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Driving safety field theory modeling and its application in pre-collision warning system

Jianqiang Wang [a,*], Jian Wu [a], Xunjia Zheng [a], Daiheng Ni [b], Keqiang Li [a,*]

[a] State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China
[b] University of Massachusetts, Amherst, MA 01003, United States

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ABSTRACT

The concept and contents of driving safety field theory were presented in our previous study. On this basis, this study focus on driving safety field theory modeling and application. First, a general model is presented, which considered the driver-vehicle-road interactions. The model include the following three parts: (i) driver behaviors, which are determined by driver characteristics, such as physical-psychological, cognition, driving skill, and traffic violations; (ii) vehicle characteristics, which are determined by velocity vectors and virtual masses of vehicles; (iii) road conditions, which are determined by virtual mass of on road non-moving objects, types of traffic signs, road adhesion coefficient, road slope, road curvature, and visibility. In order to establish concrete functional forms, the specific model is presented. This specific model provides a method for virtual mass calculation and describes the field strength and field force in detail. After that, a driving safety indicator namely DSI is defined. Finally, a vehicle collision warning algorithm based on driving safety field model is presented. This algorithm used a new index namely RDSI to evaluate the driving risk level. The effectiveness of this collision warning algorithm is verified by field experiments.

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1. Introduction

Advanced driver assistance systems (ADAS) have played an important role in improving driving safety. Since the 1990s, automotive companies have been proposing and applying several driving safety assistance algorithms to their driver safety assistance products. However, these algorithms were fairly simplistic. For longitudinal safety, in particular, the safety distance model is used to describe a vehicle's safety state. When the following distance between leading and following vehicles is less than the safety distance, the assistance system sounds an alarm and engages the brake on the following vehicle. Many safety distance models determine the vehicle's safety state by analyzing the safety distance between leading and following vehicles during relative movement (Abdel-Aty et al., 2006; Caliendo et al., 2007). Time to collision (TTC) (Kiefer et al., 2006) and time headway (THW) (Yiğiter et al., 2014) have been widely used as parameters for measuring the longitudinal driving risk. For lateral safety, driver safety assistance algorithms are based mainly on a car's current position (CCP) (Heddebaut et al., 2005), time-to-lane cross (TLC) (Mammar et al., 2006), and variable rumble strip (VRBS) (Pilutti and Ulsoy, 2003). The existing safety models are based mainly on vehicle kinematics and dynamics, and their descriptions of vehicle driving safety are generally based on information of the vehicle's state, such as position, velocity, acceleration, and yaw velocity, in

* Corresponding authors.
E-mail addresses: wjqlws@tsinghua.edu.cn (J. Wang), likq@tsinghua.edu.cn (K. Li).

