The Driving Safety Field Based on Driver–Vehicle–Road Interactions

Article *in* IEEE Transactions on Intelligent Transportation Systems · August 2015

DOI: 10.1109/TITS.2015.2401837

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The Driving Safety Field Based on Driver–Vehicle–Road Interactions

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***Abstract*—Vehicle driving safety is influenced by many factors, including drivers, vehicles, and road environments. The interactions among them are quite complex. Consequently, existing methods that evaluate driving safety perform inadequately because they only consider limited factors and their interactions. As such, it is difficult for kinematics-based and dynamics-based vehicle driving safety assistant systems to adapt to increasingly complex traffic environments. In this paper, we propose a new concept, i.e., *the driving safety field*. The concept makes use of field theory to represent risk factors owing to drivers, vehicles, road conditions, and other traffic factors. A unified model of the driving safety field is constructed, which includes the following three parts: 1) a potential field, which is determined by nonmoving objects on the roads, such as a stopped vehicle; 2) a kinetic field, which is determined by the moving objects on roads, such as vehicles and pedestrians; and 3) a behavior field, which is determined by the individual characteristics of drivers. Moreover, the applications of the model are proposed, and its application to a typical car-following scenario is illustrated, which evaluates the risks caused by multiple traffic factors. The driving safety field can reveal driver–vehicle–road interactions and their influences on driving safety, as well as predict driving safety trends owing to dynamic changes. In addition, the model can provide a new foundation for establishing driving safety measures and active vehicle control under complex traffic environments.**

***Index Terms*—Driver–vehicle–road interactions, driving safety field, risk evaluation, traffic factors, vehicle safety.**

I. Introduction

RESEARCH on driving safety assistance systems has a long history. Since the 1990s, automobile companies have proposed many driving safety assistance algorithms. For longitudinal safety, the safety distance model is mainly used. When the following distance is less than the safety distance, the assistance system will emit an alarm and automatically engage the brakes. Many safety distance models determine the vehicle's safety state by analyzing the safety distance based on the relative movement of leading and following vehicles in real time [1]–[3]. For lateral safety, driver safety assistance algorithms are mainly based on the car's current position (CCP) [4], time to lane cross (TLC) [5], and variable rumble strip (VRBS) [6]. The existing safety models are mostly based on vehicle kinematics and dynamics, and their descriptions of vehicle driving safety are generally based on information regarding the vehicle's state, such as position, velocity, acceleration, and yaw velocity, in addition to information regarding the vehicle's relative motion, including relative velocity and relative distance. However, these models suffer from a variety of potential difficulties: to reflect the effects of all types of traffic factors on driving safety; to describe the interactions among driver behavior characteristics, vehicle states, and road environments; or to provide an accurate basis of judgment for vehicle control.

Hence, several advanced safety algorithms have been studied that are based on artificial intelligence, risk homeostasis theory or other advanced modern mathematical methods and identification of the driver's intentions [7]–[14]. On the basis of risk homeostasis theory (RHT) theory and the stimulus-response concept, Lu *et al.* [12], [13] proposed a desired safety margin (DSM) model, which gives a new way to explain car-following process. To make safety algorithms better adapted to the driver's behaviors, a self-learning algorithm for driver characteristics was proposed by Tsinghua University based on the recursive least-square method with a forgetting factor, which was used in an adaptive longitudinal driver assistance system [14].

Recently, the concept of a field has been applied to a description of the risk that a driver faces, and, further, to the design of driver safety assistance systems. Sattel *et al.* [15] extended the concept of elastic bands used in robotics to the application of autonomous vehicle motion planning, and based the motion-planning algorithm on the potential field theory. Ni [16] proposed a field theory in traffic flow where lanes and vehicles form a potential field active within the minds of drivers, and that drivers always drove along low points of the potential field. Hsu [17] developed the novel gravitational car-following model based on the gravitational field concept. This model describes car-following behavior by a series of attractive and repulsive forces related to the vehicle and the space in front of it. Matsumi *et al.* [18] proposed an autonomous collision avoidance system based on the electric braking torque of an electric vehicle. In this system, the intensity of the braking maneuver is determined by the application of potential field theory, and considers potential hazards due to obstructions in an intersection. Raksincharoensak *et al.* [19] proposed a braking assistance system that considers the potential motion of pedestrians in non-signaled intersections. This system estimates driving risk by assuming that a virtual spring is attached between the vehicle and pedestrian. Zhao-Sheng Yang *et al.* [20] established a car following model based on the artificial potential field theory, where the host vehicle is treated like an individual charge in a potential field. In this way, the influences

Manuscript received October 29, 2014; revised December 30, 2014; accepted February 1, 2015. Date of publication February 26, 2015; date of current version July 31, 2015. This work was supported by the National Natural Science Foundation of China under Grant 51475254 and Grant 51175290. The Associate Editor for this paper was L. Li.

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Digital Object Identifier 10.1109/TITS.2015.2401837

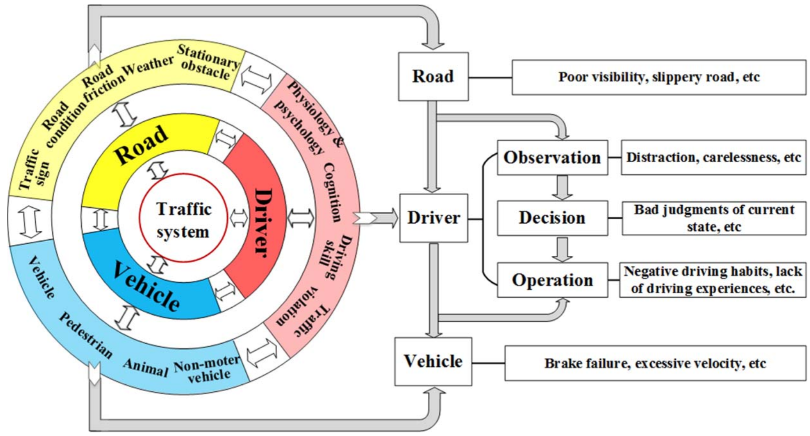

Fig. 1. Influencing factors of driving safety and traffic accidents.

of traffic factors on vehicles can be simplified as interactive attractive and repulsive forces between vehicles, which allow car following behaviors, with consideration for lateral distance, to be researched from a new perspective.

However, field theory is mainly applied to the motion planning of autonomous vehicles and driver behavior modeling in specific traffic scenarios, such as car-following. The main problems of existing models lies in their incomplete consideration of risk factors such as the personality and psychological and physiological characteristics of the driver, complex road conditions, and inadequate descriptions of driver-vehicle-road interactions. Hence practical applications of these models are limited.

In this paper, a new concept, called the driving safety field, is proposed. Based on field theory, the concept is able to represent driving risks caused by drivers, vehicles, roads, and other traffic factors. Hence, this new concept can provide a unique approach to the research of intelligent vehicle safety technology [21].

