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A human-like game theory-based controller for automatic lane changing

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ABSTRACT

Lane changing is a critical task for autonomous driving, especially in heavy traffic. Numerous automatic lane-changing algorithms have been proposed. However, surrounding vehicles are usually treated as moving obstacles without considering the interaction between vehicles/drivers. This paper presents a game theory-based lane-changing model, which mimics human behavior by interacting with surrounding drivers using the turn signal and lateral moves. The aggressiveness of the surrounding vehicles/drivers is estimated based on their reactions. With this model, the controller is capable of extracting information and learning from the interaction in real time. As such, the optimal timing and acceleration for changing lanes with respect to a variety of aggressiveness in target lane vehicle behavior are found accordingly. The game theory-based controller was tested in Simulink and dSPACE. Scenarios were designed so that a vehicle controlled by a game theory-based controller could interact with vehicles controlled by both robot and human drivers. Test results show that the game theory-based controller is capable of changing lanes in a human-like manner and outperforms fixed rule-based controllers.

1. Introduction

Autonomous vehicles have attracted increasing interest in recent years. Both technology companies and traditional automotive manufacturers are engaged in this transformation. Distinguished members of IEEE predicted up to 75% of vehicles would be autonomous by 2040 (IEEE News Releases, 2012). Fundamental tasks of autonomous driving include car following, lane keeping and lane changing (Khodayari et al., 2010). Car following and lane keeping have been extensively studied. Cruise control, adaptive cruise control (ACC), lane keeping assist and lane centering have been developed (Ozguner et al., 2007). The focus of this paper is lane changing, an essential task for navigating a vehicle in heavy traffic.

Complicated tasks such as lane changing are usually realized through planning algorithms (Zhang et al., 2013). The algorithms can be divided into four hierarchical classes: route planning, path planning, trajectory planning and manoeuver planning. It should be noted that these approaches are often combined to make a complete plan instead of being treated independently (Varaiya, 1993). Route planning is to find a globally optimal path based on traffic situations, which is out of the scope of this paper. Path planning is to determine a collision-free geometric path for the vehicle to follow (Likhachev et al., 2003; Paden et al., 2016; Urmson et al., 2008). Trajectory planning is concerned with real-time transition of vehicle states. It further optimizes the chosen geometric path to assure a smooth and feasible journey, while considering the constraints of vehicle dynamics and obstacles (Borrelli et al., 2005; Kim and Kumar, 2014; Nilsson and Sjöberg, 2013; Wang and Qi, 2001). Maneuver planning deals with a high-level characterization of vehicle

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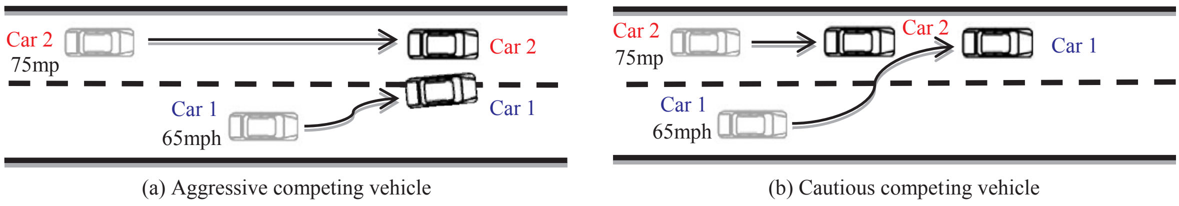

Fig. 1. Change lanes.

motion, such as 'changing lanes' and 'going straight'. Obstacle prediction and risk assessment are usually considered part of the maneuver planning process (Katrakazas et al., 2015).

Though considerable efforts have been made for path planning and trajectory planning, maneuver planning, especially obstacle prediction in the dynamic environment, remains largely unsolved. A typical lane-changing scenario is shown in Fig. 1. Car 1 is the host vehicle. It wants to move to the left lane in which Car 2 is occupying. Car 1 needs to predict the trajectory of Car 2 in order to change lanes safely. It is argued that the prediction could be improved by implementing Vehicle-to-vehicle (V2V) technology and vehicle-to-infrastructure (V2I) technology. In the V2V and V2I applications, it is assumed that vehicles are connected by communication technologies. In such a way, these vehicles can cooperate with each other to increase efficiency and safety (Kato et al., 2002). However, for years to come, it can be expected that there will be a mix of autonomous vehicles and traditional human-driven cars that do not necessarily support V2V or V2I. A self-driving car also needs to interact with human drivers, which are much less predictable than intelligent vehicles. This paper focuses on the mixed automatic/manual traffic scenario. The host vehicle should be able both to detect and predict the actions of surrounding human-driven vehicles on its own and to cooperate with surrounding connected vehicles.

