way" has been used to describe the right of traffic participants to navigate on the road. In this paper, we define it further explicitly as the right to occupy/use a special temporal-spatial area.

In the past 100 years, the progress of collaborative manners has promoted the assignment of right-of-way step by step towards standardization and efficiency, and hence enable some complex driving strategies to be implemented (Li and Wang, 2018). From the earliest "First Come First Served" (FCFS) non-information collaboration to dynamic scheduling among vehicles supported by V2X communication technologies, every revolution in road transportation indeed increases the collaborative manners and reduce the cost of collaboration. To distinguish new communication technologies and traditional collaborative manners, we refer to the collaborative manners relying on communication modules, e.g., V2X or 5 G, as *explicit communication* in this paper, and refer to those collaborative manners, e.g., headlights, gestures or horns, as *implicit communication*.

It is worth noting that these three dimensions do not constitute a complete space. Essentially, both "risk preference" and "preferred objectives" can be regarded as a kind of driving goal, and "collaboration manners" are the means to achieve the goals. Because of this logical relationship, there will be correlations between the three dimensions, but the differences between them are further greater than the correlations. In fact, it is hard to build a completely orthogonal space with proper dimensions to position all strategies in a quantitative way. So, instead, we list the evaluation dimensions we believe are important for high-level strategies research, to attract the attention of other researchers.

2.3. The definitions of four typical driving strategies

According to the trade-offs between the overall-interested and self-interested objectives, the current driving strategies fall into two categories: *adversarial driving strategies* and *collaborative driving strategies*. We refer to the driving strategies showing that the importance of self-interests is greater than the importance of overall-interests as adversarial driving strategies, which means AVs do not have the willingness or ability to actively maintain the interests of overall traffic through cooperation. According to the risk appetite of safety, the adversarial driving strategies can be further divided into risk-averse *defensive driving strategies* preferring safety objectives and risk-neutral *competitive driving strategies* preferring rapidity objectives.

Reversely, we refer to the driving strategies judging the importance of overall-interests is higher than the importance of self-interests as collaborative driving strategies, which would like to cooperate and sacrifice part of self-interests for the overall performance of traffic. This kind of driving strategy is commonly seen among AVs equipped with explicit communication devices (Hedrick et al., 1994; Li and Wang, 2006, 2007; Li et al., 2013a,b), known as Connected and Automated Vehicles (CAVs). According to the collaborative manner, the cooperative driving strategy can be further divided into *negotiated driving strategies* based on implicit communication, and *cooperative driving strategies* based on explicit communication.

According to the characteristic distribution in three dimensions, we elaborate the above four driving strategies into a spider chart in Fig. 1, and give the following definitions:

Defensive driving strategy: a kind of driving strategy that adopts negative assumptions (a high probability of irrational behaviors) about adjacent vehicles, and prescribes AVs to make independent driving decisions with the core purpose of ensuring its own safety.

Competitive driving strategy: a kind of driving strategy that adopts positive assumptions (a low probability of irrational behaviors) about adjacent vehicles, and prescribes AVs to make independent driving decisions with the core purpose of improving its own efficiency.

Negotiated driving strategy: a kind of driving strategy that prescribes AVs to negotiate with other vehicles reasonably based on implicit communication, and make driving decisions with the core purpose of pursuing both efficiency and safety.

Cooperative driving strategy: a kind of driving strategy that prescribes AVs to coordinate with multiple vehicles and accepts unified dispatch driving commands with the support of connected vehicle technology, pursuing both efficiency and safety.

The classification proposed above focuses on the interactive logic and objectives preference of the strategies, rather than detailed implement methods. Therefore, it has inclusiveness and scalability, which means it can basically cover the common high-level driving strategies common at present, and can be further modified or updated in the future with the emergence of new strategies.