In Section II, the factors of driving safety and the mechanisms by which they influence safety are analyzed. Then, the new concept of the driving safety field is proposed in which the field strength vector denotes the influence of the traffic factors on driving safety. The resulting field force on a vehicle denotes the vehicle's current driving risk. In Section III, a unified model of the driving safety field is constructed, which includes the following three parts: i) a potential field, which is determined by nonmoving objects on roads, such as a stopped vehicle; ii) a kinetic field, which is determined by moving objects on roads, such as vehicles and pedestrians; and iii) a behavior field, which is determined by the driver's individual characteristics. In Section IV, the calibration methods of the driving safety field model are proposed. In Section V, applications of the model are proposed, and the usefulness of the unified model is verified by its application to a typical car-following scenario. Section VI provides a discussion and concludes the paper.

II. Concept of the Driving Safety Field

A. Analysis of the Influencing Factors of Driving Safety and Causes of Traffic Accidents

As Fig. 1 shows, the influencing factors of driving safety can be classified into three main categories: driver factors, road user factors, and road environment factors.

Driver factors, which are expressed as "Driver" in Fig. 1, mainly refer to a driver's physiological and psychological factors. The physiological factors include the driver's age, gender, driving skills, and driving experience. The psychological factors include the driver's personality characteristics, and mental state etc. The causes of accidents owing mainly to driver factors are summarized into four categories including: i) physiology and psychology, such as incorrect or partial observations of the exterior driving environment due to carelessness or distraction; ii) cognition, such as poor decision-making due to the inaccurate perception of the current state of his or her vehicle and driving environment; iii) driving skills, such as error operation due to poor driving skill, lack of experience, or negative driving habits; and iv) traffic violations, such as driving behavior that violates traffic laws.

Road user factors, which are expressed as "Vehicle" in Fig. 1, refer mainly to the factors involving motor vehicles, non-motor vehicles, pedestrians, and animals on roads. The influences of motor vehicles and non-motor vehicles are determined by position, type, performance, and moving states, whereas those of pedestrians and animals are determined by their positions and moving states. The main causes of accidents owing to road users are: i) vehicle performance, such as brake or steering failures; and ii) pedestrian violations, such as disregarding a red light or walking on the roadway.

Road environment factors, which are expressed as "Road" in Fig. 1, refer mainly to factors involving roads and environments. The road factors include the road adhesion coefficient, road slope, and nonmoving objects such as road barriers or stopped vehicles. The environment factors include visibility and weather conditions. The main causes of accidents owing to the road environment are: i) poor road conditions, such as the slippery roads, sharp slopes, or poor visibility; and ii) a lack of safety measures, such as the absence of warning signals at the intersections of railways and roads.

B. Analysis of the Similarities Between Driving Risk and the Concept of a Field

With the rapid development of science and technology, the existence of fields such as the electric field, the magnetic field, the gravitational field has been proved. Similarly, driving risk is an objective feature that does not vary with a person's subjective will. In addition, the driving risk is an objectively plausible feature that diffuses throughout all space because driving risk changes with dynamic changes in traffic factors, and the variability is similar to the temporal and spatial variabilities of a field. A field can be measured by some defined parameters that reflect the impact of the field. For example, an electrical field can be used to describe the force acting on a positive charge positioned within the field. Accidents occur by chance, but, from analyses of traffic accident data, we can determine potential internal relationships that present some obvious regularities among such factors as the causes of accidents, influencing factors, and accident losses. Then, the evaluation of these relationships can be beneficial to the prediction and prevention of driving risk.

C. The Concept of the Driving Safety Field

As previously discussed, driving risk has similar characteristics to those of a field. Hence, the driving safety field is proposed in this section.

The driving safety field is a physical field that denotes all of the influences of traffic factors on driving safety. Although it differs from gravitational and electromagnetic fields, the driving safety field has the fundamental features of a field such that it varies with time and space due to dynamic changes in traffic factors. Moreover, the driving safety field is also a vector field due to the directed influences of the traffic factors on moving vehicles.

The driving safety field is composed of three parts: i) a potential field, which is determined by nonmoving objects on roads, such as stopped vehicles; ii) a kinetic field, which is determined by moving objects on the road, such as vehicles and pedestrians; and iii) a behavior field, which is determined by the driver's individual characteristics. These three fields are defined by the following descriptions.

1) *The potential field* is a physical field that denotes the influences of nonmoving road objects on driving safety. The magnitude and direction of its field strength vector are determined by the nonmoving objects and road conditions.
2) *The kinetic field* is a physical field that denotes the influences of moving road objects on driving safety. The magnitude and direction of its field strength vector are determined by the attributes and states of the moving objects and road conditions.
3) *The behavior field* is a physical field that denotes the influences of driver behavior characteristics on driving safety. The magnitude and direction of its field strength vector are determined by behavior characteristics of drivers. For example, the field strength of the behavior field formed by an aggressive driver is often larger than that of the behavior field formed by a conservative driver because the risk caused by the former is often higher than that caused by the latter.

Just like the electromagnetic fields formed by like charges, the driving safety fields formed by different objects are mutually exclusive to each other. As we know, if the objects touched each other, the collision happens. Specially, the behavior field formed by a driver and the kinetic field formed by his (or her) driven vehicle should been seen as a whole.

III. Modeling of the Driving Safety Field

A. Construction of the Driving Safety Field Model

As previously mentioned, the driving safety field model is comprised of the potential field, kinetic field, and behavior field. That is, driving safety field = potential field + kinetic field + behavior field. With $\boldsymbol{E}_S$ denoting the field strength vector of the driving safety field, $\boldsymbol{E}_R$ denoting the field strength vector of the potential field, $\boldsymbol{E}_V$ denoting the field strength vector of the kinetic field, and $\boldsymbol{E}_D$ denoting the field strength vector of the behavior field, 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 caused by traffic factors in actual scenarios. The risk is measured by the possibility of an accident and the severity of such an accident.

B. Potential Field

1) Content of the Potential Field: As previously mentioned, the potential field is a physical field that denotes the influences of nonmoving road objects on driving safety. The magnitude and direction of its field strength vector are determined by nonmoving objects and road conditions.

The nonmoving objects here are classified into two categories: i) nonmoving objects that can be involved in actual collisions with vehicles that cause substantial losses, such as parked vehicles, roadblocks, and so on; and ii) nonmoving objects that cannot be involved in actual collisions but impose constraints on driver behavior, such as traffic signs, lane markers, and so on.

For the nonmoving objects of the first category, some characteristics are detailed in the following points.