In the literature, a variety of maneuver planning algorithms have been developed to use on-board sensors for obstacle prediction. These models can be classified into physics-based, maneuver-based and interaction-aware models (Lefèvre et al., 2014). The first category estimates the motion of obstacle based on the laws of physics. For instance, it is commonly assumed that surrounding vehicles have constant velocities or acceleration regardless of the motion of the host vehicle. However, this assumption is not always true in the real world, which could cause some trouble. An example is shown in Fig. 1(a). Car 1 wants to change lanes while Car 2 is following far behind in the target lane. Car 1 thinks that if Car 2 has a constant velocity, it is safe to change lanes since the distance between two cars is long enough. However, if Car 2 is much faster and aggressive, it may not want to slow down and allow Car 1 into its lane. Actually, an aggressive and near hostile Car 2 may accelerate and prevent Car 1 from cutting-in upon finding the lane-change intention of Car 1. In this case, it would pose a serious risk for both vehicles.

Maneuver-based models rely on early recognition of the intentions of other traffic participants. For example Liu and Tomizuka (2016) adopted recursive regression to predict the trajectory of the competing vehicle. Alin et al. (2012) applied a grid-based Bayesian filter to inferring the trajectories of other vehicles. Nevertheless, it is still assumed the maneuvers of a vehicle are executed independently from other vehicles in these models, which could also lead to undesired results. Fig. 1(b) illustrates another scenario. Car 2 is close to Car 1 in the beginning. Car 1 thinks Car 2 will continue to move at a constant velocity based on Car 2's previous maneuvers. Therefore, Car 1 should stay in the current lane. Otherwise, it may crash into Car 2. However, Car 2 may be "cautious" or friendly and cooperative. When it finds that Car 1 starts to change lanes, it may slow down and let Car 2 change lanes successfully and safely. In summary, a lane change decision may not produce a comfortable and safe lane change maneuver if the interaction between vehicles is not considered. It is advisable for an autonomous vehicle to treat surrounding traffic as interactive emotional human-driven vehicles rather than just moving obstacles.

For the sake of capturing the dependence between vehicles, efforts have been made to study the interaction-aware models. Coupled HMM (CHMMs) were employed to model pairwise dependencies between multiple moving entities (Brand et al., 1997; Oliver and Pentland, 2000). However, though the model is able to tell when to change lanes, how to change lanes is not discussed. Another approach that has been widely used to study the interaction between vehicles is game theory. Yoo and Langari (2012, 2013) proposed an approach to modelling the interactions between vehicles during lane changing and lane merging based on a Stackelberg game. Wang et al. (2015) presented a model for car-following and lane-changing control based on a differential game. However, motion prediction of the competing vehicle was based on the assumption that the host vehicle knew the cost function of the competing vehicle beforehand in these methods. Sadigh et al. (2016) modelled the interaction between drivers by approximating the human as an optimal planner, with a reward function obtained from inverse reinforcement learning. Kita (1999) and Liu et al. (2007) modelled merging scenarios using a non-cooperative game. However, the reward functions of competing vehicles were learned offline from data sets in these approaches. These functions, whose parameters were fixed after learning, were used for online prediction of the actions of all types of drivers. The prediction might not be reliable since the differences between human drivers (e.g., aggressive or cautious) were not considered. In other words, the models were not adaptive. Bahram et al. (2016), Lawitzky et al. (2013) proposed a prediction and planning loop, which could find the most likely maneuver sequence of the host vehicle and the competing vehicle over multiple time steps. However, the intention-based maneuver probability of the competing vehicle was also learned offline and the framework assumed the host vehicle knew this probability beforehand.

This paper proposes a lane-changing controller based on a game of incomplete information. Though the system does not know the types of other drivers at first, it tries to interact with those drivers (e.g., a small lateral move) and extract information from the interaction. The information contributes to a better understanding of the situation, which helps the controller find the optimal strategy.