3. Four typical driving strategies

In this section, we will introduce the formation process, core task, interaction logic, decision mechanism, and hardware foundation of these four driving strategies. Furthermore, to show the difference between the four strategies visually and succinctly, we take the vehicle-

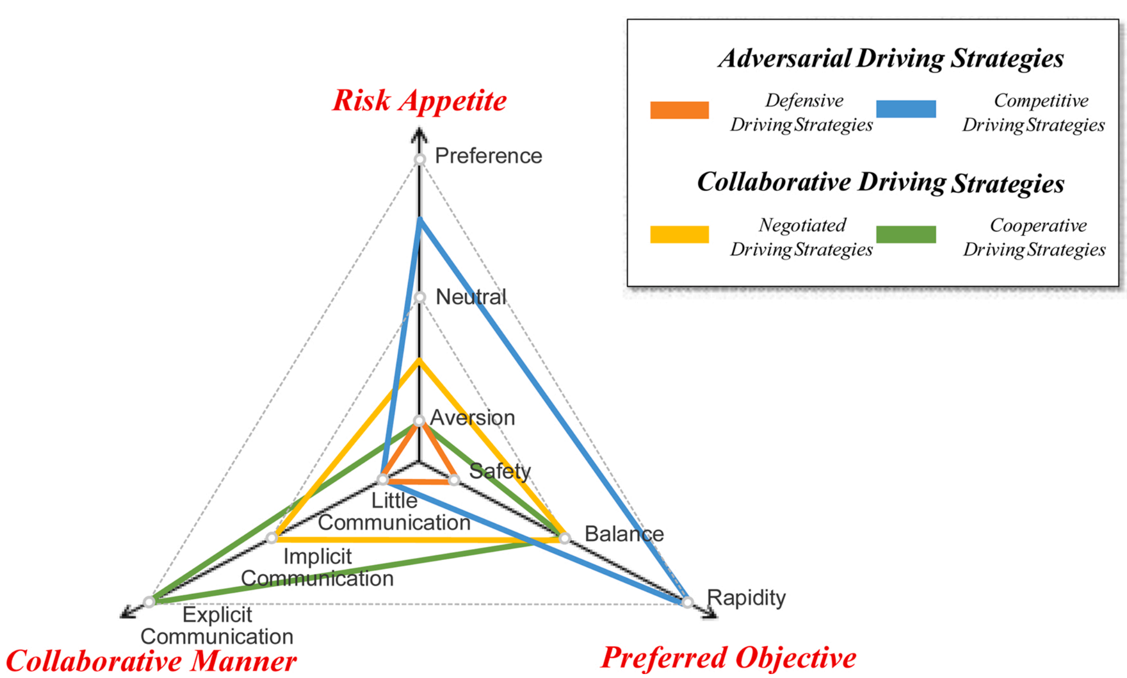

Fig. 1. The characteristic distribution of four typical driving strategies.

following scenario as an example to demonstrate how different high-level strategies are specified.

3.1. Defensive driving strategies

Defensive driving derived from the training process of novice drivers or violators in the 1950s (Hill and Jamieson, 1978; Lund and Williams, 1985). It is a set of systematic, straightforward, preventative driving skills, designed for the characteristics of unskilled drivers with insufficient driving experience and insufficient emergency capabilities. With the development of autonomous driving technology in this century, defensive driving strategies have been introduced into the study naturally, because of many similarities existing between the AV prototypes and human drivers.

In short, the core task of defensive driving strategies (also known as robust driving strategies) is to "prevent all potential danger against uncertainties" (Steimetz, 2008; Li and Sun, 2016). AVs with this kind of driving strategy are averse to risk and thus have negative assumptions about the surrounding traffic environment. This means the ego vehicle is always on guard for grabbing for right-of-way in some irrational manners (such as rapid braking, no warning, and cutting in), so it is necessary to yield in advance to avoid or mitigate potential risks. Under the prescription of defensive driving strategy, AVs will always be more inclined to give up the right-of-way voluntarily in the mixed traffic conditions, without complicated collaborative interaction actions generated in this process. Due to active avoidance of potential conflicts, defensive driving has relatively low accuracy requirements for perception and prediction algorithms and good universality for different scenarios (Shalev-Shwartz et al., 2017; Nistér et al., 2017).

