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Human-like motion planning model for driving in signalized intersections

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ABSTRACT

Highly automated and fully autonomous vehicles are much more likely to be accepted if they react in the same way as human drivers do, especially in a hybrid traffic situation, which allows autonomous vehicles and human-driven vehicles to share the same road. This paper proposes a human-like motion planning model to represent how human drivers assess environments and operate vehicles in signalized intersections. The developed model consists of a pedestrian intention detection model, gap detection model, and vehicle control model. These three submodels are individually responsible for situation assessment, decision making, and action, and also depend on each other in the process of motion planning. In addition, these submodels are constructed and learned on the basis of human drivers' data collected from real traffic environments. To verify the effectiveness of the proposed motion planning model, we compared the proposed model with actual human driver and pedestrian data. The experimental results showed that our proposed model and actual human driver behaviors are highly similar with respect to gap acceptance in intersections.

1. Introduction

Recent developments in advanced driver assistance systems and autonomous robots seem to suggest that cars will be able to drive without human intervention in the near future. Thus, autonomous vehicles will join human drivers on the road soon. Currently, research studies on autonomous vehicles focus on their safety aspects to reduce accidents. These studies have adopted various sensors, such as LIDAR, radar, and vision, to perceive the surrounding environment and avoid collision with other vehicles and pedestrians. There is another critical issue in a hybrid traffic situation. Humans, including pedestrians and drivers, should not be affected by autonomous vehicles. In other words, the behavior of an autonomous vehicle is supposed to be similar to that of a human-driven vehicle, to avoid confusing pedestrians and other drivers in decision making. The accident reports on Google's driverless car also suggested that robot cars might actually be too cautious and careful. Google is actually working to correct this cautiousness and make its cars drive more similarly to humans to reduce the number of accidents [1]. This paper proposes a human-like motion planning model that can control vehicles like humans do.

Vehicle motion models can be divided into three levels with an increasing degree of abstraction: physics-based motion models, maneuver-based motion models, and interaction-aware motion models [2]. The physics-based motion models explain the vehicle motion by velocity, acceleration, mass of the vehicle, road surface friction coefficient, and the laws of physics. This type of models can be used for predicting the evolution of the state of the vehicle [3,4], but is limited to short-term (less than 1 s) motion prediction [2]. The maneuver-based motion models represent vehicles as independent maneuvering entities and could provide long-term predictions of driver intentions. Campbell et al. and Amsalu et al. proposed to use the continuous vehicle dynamics to recognize the different driving maneuvers, including lane keeping, straightly passing intersections, and turning at intersections [5,6]. However, autonomous vehicles are expected to automatically decide the driving maneuvers on the basis of the awareness of the surrounding environment.

The interaction-aware motion models consider vehicles as maneuvering entities that interact with other road users and environment. Gindele et al. presented a dynamic Bayesian network (DBN) that can simultaneously estimate the behaviors of vehicles and anticipate their future trajectories. This estimation is achieved by recognizing the type of

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situation derived from the local situational context [7,8]. Platho et al. proposed to decompose the complex situations into smaller and more manageable parts to recognize and understand the driving situations [9]. Hulsen et al. suggested that driving behavior is greatly influenced by four aspects: traffic rules, assessment of allowed actions, expected behaviors, and impacts of traffic participants on each other [10,11]. They introduced an ontology to model traffic situations at complex intersections and enabled reasoning about traffic rules for involved vehicles. Obviously, the influence of contextual information, such as traffic rules, road structure, and actions of other road users, should be considered in the motion planning model.

To model and represent human-like motion planning, we need to understand how the contextual information affects a driver's action. The influence can be modeled and analyzed on the basis of data collected from real traffic environments. In particular, most research studies on autonomous vehicles focus on right- or left-turning vehicles at intersections and discuss how vehicles pass the intersections in the case of sharing the road with other road users. The driving maneuver, in which a turning vehicle passes the intersection, is called gap acceptance. The basic idea of gap acceptance is to estimate the time difference between two consecutive pedestrians and vehicles [12]. Ragland et al. analyzed the distribution of accepted and rejected gaps in the left turn across path/opposite direction scenarios and proposed to characterize gap acceptance by a logistic model [13]. Zohdy also proposed to determine the critical gaps using a logit function [14]. Schroeder et al. explored factors associated with driver-yielding behavior at unsignalized pedestrian crossings and developed predictive models by using logistic regression [15]. Rather than at common intersections, Salamati et al. aimed to identify the contributing factors affecting the likelihood of a driver yielding to pedestrians at two-lane roundabouts [16]. Alhajyaseen et al. [17] and Wolfermann et al. [18] explained the stochastic speed profiles and the stochastic path models of free-flowing left- and right-turning vehicles from the aspect of intersection layout. Moreover, Alhajyaseen et al. [19,20] analyzed the vehicle gap acceptance behaviors against pedestrians and further proposed an integrated model. The integrated model represented the variations in the maneuvers of left-turners (left-hand traffic) at signalized intersections, and the proposed model dynamically considered the vehicle reaction to intersection geometry and crossing pedestrians [21]. Those research studies focused on analyzing how contextual information affects the driver's behavior.