- The present study employs the concept of a virtual mass rather than a general physical mass, which will be discussed subsequently. Just as when employing the physical mass, an increasing severity of a collision with a vehicle is associated with an increase in the virtual mass of the object.
- A shorter distance between a vehicle and an object indicates a greater possibility of collision and thus a higher driving risk. However, the risk does not increase linearly with decreasing distance. As the distance decreases, the rate of increasing risk becomes greater. Hence, in this paper, a power function form is assumed for the driving risk with respect to the distance of vehicle-object separation.
- It is also assumed that the power function form of increasing risk does not depend on the direction from which the vehicle approaches the nonmoving object.

For the nonmoving objects of the second category, infringement of these constraints represents a violation rather than a collision, and the risk associated with this violation is determined by the traffic laws and regulations. For example, it is stipulated by the traffic laws and regulations that vehicles must not drive on or cross over solid lane lines. If, however, the driver unconsciously departs from the current lane, he or she would perceive the risk of violating the lane marker constraint, which causes the driver to drive the vehicle toward the center of the lane. Moreover, the closer the vehicle is to the lane marker, the larger the risk.

Driving risk is also associated with road conditions, wherein poor road conditions relate to high risk. Moreover, driving risk caused by nonmoving objects on a road is mainly influenced by visibility, where lower visibility translates to higher driving risk.

2) Potential Field Model: For the nonmoving objects of the first category, according to the above analysis, the field strength vector $\boldsymbol{E}_{R\_aj\_o}$ at (x_j, y_j) of the potential field formed by nonmoving object a at (x_a, y_a) on the road is

$$\boldsymbol{E}_{R\_aj\_o} = \frac{G \cdot R_a \cdot M_a}{|\boldsymbol{r}_{aj}|^{k_1}} \cdot \frac{\boldsymbol{r}_{aj}}{|\boldsymbol{r}_{aj}|} \tag{2}$$

where the x-axis lies along the road line, the y-axis is perpendicular to the road line, and the coordinates of the center of mass of object a is (x_a, y_a). In addition, $\boldsymbol{r}_{aj} = (x_j - x_a, y_j - y_a)$ is the distance vector, k_1 and G are undetermined constants greater than zero, M_i is the virtual mass of object i, and R_i is the influencing factor of the road conditions at (x_a, y_a). The terms M_i and R_i will be discussed subsequently. The vector $\boldsymbol{E}_{R\_aj\_o}$ denotes the potential risk of surroundings caused by the nonmoving object denoted by i under the prevailing road conditions. A larger magnitude of $\boldsymbol{E}_{R\_aj\_o}$ indicates higher risk. The direction of $\boldsymbol{E}_{R\_aj\_o}$ is the same as that of $\boldsymbol{r}_{aj}$, which is also the gradient descent direction of the field strength.

Sketches of the potential field strength are shown in Fig. 2. The center of the potential field is the object's center of mass. The field strength at that point is infinite, and any object reaching this position indicates that a collision must have occurred. As the distance to an object increases, the field strength decreases, indicating that the potential risk decreases with increasing distance. Moreover, as the distance increases to a certain degree, the object poses no safety threat and the risk can be ignored.

For nonmoving objects of the second category, the lane marker model has been employed. As Fig. 3 shows, the field strength vector $\boldsymbol{E}_{R\_aj\_L}$ at (x_a, y_a) of the potential field owing to lane marker a is

$$\boldsymbol{E}_{R\_aj\_L} = LT_a \cdot R_a \cdot \left(\frac{D}{2} - |\boldsymbol{r}_{aj}|\right)^{k_2} \cdot \frac{\boldsymbol{r}_{aj}}{|\boldsymbol{r}_{aj}|} \tag{3}$$

where LT_a is the type of lane marker, which is determined by the traffic laws and regulations, for example, the value of lane marker 1 (white solid line) is larger than that of lane marker 2 (white dotted line), R_a is the road condition influencing factor at (x_a, y_a), D is the width of the lane, $\boldsymbol{r}_{aj} = (x_j - x_a, y_j - y_a)$ is the distance vector between lane marker a and the center of mass of the vehicle (which is shown as a white rectangle in Fig. 3, indicating that the magnitude of $\boldsymbol{r}_{aj}$ changes from 0 to $D/2$), and k_2 is an undetermined constant greater than zero. The direction of the vector $\boldsymbol{E}_{R\_aj\_L}$ is the same as that of $\boldsymbol{r}_{aj}$, which is also the gradient descent direction of the field strength.

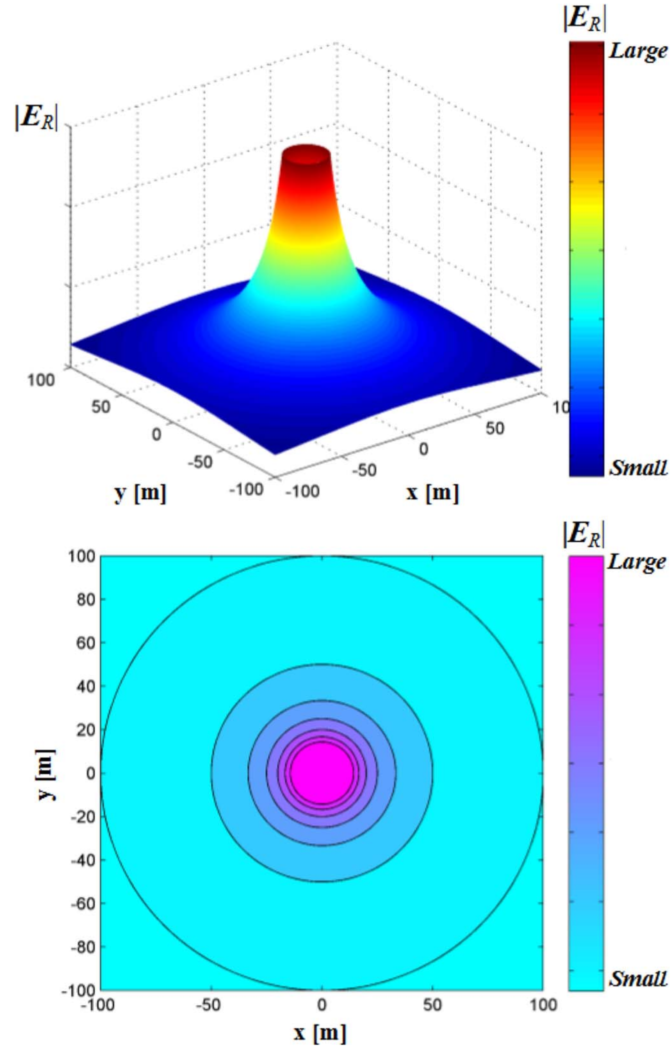

Fig. 2. Sketches of the potential field strength given by (2).

Moreover, several nonmoving objects and the field strength of their corresponding potential field is shown in Fig. 4. From the figure, we can easily determine the distribution of the driving risk.

3) Virtual Mass: Whether it is moving or nonmoving, an object on a road represents a potential risk to driving vehicles.