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addition to information about the vehicle's relative movement, relative velocity, and relative distance. However, it is difficult for these models to reflect the effects of a greater number of traffic factors on driving safety, describe interactions among driver behavior characteristics, vehicle states, and road environment, or provide accurate judgment bases for vehicle control. On the basis of the risk homeostasis theory (RHT) and the stimulus-response concept, Lu et al. (2012, 2013) proposed a desired safety margin (DSM) model, which serves as a new way to explain car following. In addition, the drivability maps method was well applied in the researches of intelligent vehicle control (Neuhaus et al., 2009; Tawari et al., 2014; Schwarz and Behnke, 2014). In order to estimate the risk effects of distracted driving, Przybyla et al. (2015) incorporated a dynamic, data-driven car-following model in an algorithmic framework. Similarly, M. Wang et al. (2015) presented an approach to generate optimal lane change decisions in the predicted future, including strategic overtaking, cooperative merging and selection of a safe gap. On the other hand, artificial potential field theory have been widely used for motion planning and collision avoidance for automated vehicles and robots. The first application of artificial potential field for mobile robot obstacle avoidance was by Khatib (1986), he proposed the virtual obstacle concept to escape local minimums in local path planning based on artificial potential field approach. Over the following decade, artificial potential field theory was widely used in mobile robot path planning (Warren, 1990; Rimon and Koditschek, 1992; Kitamura et al., 1995; Veelaert and Bogaerts, 1999), in the meanwhile, intelligent transport system have been promoted rapidly (Van Der Laan et al., 1997; Bourhis et al., 2001; Cui and Ge, 2003; Li et al., 2004; Beard et al., 2005). Because the advantage of the artificial potential field, some researchers used it to study the autonomous vehicle control. Rossetter and Gerdes (2006) proposed a method by which an energy term consisting of the vehicle's kinetic energy and the artificial potential energy can be bounded, leading to a bound on lateral deviation; instead of, this method is only applicable to lane-keeping scenarios. In the last decade, the ITS technologies developed rapidly, and the applications of artificial potential field theory become more and more mature and widespread. Pengfei et al. (2011) improved the simulation accuracy of car-following model and describing the characteristics of car-following driving behavior by using artificial potential field theory. In order to reduce the risk of vehicle collision, some researchers put their focus on right-turning traffic collision scenarios (Dabbour and Easa, 2014) or general traffic scenarios (Ward et al., 2015). Moreover, artificial potential theory is beneficial for transportation research (Jacob and Abdulhai, 2010; Suzuki et al., 2010). In 2013, Raksincharoensak et al. (2013) proposed a braking assistance system algorithm for collision avoidance, designed based on pedestrian motion prediction and risk potential. Recently, Ni (2013) introduced a Field Theory with an emphasis on traffic flow modeling at the microscopic level. In this theory, highways and vehicles were perceived as a field by a driver whose driving strategy is to navigate through the field along its valley. Similarly, Jian et al. (2014) proposed a perceived potential field and an aggregated force field for navigation of pedestrians in a walking domain with poor visibility or complex geometries, but this research mainly focuses on the pedestrian. To better adapt safety algorithms to driver behavior, an algorithm that autonomously learns driver characteristics was proposed by researchers at Tsinghua University based on the recursive least-square method with a forgetting factor; this algorithm was used in an adaptive longitudinal driver assistance system (Wang et al., 2013). However, there are some drawbacks to the existing safety-assistance methods. Firstly, only a limited number of driving safety influence factors and their effects are considered. Secondly, most applications of these methods are limited to simple scenarios. Furthermore, these methods are difficult to adapt to increasingly complex traffic environments, particularly the vehicle kinematics- and dynamics-based methods.

Recently, a new research method for driving safety, called the driving safety field, was proposed (J. Wang et al., 2014, 2015). This method uses field theory to represent the driving risk due to various traffic factors, and it could be used to evaluate potential driving risk in real traffic scenarios. In this study, we formulated a general model of the driving safety field and proposed a novel vehicle collision warning algorithm based on the driving safety field. This algorithm overcomes some of the aforementioned drawbacks, and can be applied to multi-vehicle scenarios.

The rest of this paper is arranged as follows. In Section 2, the new concept and modified general model of the driving safety field is described briefly. In Section 3, a specific model of driving safety field is proposed. In Section 4, a vehicle collision warning algorithm is designed based on the specific driving safety field model. In Section 5, three experimental vehicles are introduced and field experiments are described. The vehicle collision warning algorithm is verified by applying it in a typical car-following scenario on a multi-lane road. Section 6 presents the discussions of this study. Section 7 presents the conclusions of this study.

2. General model of driving safety field

In this section, the driving safety field concept is introduced. Based on J. Wang et al. (2014, 2015), the driving safety field model comprises the potential, kinetic, and behavior fields, $\boldsymbol{E}_S$, $\boldsymbol{E}_R$, $\boldsymbol{E}_V$, and $\boldsymbol{E}_D$ denoting the field strength vectors of the driving safety field, potential field, kinetic field, and behavior field, respectively, the driving safety field model can be expressed as

$$\boldsymbol{E}_S = \boldsymbol{E}_R + \boldsymbol{E}_V + \boldsymbol{E}_D \tag{1}$$

The field strength vectors in (1) describe the potential driving risks due to traffic factors in actual scenarios. The risk is measured by the possibility of an accident and the severity of such an accident. For non-moving objects of the first category, according to the above analysis, the field strength vector $\boldsymbol{E}_{R1,aj}$ at (x_j, y_j) in the potential field formed by a non-moving object a at (x_a, y_a) on the road is

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