In order to ensure absolute safety, Mobileye researchers recently proposed the Responsibility Sensitive Safety (RSS) strategy (Shalev-Shwartz et al., 2017). The RSS model is designed to formalize different driving situations, and explain them as an executable and interpretable set of rules and principles. The setting of RSS in vehicle-following collision avoidance is similar to NETSIM, a microscopic human-driving urban traffic simulation model that was widely used and continuously updated since released in 1971 (FHWA, 2017); Aycin and Benekohal, 1999; Li et al., 2010). However, NETSIM focused on modeling the movement of an individual vehicle rather than the interaction among clusters. This setting leads to poor performance in traffic efficiency and the lack of attention in this century (Parker, 1996). RSS converts the driving body from human to autonomous driving system and adopts a more cautious attitude to risk. RSS requires AVs to avoid potential danger as much as possible, without causing new accidents.

Let us take the vehicle-following scenario as an example to illustrate the difference between various strategies. The RSS model almost complies the setting of NETSIM and calculates the safety following gap h (Rakha and Crowther, 2002) by:

$$h = h_j + \Delta r + S_f - S_l = h_j + \Delta r + \frac{v_f^2}{a_f} - \frac{v_l^2}{a_l} \tag{1}$$

where h_j is the acceptable distance between the leading vehicle and the following vehicle when they completely stop. Δr is the distance traveled by the following vehicle within the reaction time. S_f and S_l are the distances required for the leading and following vehicles to decelerate. v and a are their original speed and the deceleration when slowing down.

Obviously, the safety following gap is closely related to traffic efficiency and other complex traffic scenarios, e.g., lane-changing and intersection. If it is set too long, the traffic flow at saturation will be severely affected when saturated, while too short, the collision probability will be greatly increased. In the calculation of (1), RSS assumes that the following vehicle will decelerate with the minimum deceleration regardless of the deceleration of the leading vehicle, which is inconsistent with the reality and greatly increases h as follows:

$$h_{\mathrm{RSS}} = h_j + \Delta r + \frac{v_f^2}{a_{f\min}} - \frac{v_l^2}{a_{l\max}} > h_j + \Delta r + \frac{v_f^2}{a_f} - \frac{v_l^2}{a_{l\max}} = h_{\mathrm{need}}, \text{where} a_{f\min} < a_f \tag{2}$$

Under this setting, an excessively long S_f will greatly increase the safety following gap and result in a decrease in traffic capacity (Li et al., 2018b). After the literature (Li et al., 2018b) modifying this conservative setting according to the intention of the following vehicles (i.e., approaching, departing, and following), the traffic efficiency increased by more than three times and the safety could be ensured too. The result demonstrates that an overly defensive driving strategy will inevitably block traffic and limit the scalability of system deployment. During actual operation, the defensive driving strategies also need to consider efficient issues.

It is worth emphasizing that the above models all default that AVs are trying to reach a particular (desired or optimal) from the vehicle ahead. But we have also noticed that some studies have shown that as the proportion of AVs increases, this setting will have a higher probability of causing traffic congestion or even breakdown (Kerner, 2018a,b). Reversely, the setting of TPACC mentioned above can effectively avoid this problem. However, few studies of high-level autonomous driving strategy based on the TPACC have been done up to now (Kerner, 2018a, b). So, this paper does not expand here and provides more details to refer to in Section 4.

3.2. Competitive driving strategies

As the research moves along, various disadvantages of defensive driving strategies gradually appear, such as the lack of long-term decision-making, the sacrifice of traffic efficiency. To fix these difficult problems, people introduced the idea of "learning" into autonomous driving, trying to teach machines to make decisions like humans, based on experience and evaluation between expected benefits and potential risks (Mnih et al., 2015). Based on this theory, AVs will regard road traffic as a "non-cooperative dynamic game", and always look for the possibility of increasing driving benefits (Basar and Olsder, 1999; Schwarting et al., 2019). We call this kind of driving strategy as a competitive driving strategy.

The core task of competitive driving is to "increase its own driving benefits under the assumption that other vehicles will drive rationally". Competitive driving is commonly implemented by using deep learning (Wang et al., 2017) or reinforcement learning (Min and Kim, 2018). The input of the learning model is generally a high-dimensional semantic description of the scenario formed by the parameterization of the sensor signal. The output is a decision vector consisting of a series of sequential maneuvering instructions and passed to the execution layer. During the training process, the model will keep calculating the corresponding reward under different decisions, until finding the direction most profitable, i.e., the optimal solution or approximate optimal solution (Wolf et al., 2018).

