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Modeling discretionary cut-in risks using naturalistic driving data

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ABSTRACT

One of the operational issues that intelligent vehicles have to deal with is cut-into and by other vehicles. A vehicle cut-in risk model helps determine how an intelligent vehicle should react to the other vehicle's cut-in behavior. On the other hand, such a model could also help intelligent vehicles carry out cut-in maneuver in a considerate manner to minimize the impact on following vehicles in the target lane. In this study, a discretionary cut-in risk model for vehicles is developed on the basis of field driving data and machine learning methods, namely, decision trees and Support Vector Machine (SVM). A united algorithm is developed to combine the two machine learning models for achieving enhanced conservativeness to the traffic states with high misclassification costs. To build the naturalistic driving database, the wavelet method is employed for filtering; the K-means approach, an unsupervised data learning method, is used to categorize the cut-in impact on the following vehicles in the target lane into three groups. The impact is indicated by the following vehicle's average and maximum deceleration. Using this model, intelligent vehicles can assess the risk level during other vehicles' cut-in process as well as their own impact on the following vehicle in the target lane when carrying out cut-in maneuver.

1. Introduction

Intelligent vehicles have received extensive research interest because they show great potential for use in a more efficient, safer and cleaner transportation system (van Arem, 2012). Control over the lateral motion of intelligent vehicles, such as cut-in behavior is critical to the success of such a system. The primary goal of such control is to ensure safety not only of own vehicle but also of others nearby. Meanwhile, traffic efficiency and safety are influenced greatly by the cut-in behavior. For example, a cut-in maneuver that leaves only a small gap for the following vehicle may cause that vehicle to apply emergency brake. The consequences can become even worse when considering a group of vehicles where the cut-in might cause a traffic wave to propagate and be amplified, resulting in subsequent vehicles' instability. As a result, accidents and local con-

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gestion ensue (Wang, Li, Zheng, & Lu, 2015). Hence, intelligent vehicles should ensure traffic safety during car-following, cut-in, and other maneuvers.

Extensive research has been conducted on risk models for intelligent. Based on time-to-collision (TTC) or time headway (THW), a car-following model was proposed for adaptive cruise control (ACC) systems to ensure vehicle safety (Zhang, Li, & Wang, 2012). However, this model is limited because it considers only vehicles in the same lane. Therefore, in the cases shown in Fig. 1, in which a vehicle equipped with aforementioned ACC is cut in by another vehicle in the adjacent lane, such an ACC system might not be able to ensure safety and traffic accidents are likely to occur. (Hou, Edara, & Sun, 2014; Wang, You, Cui, & Yu, 2005). The trajectory planning model is based on absolute local trajectory planning, and intelligent vehicles only need to track the planned trajectory by calculating the minimum safety spacing (MSS) for ensuring safety (Wang et al., 2005). This model dealt well with lane-changing behaviors but failed to handle increasingly complex and dynamic conditions, especially those considering the randomness created by human participation in traffic and the nonlinear nature of the trajectory-planning model. In addition, MSS cannot reflect the level of safety, which is a significant factor of driving behavior.

Machine learning methods are effective for discovering rules and learning rules from database. Knowledge extracted from naturalistic driving data could provide safe and dynamic guidance for modeling intelligent vehicles' behaviors. In this study, a vehicle cut-in risk model is proposed that can reflect dynamic risk conditions in real time based on field driving data about cut-ins.

The objectives of this study are as follows: (1) investigate the impact of vehicles' cut-in maneuvers on micro traffic safety, (2) build a cut-in risk model for intelligent vehicles to capture the risk when other vehicles cut in and represent the impact of its own cut-in maneuver on the following vehicle in the target lane. In this study, it is assumed that the impact on the following vehicle in the target lane is influenced only by the cut-in vehicle. By using machine learning methods, namely, decision tree and SVM, a vehicle cut-in risk model is proposed by analyzing on-road data. In this study, the vehicle cut-in risk model refers only to the discretionary cut-in scenarios. Mandatory lane changes such as those entering from a ramp or exiting the mainline are not in the scope of this study.

The remainder of this paper is organized as follows: Section 2 introduces the related efforts pertaining to vehicle risk models. Section 3 provides an overview of building the naturalistic driving database, including field data acquisition, data filtering, data clustering, and input parameter introduction. The learning methodologies are described in Section 4. Section 5 analyzes the learning results, and Section 6 presents conclusive remarks.

2. Related work

Many research efforts have been expended on building risk models for actions of intelligent vehicles such as lane-change, in which safety is the priority (Lefèvre, Vasquez, & Laugier, 2014).

One such approach is based on vehicle dynamic models (Li, Gao, & Duan, 2010; Li, Lu, Wang, & Tian, 2014; Wang et al., 2005; Xu, Liu, Ou, & Song, 2012; Ziegler & Stiller, 2009). In lane-change models, MSS is used as an index of safe lane-changing by analyzing the kinematics of the vehicles (Wang et al., 2005). It is assumed that the velocity of the surrounding vehicle does not change. In ACC systems, a non-dimensional warning index and the inverse of time-to-collision are adopted to evaluate the safety conditions in a car-following environment (Moon & Yi, 2008). A safety-based approaching behavioral model for ACC was developed based on driving human factor analysis (Wang, Zhang, Guo, Bubb, & Ikeuchi, 2011). These models are limited to the car-following behavior and cannot be extended to complex and dynamic situations. Ward, Agamennoni, Worrall, Bender, and Nebot (2015) proposed a method for generalizing TTC calculations to uncontrolled vehicle motion. The concept of driving safety field was proposed and it makes use of field theory to represent risk factors owing to drivers, vehicles, road conditions, and other traffic factors (Wang, Wu, & Li, 2015). This concept could deal with the traffic risk in the complex driving environment by considering the driver-vehicle-road interactions (Wang, Wu, Zheng, Ni, & Li, 2016). Samiee et al. (2016) developed the performance evaluation algorithm for the novel emergency lane change based on the vehicle dynamics and environment conditions. In this study, the safe condition of the lane change maneuver included the lateral position of other vehicles on the road, the tire-road friction and so on. By using communication devices for more accurate information, the safety of the lane changing maneuver is based on the dynamic collision avoidance (Luo, Xiang, Cao, & Li, 2016).

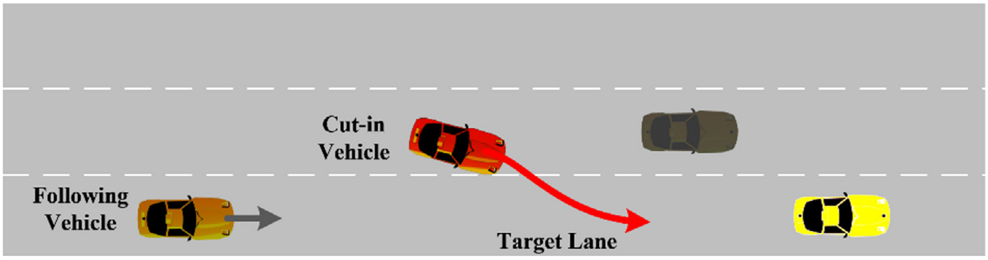

Fig. 1. Vehicle cut-in scenario.

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