This risk is associated with the attributes of the object, such as its mass, type, moving state, and, in particular, speed. All of the factors can be expressed as virtual mass. The virtual mass M_i of object i is defined as

$$M_i = M_i(m_i, T_i, v_i) = T_i \cdot m_i \cdot \left(1 + \sum_k \alpha_k \cdot v_i^{\beta_k}\right) \tag{4}$$

where m_i is the actual physical mass, T_i is the type, and v_i is the velocity of object i, and α_k and β_k are undetermined constants. Moreover, object i can be either nonmoving or moving.

M_i is used to measure the potential driving risk caused by the attributes of object i. Here the potential driving risk mainly refers to potential losses caused by a collision between object i and a vehicle. With other conditions being constant, as M_i increases, the potential loss increases. For objects of the same

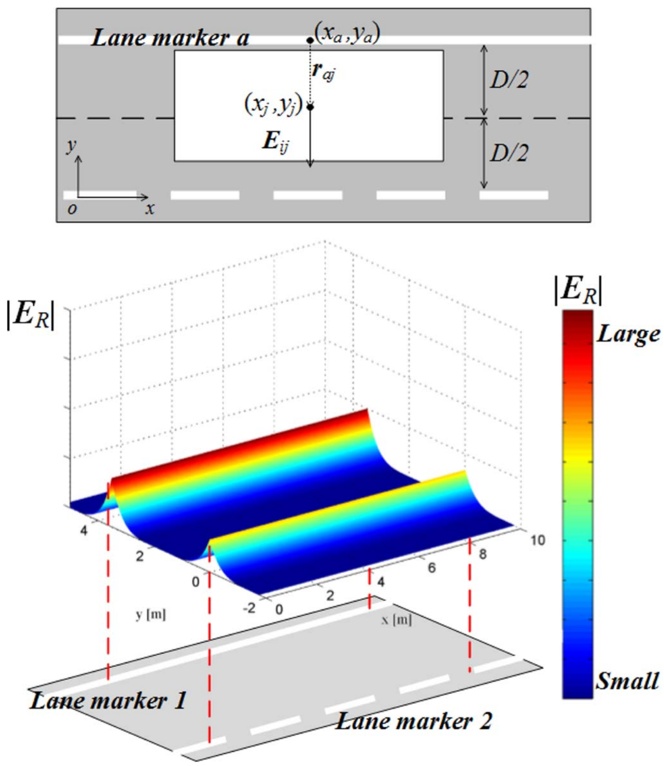

Fig. 3. Diagrams of the lane marker model and its potential field strength given by (3).

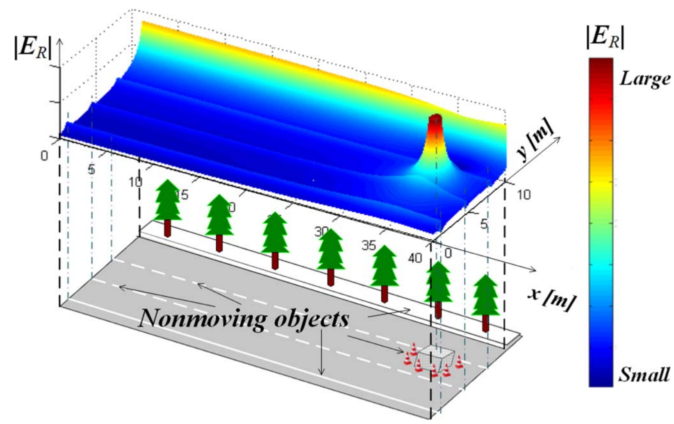

Fig. 4. Nonmoving objects and the field strength of their corresponding potential field.

type, a greater physical mass and speed of the object reflect a larger virtual mass and higher potential losses. Moreover, with the same physical mass and speed, potential losses caused by a collision depend on the object type. For example, the losses caused by a collision between a pedestrian and a vehicle are larger than those caused by a collision between an animal and a vehicle.

In its 2004 report entitled "World report on road traffic injury prevention," the World Health Organization (WHO) proposed that, in developing countries, the number of traffic accidents and associated injuries and deaths are respectively related to the second, third, and fourth power of the average road speed. Hence, in this paper, the polynomial of speed $1 + \sum_k \alpha_k \cdot v_i^{\beta_k}$ on the right-hand side of (4) is used to denote the influence of speed on the virtual mass.

4) Road Condition Influencing Factor: As previously mentioned, driving risk is associated with road conditions because poor road conditions are related to higher risk. Such road conditions include the road adhesion coefficient, road slope, road curvature, and visibility. All of these factors can be expressed as a road condition influencing factor. The road condition influencing factor R_i at (x_i, y_i) is defined as

$$\begin{aligned} R_i &= R_i(\delta_i, \mu_i, \rho_i, \tau_i) \\ &= \left(\frac{\delta_i}{\delta^*}\right)^{\gamma_1} \cdot \left(\frac{\mu_i}{\mu^*}\right)^{\gamma_2} \cdot \exp\left[(\rho_i - \rho^*)^{\gamma_3} + (\tau_i - \tau^*)^{\gamma_4}\right] \end{aligned} \quad (5)$$

where δ_i is the visibility, μ_i is the road adhesion coefficient, ρ_i is the curvature of the road, and τ_i is the slope of the road at the position of object i. In addition, γ_1 through γ_4 are undetermined constants $(\gamma_1, \gamma_2 < 0, \gamma_3, \gamma_4 > 0)$, δ^* is the standard value of visibility, μ^* is the standard value of the road adhesion coefficient, ρ^* is the standard value of curvature, and τ^* is the standard value of slope. Specifically, if object i is a nonmoving object, $R_i = (\delta_i/\delta^*)^{\gamma_1}$.

R_i is used to indicate the potential driving risk caused by road conditions at (x_i, y_i). Here, the potential driving risk refers mainly to both the possibility and severity of a collision between object i and a vehicle. For a moving object, R_i is determined by the visibility δ_i, road adhesion coefficient μ_i, curvature ρ_i, and slope τ_i at (x_i, y_i). Other factors are temporary and are not discussed in this paper. A decrease in δ_i and μ_i or an increase in ρ_i and τ_i results in an increasing possibility and severity of a collision between object i and a vehicle at (x_i, y_i). In other words, as the risk increases, R_i increases. For a nonmoving object, R_i is mainly determined by visibility δ_i, and, as δ_i decreases, R_i increases.

C. Kinetic Field

1) Content of the Kinetic Field: As previously mentioned, the kinetic field is a physical field that denotes the influences of moving objects on driving safety. The magnitude and direction of its field strength vector are determined by the attributes and states of the moving objects and road conditions.

The moving objects here refer to moving objects that can actually collide with vehicles to cause significant losses. For such a moving object, some characteristics are detailed in the following points.