The biggest difference between competitive driving and defensive driving lies in the more idealized assumption of former that the adjacent vehicles will drive rationally and stably. However, it is dangerous for AVs to overconfidently accept this assumption without interaction to confirm. The investigation has proved that this may cause AVs to lose vigilance for unexpected situations, and further lead to potentially dangerous behavior due to overconfidence in the behavior model (Schwarting et al., 2018). More than that, this setting will make the AV pursue self-driving interests selfishly, leading to a decrease in overall efficiency (Wang et al., 2021).

The logic behind this phenomenon is that the lack of interaction leads to insufficient consideration of risk factors. Especially, the performance of competitive driving strategies is basically determined by prior knowledge from experience or experts. There lacks a rigorous and standardized analysis of safety. Most studies formulate the reward functions as a combination of some self-interested objectives, including rapidity (the difference between the expected speed and the current speed), comfort (a derivative of acceleration), energy consumption (integral of brake deceleration) and so on (Fridman et al., 2018; Wang et al., 2019). However, the potential risks are not fully considered in advance (Liu et al., 2018). This results as the training proceeds, the attitude towards risk will inevitably gradually convert to neutral, even preference. The AV believes that others will maintain rational driving according to historical experience, so it will act more aggressively, and the risk of collisions will also rise gradually.

Similarly, take the safety following gap h of Formula (1) as an example. When AV become not cautious enough and makes positive judgments about adjacent vehicles, it will easily believe that the leading vehicle ahead will not make a sudden stop with a maximum deceleration, shown as follows:

$$h_{\text{competitive driving}} = h_j + \Delta r + \frac{v_f^2}{a_f} - \frac{v_l^2}{a_l} < h_j + \Delta r + \frac{v_f^2}{a_f} - \frac{v_l^2}{a_{l\max}} = h_{\text{need}}, \text{where} a_l < a_{l\max} \tag{3}$$

This will sharply shorten h, so that the following vehicle is likely to fall into danger when the leading vehicle brakes suddenly.

Another negative consequence of over competition is the loss of traffic efficiency. In the investigation (Wang et al., 2021), the researchers utilized reinforcement learning to train AVs in the lane-changing scenarios. Similar to other presentative studies, the training goal of this model is set as each individual strives for passing the designated road as soon as possible. During the whole simulation process, each AV was searching for a changing opportunity constantly to acquire the expected speed. However, tests resulted in a massive traffic jam, i.e., many AVs, after changing lanes multiple times, fell into a severe congestion caused by deadlock. Subsequently, the researchers added a penalty term to punish the "multiple changes" behavior, and the result was noticeably improved. This research indicated that the performance of competitive driving is quite sensitive to the setting of reward function: If it does not consider the overall efficiency fully, the self-interested objectives will push AVs to become increasingly selfish.

In general, when two competing actions are each scrambling to finish or waiting for the other, the conflict or deadlock will exist everywhere. Therefore, introducing a collaboration mechanism into road traffic to coordinate individual intentions is considered as a more promising development direction (de Melo et al., 2019; Perronnet et al., 2019).

3.3. Negotiated driving strategies

Gaciarz et al. (2015) proposed a kind of right-of-way awarding mechanism based on FCFS. This driving strategy clarified the concepts of "right-of-way owners" and "right-of-way requesters", and formulated a set of effective negotiation rules based on human driving logic to ensure that right-of-way can be converted safely and smoothly. This study showed the possibility of a new framework of interactions, which we called as negotiated driving.

The core task of negotiated driving is to "assign right-of-way through interaction". Similar to defensive driving, negotiated driving recognizes the possibility of irrational driving behaviors from other vehicles, but reduces the potential risk in an interactive way rather than avoidance. This kind of strategy emphasizes the negotiation process between vehicles but not limited to a specific communication method. The differences between negotiated driving and adversarial driving can be summarized as follows:

First, the real-time interaction between vehicles is also taken into account.

Second, compared with the non-cooperative instantaneous decision-making of adversarial driving, the continuous decision mechanism process of negotiated driving is closer to humans.