Recently, researchers applied motion models to control vehicles. Kye et al. presented intention-aware automated driving at unsignalized intersections. The intention-aware decision-making problem is modeled as a partially observable Markov decision process [22]. As for collision avoidance, Kohler et al. proposed to recognize the pedestrians standing at the curb and intending to cross the street despite an approaching car. The proposed active pedestrian protection system can perform an autonomous lane-keeping evasive maneuver in urban traffic scenarios to avoid braking [23]. Keller et al. and Braeuchle et al. proposed an active pedestrian safety system that combines sensing, situation analysis, decision making, and vehicle control. The proposed system can decide whether it will perform automatic braking or evasive steering and reliably execute this maneuver at relatively high vehicle speed [24]. Moreover, Pongsathorn and Akagi et al. proposed to reduce collisions at potentially hazardous areas by suggesting an appropriate speed, which is learned from actual driving data of expert drivers [25,26].

This paper focuses on the scenario at an intersection, one of the most challenging traffic scenarios, and proposes a human-like motion planning model for left-turning vehicles. Fig. 1 illustrates a traffic scenario wherein a vehicle turns and passes an intersection while there are pedestrians walking on or to the crosswalk. In this case, the driver will wait for an appropriate moment and then cross the intersection by iteratively assessing pedestrian situations, making decisions, and adjusting actions. The proposed model represents the whole driving process, as shown in Fig. 2. The proposed model consists of three submodels: pedestrian intention detection model, gap detection model, and vehicle control model. These three submodels are separately responsible for situation assessment, decision making, and action. They also depend on each other in the proposed motion planning model.

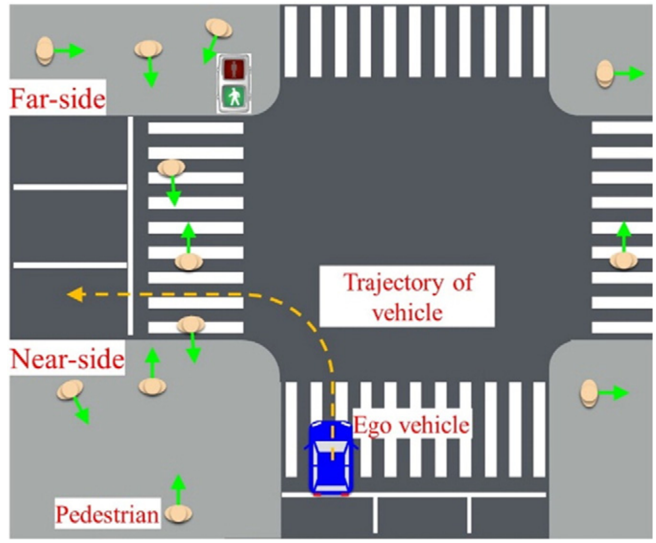

Fig. 1. A left-turning vehicle at an intersection with pedestrians.

In addition, the construction of the motion planning model was conducted on the basis of the analysis of actual human driver data. To obtain a credible model, we collected real data at an intersection in Tokyo City. In the verification of the effectiveness of the proposed idea, the model was implemented as a virtual driver, which allows for comparison with the behavior of human drivers. The contribution of this paper is the development of a human-like motion planning model by integrating a pedestrian intention detection model, gap detection model, and vehicle control model. This paper presents the proposed model and its performance in Sections 2 and 3, respectively. Finally, this paper will be concluded in Section 4.

2. Motion planning model

As shown in Fig. 2, the proposed motion planning model includes different submodels. This section explains the construction of each submodel and describes the relationships between the submodels as well. Before the explanations, we clarify the assumptions for the developed models.

a. The vehicle trajectory has been determined before the vehicle turns. It means that the proposed model controls the vehicle position along the longitudinal direction rather than changing the trajectory [27]. This assumption is consistent with the common actions of human drivers at intersections.
b. The road structure, traffic signal phase, and elapsed time of the phase are assumed to be known, which can be transmitted from a vehicle-to-infrastructure system [28].

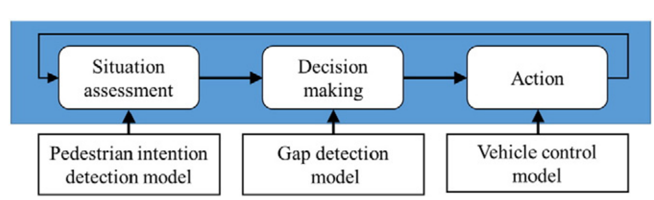

Fig. 2. Flowchart of the proposed motion planning model.