- The severity of a collision with a vehicle is associated with the virtual mass of the object. Greater virtual mass relates to the potential for a more severe collision.
- A shorter distance between a vehicle and the object relates to a greater possibility of collision, and, thus, a higher driving risk. However, the risk does not increase linearly with decreasing distance. As the distance decreases, the rate of increasing risk becomes greater. Hence, in this paper, a power function form is assumed for the driving risk as a function of the vehicle-object distance.

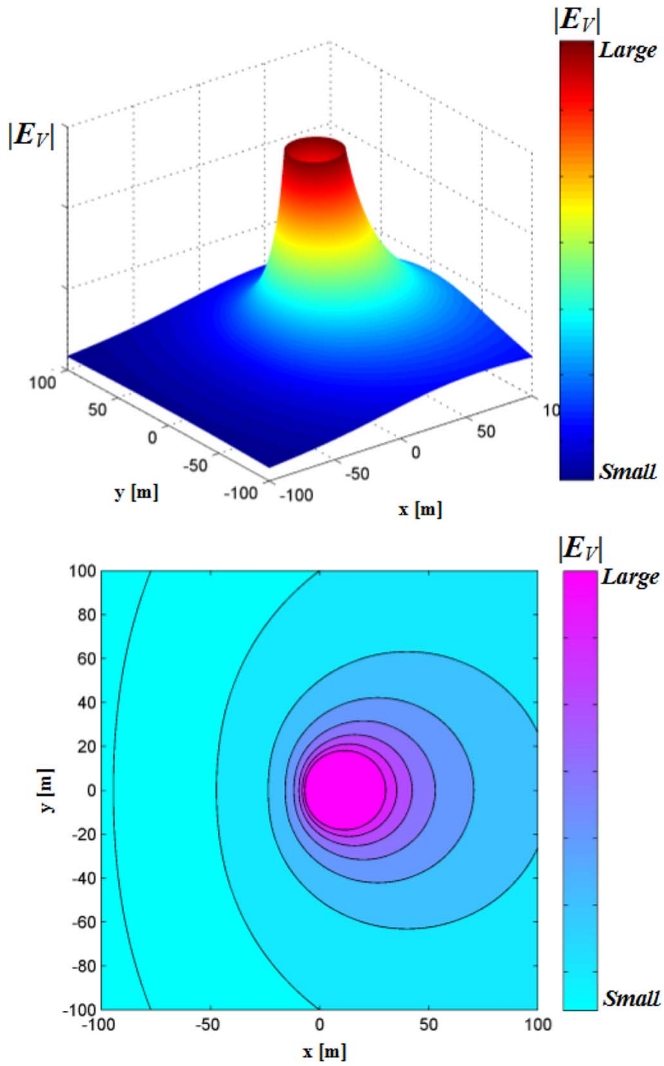

Fig. 5. Sketches of the kinetic field strength. The object is moving along the positive x-axis.

- The power function form of the driving risk changes in accordance with the direction from which the vehicle approaches and the velocity of the object. At the same distance, the driving risk is highest when the vehicle approaches from the front of the moving object, and is lowest when the vehicle approaches from the rear of the moving object.

2) Kinetic Field Model: According to the above analysis, the field strength vector $\boldsymbol{E}_{V\_bj}$ at (x_j, y_j) of the kinetic field formed by a moving object b at (x_b, y_b) on the road is

$$\boldsymbol{E}_{V\_bj} = \frac{G \cdot R_b \cdot M_b}{|\boldsymbol{r}_{bj}|^{k_1}} \cdot \frac{\boldsymbol{r}_{bj}}{|\boldsymbol{r}_{bj}|} \cdot \exp(k_3 v_b \cos\theta_b) \qquad (6)$$

where k_3 is an undetermined constant greater than zero, v_b is the velocity of object b, and θ_b is the angle between the direction of v_b and $\boldsymbol{r}_{bj}$ (clockwise is positive). The vector $\boldsymbol{E}_{V\_bj}$ denotes the potential risk to the surroundings caused by a moving object b under the prevailing road conditions. A larger magnitude of $\boldsymbol{E}_{V\_bj}$ relates to higher risk. The direction of $\boldsymbol{E}_{V\_bj}$ is the same

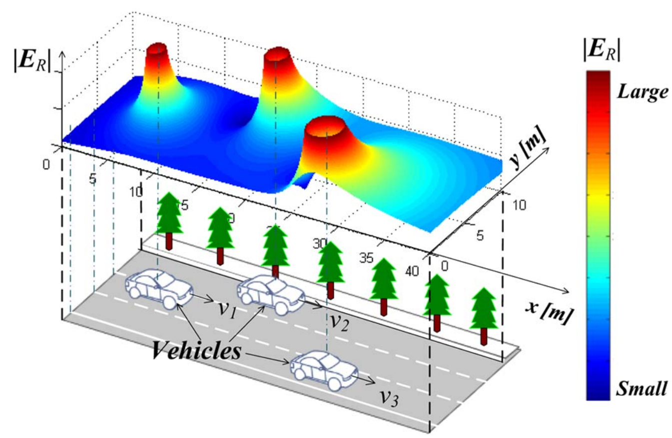

Fig. 6. Moving objects and the field strength of their corresponding kinetic field.

as that of $\boldsymbol{r}_{bj}$, which is also the gradient descent direction of the field strength. The kinetic field strength in (5) is shown in Fig. 5. The center of the kinetic field is the object's center of mass. Contrary to the behavior of the potential field formed by a nonmoving object, at an equivalent distance, the field strength increases the closer the direction of motion of the object (v_b) coincides with the direction of $\boldsymbol{r}_{bj}$. In addition, several moving objects and the field strength of their corresponding kinetic field is shown in Fig. 6.

D. Behavior Field

1) Content and Model of the Behavior Field: As previously mentioned, the behavior field is a physical field that denotes the influences of the characteristics of driver behavior on driving safety. The magnitude and direction of its field strength vector are determined by the behavior characteristics of drivers. For example, the field strength of the behavior field formed by an aggressive driver is often larger than that of the behavior field formed by a conservative driver because the risk caused by the former is often higher than that caused by the latter.

In fact, the influences of drivers on driving safety are transferred from the vehicles they drive to the surroundings. Hence, in the model, the field strength of the behavior field formed by the driver can be denoted as the product of a driver risk factor and the field strength of the kinetic field formed by the vehicle driven by the driver. The driver risk factor is used to denote the influences of the characteristics of driver behavior, and will be discussed subsequently.