Negotiated driving strategies build a coordination mechanism that is useful to ease traffic pressure, minimize time losses, and meet safety constraints (Gaciarz et al., 2015). As mentioned above, the purpose of the interaction is assisting the assignment of the right-of-way and negotiated driving strategies to embody this process more precisely: First, the strategy requires that non-owners (of right-of-way) have the responsibility to avoid entering the right-of-way zone. Second, all vehicles need to follow the FCFS principle in a non-right-of-way zone. If a non-owner intends to enter the right-of-way zone, it must negotiate with the owner based on the predefined rules, and the owner has the right to refuse. Third, when encountering an irrational vehicle refusing to interact, negotiated driving can degrade to defensive driving to avoid accidents. Consequently, AV can show similar caution as defensive driving, but also avoid the disadvantages of substantial concessions due to over-conservation.

The negotiated driving strategies make it feasible to guarantee both traffic efficiency and traffic safety simultaneously. As take the safety following gap h as an example. Since negotiated driving can be regarded as an improvement to defensive driving, the calculation of h is basically same with Formula (1). However, as the following vehicle is not the owner of right-of-way, it must pay continuous attention to the behavior of the leading vehicle, which will shorten the reaction time partly as follows:

$$h_{\text{negotiated driving}} = h_j + \Delta r_{\text{negotiated driving}} + \frac{v_f^2}{a_f} - \frac{v_l^2}{a_l}, \text{where} \Delta r_{\text{negotiated driving}} < \Delta r_{\text{adversarial driving}} \tag{4}$$

In other complex scenarios, the advantages of negotiated driving strategy are more evident. The studies (Zhao et al., 2019; Xing et al., 2019) respectively applied the negotiated driving to lane-changing and no-signal intersection scenarios, and compared the simulation results with RSS model. The results demonstrated that with the help of negotiated driving, the efficiency of road passage had been improved noticeably. However, AVs in mixed traffic flows will inevitably encounter with human-driving vehicles. Accordingly, the successful use of negotiated driving needs a systematic modeling of human driving habits, and a standardized communication framework that takes all kinds of vehicles into account.

3.4. Cooperative driving strategies

The increasing communication abilities of AVs and recent advances in distributed cooperative decision-making models enables the design of traffic control methods based on real-time information. The proposition of cooperative driving can be traced back to the early 1990s (Hedrick et al., 1994; Tsugawa, 2002). The original intention of people to build cooperative driving is to address the problem of road resource utilization and traffic safety aided by intervehicle communications (Tsugawa, 2000; Shladover, 2009; Wang et al., 2020). Today, it has been given more expectations, including increasing the comfort of travel, improving transportation efficiency, and providing other value-added services.

The core task of collaborative driving is to "formulate and execute a global optimal transportation scheme". The basic assumption underlying cooperative driving is all AVs can notify the control system about their positions and states, and follow the movement plans assigned by the control system. Under this assumption, all traffic participants in the area, even infrastructures, can share information including position, intention, speed, and so on through explicit communication (Tokuda et al., 2000; Dresner and Stone, 2008; Sukuvaara and Nurmi, 2009; Roessler, 2010; Aycard et al., 2011). Utilizing this efficient collaborative manner with strong real-time and high accuracy, AVs can easily obtain additional information beyond those collected by vehicle-based sensors. Meanwhile, cooperative driving enables AVs to get rid of communication uncertainty and the tedious process of filtering information. It removes the need for complicated trajectory prediction and risk assessment as before. Thus, it can obtain a more reliable global-optimal plan with the maximum utilization of road resources as well as the minimal computational cost. (Hedrick et al., 1994; Kato, 2000; Li and Wang, 2006, 2007).

The successful implementation of cooperative driving requires solving three key issues (Meng et al., 2017). First, a low-latency, high-bandwidth, high-reliability technical equipment with a uniformed and standardized protocol. (Tsugawa, 2002; ASTM, 2003; Li et al., 2013a,b; Johri et al., 2016). Second, a unified traffic management system used to generate and distribute maneuvering schemes (Tsugawa et al., 2000; Commission, 2010; Deng et al., 2019), and all vehicles can implement the assigned scheme accurately. Third, a real-time and efficient swarm collaborative decision-making and control algorithm, which can find a global optimal or approximate global optimal feasible scheme in an acceptable time (Kato et al., 2002; Kianfar et al., 2012; Chen and Englund, 2015). Apparently, the third one is the major concern of this paper.