According to the above analysis, the field strength vector $\boldsymbol{E}_{D\_cj}$ at (x_j, y_j) of the behavior field formed by the driver of vehicle c (not the controlling vehicle) at (x_c, y_c) is

$$\boldsymbol{E}_{D\_cj} = \boldsymbol{E}_{V\_cj} \cdot DR_c \qquad (7)$$

where DR_c is the driver risk factor associated with the driver of vehicle c, and $\boldsymbol{E}_{V\_cj}$ is the field strength vector of the kinetic field formed by vehicle c. The vector $\boldsymbol{E}_{D\_cj}$ expresses the potential risk to the surroundings caused by the driver of vehicle c under the prevailing road conditions. A larger $\boldsymbol{E}_{D\_cj}$ value

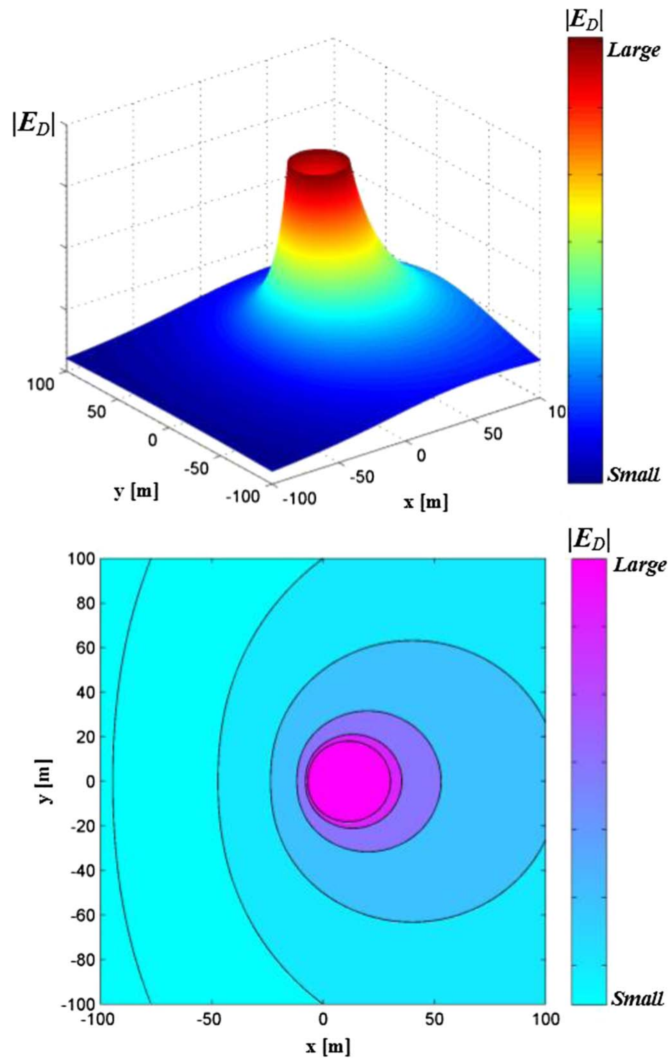

Fig. 7. Sketches of the behavior field strength formed by the driver of vehicle c, which is moving along the positive x-axis.

reflects a higher risk. The direction of $\boldsymbol{E}_{D\_cj}$ is the same as that of $\boldsymbol{E}_{V\_cj}$, which is also the gradient descent direction of the field strength. The behavior field formed by the driver of vehicle c is shown in Fig. 7, which is similar to the kinetic field formed by vehicle c.

2) Driver Risk Factor: As previously mentioned, the driver is the primary cause of traffic accidents. The main reasons for accidents caused by drivers are summarized into four categories including physiology and psychology, cognition, driving skill, and traffic violations.

The driver risk factor DR_c is a dimensionless value between 0 and 1 that is determined according to the driver's performance regarding the above four aspects. A larger DR_c value reflects a higher driving risk owing to the driver.

E. Driving Safety Field

1) Field Force on the Vehicle: A vehicle in the driving safety field, which includes the three aforementioned fields, experiences a field force, which denotes the current driving risk on the vehicle. This risk is measured according to the potential for an accident and its severity. The field force on the vehicle is determined by the field strength vector, the prevailing road conditions at the vehicle's location, the vehicle's attributes, the vehicle's moving state, and the driver's behavior characteristics. Details of these parameters are summarized in the following.

- *Field strength vector*: The direction of the force on the vehicle is the same as that of the field strength. In particular, the force on the vehicle is a repulsive force, which prevents the vehicle from approaching other objects including nonmoving objects, moving objects, and drivers. Moreover, with other conditions being constant, a greater field strength indicates a higher driving risk and thus a larger field force on the vehicle.
- *Road conditions at the vehicle's location*: With other conditions being constant, deteriorating road conditions relate to a greater possibility of a collision and thus a larger field force on the vehicle.
- *Vehicle attributes*: As previously mentioned, the virtual mass is determined by the vehicle's attributes. With other conditions being constant, a larger virtual mass relates to a greater possibility of an increasingly severe collision and thus a larger field force.
- *Vehicle moving state*: The possibility of collision is associated with the velocity vector of the vehicle. For a given magnitude of the vehicle's velocity vector, the extent to which the direction of the vehicle's velocity matches the direction of the field strength vector (in which the field strength decreases most quickly), the smaller the possibility of collision, and, accordingly, the smaller the field force. Moreover, when the vehicle is moving toward the direction in which the field strength increases, the possibility of a collision increases with an increase in the vehicle's velocity, and, accordingly, the field force increases. On the other hand, when the vehicle is moving toward the direction in which the field strength decreases, the possibility of a collision decreases with an increase in the vehicle's velocity; thus, the field force decreases.
- *Driver's behavior characteristics*: The driver's behavior characteristics can influence the current driving risk to the vehicle. For example, with other conditions being constant, a vehicle driven by a skilled driver may have a lower risk than that driven by an unskilled driver.

According to the above analysis, the field force F_j on vehicle j at (x_j, y_j) is

$$\boldsymbol{F}_j = \boldsymbol{E}_j M_j \left[R_j \cdot \exp(-k_3 v_j \cos\theta_j) \cdot (1 + DR_j)\right] \tag{8}$$

where $\boldsymbol{E}_j$ is the field strength vector of the driving safety field at (x_j, y_j), M_j is the virtual mass of vehicle j, R_j is the road condition influencing factor at (x_i, y_i), v_j is the velocity of vehicle j, θ_j is the angle between the direction of vectors v_j and $\boldsymbol{E}_j$ (clockwise is positive), and DR_j is the driver risk factor of vehicle j's driver. The vector $\boldsymbol{F}_j$ denotes the current driving risk on vehicle j. A larger $\boldsymbol{F}_j$ value relates to a higher risk. The direction of $\boldsymbol{F}_j$ is the same as that of $\boldsymbol{E}_j$.

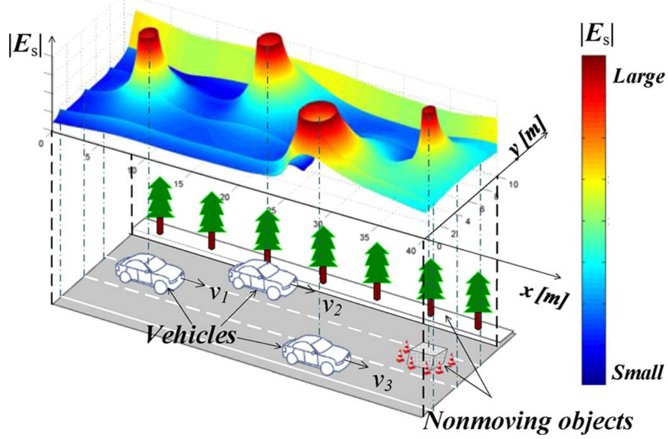

Fig. 8. Complex traffic scenario, and the field strength of the corresponding driving safety field.

2) Unified Model of the Driving Safety Field: In summary, the unified model of the driving safety field is

$$\begin{cases} \boldsymbol{E}_{S\_j} = \boldsymbol{E}_{R\_j} + \boldsymbol{E}_{V\_j} + \boldsymbol{E}_{D\_j} \\ \qquad = \sum\limits_{a} \boldsymbol{E}_{R\_aj} + \sum\limits_{b} \boldsymbol{E}_{V\_bj} + \sum\limits_{c} \boldsymbol{E}_{D\_cj} \\ \boldsymbol{F}_j = \boldsymbol{E}_{S\_j} M_j \left[R_j \cdot \exp(-k_3 v_j \cos\theta_j) \cdot (1 + DR_j) \right] \end{cases} \tag{9}$$

where $\boldsymbol{E}_{S\_j}$ is the total field strength vector of the driving safety field at the location of vehicle j; $\boldsymbol{E}_{R\_j}$, $\boldsymbol{E}_{V\_j}$, and $\boldsymbol{E}_{D\_j}$ are respectively the total field strength vectors of the potential field, kinetic field, and behavior field at the location of vehicle j; $\boldsymbol{E}_{R\_aj}$, $\boldsymbol{E}_{V\_bj}$, and $\boldsymbol{E}_{D\_cj}$ are respectively the field strength vectors of the individual potential field, kinetic field, and behavior field at the location of vehicle j.

The total field strength vector of the driving safety field is the sum of the field strength vectors of the potential field, kinetic field, and behavior field. The driving risk on vehicle j is denoted by $\boldsymbol{F}_j$, which can be calculated according to the second formula in (9).

A complex traffic scenario and the field strength of the corresponding driving safety field are shown in Fig. 8. In this scenario, there are three vehicles, each moving along a lane. Moreover, three types of nonmoving objects are shown. The first object is surrounded by traffic cones in the middle lane, the second is a green belt of trees beside the road, and the last is the three lane markers. The driving safety field of the scenario consists of the potential field, which is formed by the nonmoving objects; the kinetic field, which is formed by the three moving vehicles; and the behavior field, which is formed by the drivers of the vehicles. The influences of the traffic factors on driving safety in this scenario can be evaluated intuitively by the distribution of the field strength.

IV. Model Calibration

Numerous parameters have been defined in the driving safety field model, and their values have a substantial influence on the evaluation of driving risk. Hence, the calibration methods are discussed in this section.

A. Virtual Mass

As previously mentioned, the virtual mass is used to measure the potential driving risk according to the attributes of the object, where the potential driving risk refers mainly to potential losses caused by a collision between the object and a vehicle. Hence, the calibration can be implemented according to the analysis of real traffic accident data. According to the definition of virtual mass in (4), the parameters are α_k, β_k (undetermined constants), and T_i (type of object).

1) T_i: First, we choose a certain type of object as a standard, and set the T value of this type of object as 1. Then, for other types of objects, the T values are given as the ratio of the average losses of this type of object and the average losses of the standard object type, when involved in traffic accidents.

However, classification can at times be very difficult. In the case of a pedestrian, for example, the age is a very important element that influences accident severity because, compared with older people, young people tend to suffer less injury in an equivalent accident. However, it is difficult to distinguish age in a field application. Further research is necessary in this aspect of classification.

In addition, an appropriate method for the calculation of accident losses (or accident severity) is another issue that requires clarification. Both personal and property losses should be taken into consideration. Hence, further research is necessary to obtain a proper evaluation method for losses due to traffic accidents.

2) α_k and β_k : These constants can be determined by fitting the accident losses as a function of the velocity according to a polynomial of a suitable order when an accident occurs. And according to the 2004 report of WHO which has been referred before, a four order is suggested.

B. Road Condition Influencing Factor

As previously mentioned, the road condition influencing factor is used to measure the potential driving risk caused by road conditions, where the potential driving risk refers to both the possibility and the severity of a collision between the object and a vehicle. Hence, similarly as was done for the calibration of virtual mass, the calibration of the road condition influencing factor can be implemented according to the analysis of real traffic accident data. According to the definition of the road condition influencing factor in (5), the parameters are $\gamma_1 \sim \gamma_4$ (undetermined constants), δ^*, μ^*, ρ^*, and τ^* (standard values of visibility, road adhesion coefficient, curvature, and slope, respectively).

1) δ^*, μ^*, ρ^*, and τ^*: The standard values can be selected according to real traffic accident data. Taking μ^* as an example, a distribution of the number of traffic accidents versus the road adhesion coefficient should be accumulated first. Then, the road adhesion coefficient value that results in the largest number of traffic accidents should be chosen as μ^*. Moreover, in this way, the statistical error caused by the sample size can be reduced.

2) $\gamma_1 \sim \gamma_4$: It is established that the road condition influencing factor is proportional to the expected accident losses, which is the product of the traffic accident rate and the average accident losses under certain road conditions. Hence, these four constants can be determined according to this data. Taking γ_2 as an example, according to the data, we obtain

$$\left(\frac{\mu_i}{\mu^*}\right)^{\gamma_2} = \frac{(loss_{avg} \cdot p)|_{\mu=\mu_i}}{(loss_{avg} \cdot p)|_{\mu=\mu^*}} \tag{10}$$

where $loss_{avg}$ is the average losses caused by traffic accidents, and p is the accident rate (which is calculated according to the number of traffic accidents, the number of passed vehicles at a standard period of time, and road length).

Manipulation of (10) yields (11), from which we can obtain γ_2 as

$$\gamma_2 = \ln\left[\frac{(loss_{avg} \cdot p)|_{\mu=\mu_i}}{(loss_{avg} \cdot p)|_{\mu=\mu^*}}\right] \Big/ \ln\left(\frac{\mu_i}{\mu^*}\right) \tag{11}$$

However, this is merely a simplified representation of the calculation of γ_2. In actuality, γ_2 is the result of fitting to more than two values of μ. Moreover, $(\mu_i/\mu^*)^{\gamma_2}$ is just an assumed form to measure the influences of the road adhesion coefficient. If necessary, a more suitable form can be proposed after an analysis of real traffic accident data.