When the first issue and the second issue are solved, the individual driving strategy actually becomes a traffic control strategy. Since the uncertainty of individual vehicle trajectories is eliminated, the improvement of overall traffic efficiency is prominent and remarkable. Similarly, we take the vehicle-following scenario as an example. In cooperative driving, the ideal safety following gap h can be rewritten as:

$$h_{\text{cooperative driving}} = h_j + S_f - S_{l\text{real}} \tag{5}$$

Since the whole traffic flow is controllable, the leading vehicle will never produce irrational behaviors such as sudden braking. So S_l will transform from an estimated value to a determined value $S_{l\text{real}}$, which means the actual braking distance for the leading vehicle. At the same time, reaction time can be removed because the following vehicle can directly accept the command from the control system, rather than make a delayed response to the behaviors of vehicle ahead. As a result, the smaller minimum following gap will significantly promote efficiency, especially in heavy traffic.

Different from the individual optimized strategies aforementioned, the cooperative driving becomes a swarm optimization problem, covering from microscopic vehicles to mesoscopic fleets (5–20 vehicles) to macroscopic regional traffic flows. In the past 20 years, cooperative driving has been successfully applied to mesoscopic fleets (Kato et al., 2002; Bonnet, 2003; Stiller et al., 2007; Frese et al., 2007; Geiger et al., 2012; Wang et al., 2018), which proves it can complete many complex tasks, e.g., cruise control, lane-keeping and concerted lane change, and active obstacle avoidance maneuvers. For multi-vehicle cooperation under specific traffic scenarios, the traffic scheduling problems can be simplified to the problem of optimal traffic sequence (Guler et al., 2014), and further expressed as a mixed-integer linear programming problem (Müller et al., 2016a,b; Li and Zhou, 2017) or a tree search problem (Li and Wang, 2006; Xu et al., 2019), with the optimization goal to minimize the total passage time of all vehicles. In general, cooperative driving brings more certainty to traffic control and strengthens the traffic system efficiency. Thus, many researchers believe that the capacities of highway and intersection are projected to lift to a higher level through this advanced cooperation technology (Fagnant and Kockelman, 2015; Olia et al., 2018).

However, the current cooperative driving also has limitations. First, the second issue is too ideal and challenging to implement. In the mixed traffic flow, since the existence of human drivers and the performance difference of vehicles, the desired driving plan may become invalid due to the unforeseen actions of human drivers. This is the biggest obstacle of cooperative driving to the practical application, and more detailed discussion can be found in Frese and Beyerer (2007), Kowshik et al. (2011), and Lee and Park (2012). However, some investigations indicate that CAVs can bring compelling benefits to safety and efficiency even at relatively low road penetration rates (Virdi et al., 2019; Papadoulis et al., 2019). Second, the complexity of finding the optimal solution will rise sharply with the increase in traffic flow. Consequently, some researchers tried to use mathematical programming or heuristic algorithms to find some near-optimal solutions recently, including Monte Carlo Search (Xu et al., 2019), genetic algorithm (Ghaffarian et al., 2012), ant-colony algorithm (Ahmane et al., 2013), etc. Third, limited by the above difficulties and high testing costs, most of the cooperative driving still basically remains at simulation stages.

4. Supplementary discussion on traffic efficiency

While the main theme of this paper is on the vehicle-side design for traffic safety, it is still necessary to distinguish the objective of achieving driving efficiency for AVs and the resulting traffic efficiency. Therefore, this section will make a supplementary discussion to this problem.

Although some driving strategies were proposed to achieve driving efficiency, they may lead to traffic breakdown in some situations. The cooperative driving strategy discussed in this paper may not result in traffic breakdown, since the movement of every vehicle is appropriately scheduled and precisely controlled in the road network. The other three driving strategies may lead to traffic congestions if the detailed driving rules are not properly designed. A small disturbance may evolve into large fluctuations and breakdown, due to the nucleation nature of traffic breakdown and other intrinsic properties of traffic dynamics.

As one of tentative solutions to the above problem, the research named the empirical nucleation nature is an important theory in this field (Kerner, 2004, 2009; Kerner, 2013, 2015; Kerner, 2017, 2019; Kerner, 2019a,b,c; Kerner, 2016). It regards the empirical nucleation nature of traffic breakdown as the basis empirical feature of vehicular traffic that determines traffic efficiently and safety in mixed traffic flow.

In the face of traffic breakdown, TPACC may be able to perform better, because it leans about driving strategies of human drivers and is consistent with the empirical nucleation nature of traffic breakdown (Kerner, 2018a,b; Kerner, 2019a,b,c). TPACC is a kind of adaptive cruise control theory that determines the headway instead of a high-level strategy, but considering that the headway is the basis of all AV driving strategies, it is necessary to discuss it separately. Under TPACC, the AV agent system should adapt the speed while keeping following distance in a range, rather than pursue the optimal following distance (Kerner, 2018a,b). This range can be calculated by:

$$h_{\min} \le h \le h_{\text{synchronization}}, \tag{6}$$

where $h_{\min}$ denotes the minimum safety following distance, and $h_{\text{synchronization}}$ denotes the synchronization space for vehicle to decelerate to the speed of the leading vehicle. And the actual following distance could be any value in between, which is more consistent with real human driving behavior.

Although this strategy may lead to an increase in the expected travel time of an individual, it also improves the stability of the overall traffic flow. What needs to be admitted is that quantifying and comparing the benefits of the two is a complicated process, and meanwhile, this result will also be affected by the changes in the proportion of AVs and the density of traffic flow. However, some simulations have initially confirmed that: in the mixed traffic, enough AVs with TPACC will significantly reduce both the speed disturbances and the probability of congestion (Kerner, 2018a,b).

Based on this, we believe that future strategy researchers need to consider TPACC or other similar control algorithms more, which may provide a new solving idea to the core question of "how to make a trade-off between overall interests and individual interests" discussed in this paper.

5. Summary and outlook

Under the characteristic dimensions proposed in this paper, the four typical driving strategies mentioned above have advantages but also limitations. Adversarial driving strategies have a wide range of application scenarios but may meet difficulties in balancing safety and efficiency. Collaborative driving strategies hold a great promise for solving the problem but still have a long way to go for applications in mixed traffic.

We believe that future research should focus on the following valuable directions:

1) Limited by the level of hardware and algorithm, there is still much room for improvement in the accuracy and range of the current perception system. Therefore, as the latter segment of perception, the driving strategies of AVs need to be designed specifically based on some limitations and assumptions of perception, and hence cannot solve all problems in a generic way.
2) The current driving strategies are based on an indispensable assumption of using identical technical equipment and the same control strategy for all vehicles (Geiger et al., 2012). However, due to the inconsistency of interpretation models and preferred objectives, different AVs may have different understandings and responses to the same scenarios. When they lack necessary communication or communication channels are disturbed, their misunderstandings and misjudgments will become a new trigger to danger. Therefore, how to formulate a framework to ensure that AVs with different driving strategies still can reach consensus is an urgent issue for future researchers.
3) So far, research on risk appetite, the feature closely related to safety, is still insufficient and deserves further advancement. Especially, how should the risk appetite of different strategies be tested, evaluated, and quantified. In consideration of the long-tail problem, how to design simulation tests to reflect the risk appetite of the strategies accurately (Li et al., 2016, 2018a; Li et al., 2019a,b).
4) Future research should focus more on communication and collaboration between vehicles. For collaboration with other AVs, the unification of communication rules and protocols should be accelerated, to form a standardized and extensible inter-vehicle communication mechanism.
5) For collaboration with human-driven vehicles, we should further construct human driver models from the cognitive level rather than the behaviors itself (Efrati, 2018; Stewart, 2018; Ma et al., 2010; Schwarting et al., 2019; Li et al., 2018b; Michon, 1985). It can help massively to develop a more reasonable collaborative driving strategy and improve the probability of understanding each other correctly when AVs interact with human-driven vehicles.
6) In the next step, researchers should pay more attention to TPACC and explore the possibility of combining it with collaborative driving. It is a meaningful work to accurately compare the individual benefits and the overall benefits through theoretical calculations or simulation tests.
7) The purpose of this paper is to draw attention of researchers towards these important directions. We expect more exciting results will be obtained soon.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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