C. Driver Risk Factor

As is known, the driver is the main factor that causes traffic accidents. In this paper, the main reasons for accidents caused by drivers are summarized into four categories including physiology and psychology, cognition, driving skill, and traffic violations. The driver risk factor DR_c is a dimensionless value between 0 and 1 that is determined according to the driver's performance regarding the above four aspects. Hence, we can define four indexes to evaluate the four aspects, respectively, and then obtain the driver risk factor as a hybrid result of them, just as (11) shows

$$DR_c = \eta_1 \cdot DR_{c\_phy\&psy} + \eta_2 \cdot DR_{c\_cognition} + \eta_3 \cdot DR_{c\_skill} + \eta_4 \cdot DR_{c\_violation} \tag{12}$$

where $DR_{c\_phy\&psy}$ is the risk factor associated with the driver's physiology and psychology, $DR_{c\_cognition}$ is the risk factor associated with the driver's cognition, DR_{c_skill} is the risk factor associated with the driver's driving skills, $DR_{c\_violation}$ is the risk factor associated with the driver violation of traffic laws, and $\eta_i (i = 1, 2, 3, 4)$ is the weight coefficient. In addition, these new risk factors are dimensionless values between 0 and 1. Fundamentally, the calibration of these factors can be accomplished by establishing the rules of association between traffic accidents and the aspects the factors refer to. However, the research remains ongoing.

D. k_1, k_2, k_3, and G

These four parameters are very important for the evaluation of driving risk, and are used to establish the driving risk as a function of the distance and velocity.

To evaluate the risk in an objective way, the physiological indexes of drivers are used. Experiments could be implemented using a driving simulator that monitors driver performance in simple scenarios.

To obtain k_1, k_3, and G, we could ask the monitored drivers to drive in a scenario with another controlled vehicle, and then test and record drivers' physiological indexes (heartbeats, pulse, brainwaves, etc.) as a function of the distance and relative velocity between vehicles. Afterwards, from the analysis of the indexes, an appropriate index (a single index or a hybrid index) could be selected to initially denote the driving risk perceived by the driver. This can be used to verify the feasibility and usefulness of the driving safety field concept. Finally, the proper index could be fit as the function of the distance and velocity proposed in (2) and (6) to obtain the values of k_1, k_3, and G.

To obtain k_2, we could ask the monitored drivers to maintain different lanes while driving, and test and record the drivers' physiological indexes as a function of the distance between the vehicle and lane markers. Finally, the appropriate index could be fit as the function proposed in (3) to obtain the value of k_2.

The sample size of the drivers tested should be sufficiently large to reduce the influences of the subjective characteristics of drivers. Last but not least, the power function form of distance and the exponential function form of velocity are also assumed forms that could be adjusted according to fitting results.

V. Model Application

In this section, the model applications are introduced. Afterwards, the application in a typical car-following scenario is illustrated.

A. Applications

Based on the driving safety field model, there are five categories of applications as follows:

1) The calculation of the distribution of the driving safety field strength vector in a single traffic area at any time. According to the model, the field strength vector represents the potential driving risk caused by the traffic factors in the area. Moreover, with the development of vehicular information perception technologies and communication technologies, the traffic information, such as the states of vehicles, road conditions, the physiological data of drivers, and so on, can be obtained and shared in real-time. By applying this information to the driving safety field model, the distribution of driving risk can be made available, as Fig. 8 shows.
2) The calculation of the driving risk at the position of any object caused by other traffic factors. As shown in (9), field forces from the other traffic factors act at the point of any object in the driving safety field. The resultant force denotes the driving risk to which the object is subjected. For vehicles, the safety field model can evaluate the potential driving risk in real time, which can serve as a foundation for the safety decisions of driving-assistance systems.
3) The prediction of driving risk according to the trends associated with the dynamic changes of moving vehicles.

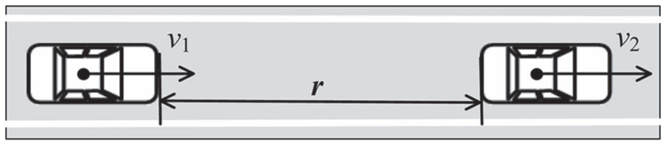

Fig. 9. Typical car following scenario.

Using the global information of vehicles and roads provided by sensor and communication technologies, in addition to evaluating the current driving risk of vehicles, the driving risk at a future time can be predicted according to the motion trends of all surrounding moving objects. Moreover, with the progress of communication technologies, the accuracy of evaluation and prediction of driving risk would be improved.

4) Dynamic drivable area planning or path planning based on the minimization of driving risk. Based on the distribution of the field strength of the driving safety field, which denotes the distribution of driving risk, a vehicle can plan its path according to low risk areas. As shown in Fig. 8, based upon the blue area, vehicle 1 can either follow the leading vehicle or overtake it with equal safety. Moreover, path planning based on the driving safety field model is useful for autonomous vehicles.
5) Vehicle driving safety decisions and active safety control in complex scenarios. Because the driving safety field model can evaluate the magnitude and direction of the driving risk for vehicles, the model can be employed to assist vehicles to determine the safest possible behavior.

B. A Model Application Example

A typical car following scenario is shown in Fig. 9, involving two vehicles driving along the centerline of the lane so that the influences of lane markers can be ignored. The velocities of vehicle 1 and vehicle 2 are v_1 and v_2, respectively. The distance between the two vehicles is r. The influences of vehicle 2 on the driving safety of vehicle 1 can be denoted as a driving safety field that consists of two parts: 1) the kinetic field formed by vehicle 2; 2) the behavior field formed by the driver of vehicle 2. The directions of the field strength vectors of the above two fields point from vehicle 2 to vehicle 1. Moreover, according to the model given in Section III, we

$$\begin{cases} E_{V\_21} = \frac{GR_2M_2}{r^{k_1}} \cdot \exp(-k_3v_2) \\ E_{D\_21} = E_{V\_21} \cdot DR_2 \\ E_{S\_21} = E_{V\_21} + E_{D\_21} \\ F_1 = E_{S\_21}M_1\left[R_1 \cdot \exp(k_3v_1) \cdot (1+DR_1)\right] \end{cases} \tag{13}$$

where E_{V_21} is the field strength of the kinetic field formed by vehicle 2 at the location of vehicle 1; E_{D_21} is the field strength of the behavior field formed by the driver of vehicle 2 at the location of vehicle 1; E_{S_1} is the total field strength of the driving safety field at the location of vehicle 1; F_1 is the field force on vehicle 1; R_1 and R_2 are the road condition influencing factors at the locations of vehicle 1 and vehicle 2, respectively; M_1 and M_2 are the virtual masses of vehicle 1 and vehicle 2, respectively; DR_1 and DR_2 are the driver risk factors of the drivers of vehicle 1 and vehicle 2, respectively. According to (13), we obtain

$$F_1 = \frac{GR_1R_2M_1M_2}{r^{k_1}} \cdot (1+DR_1) \cdot (1+DR_2)\exp[k_3(v_1-v_2)] \tag{14}$$

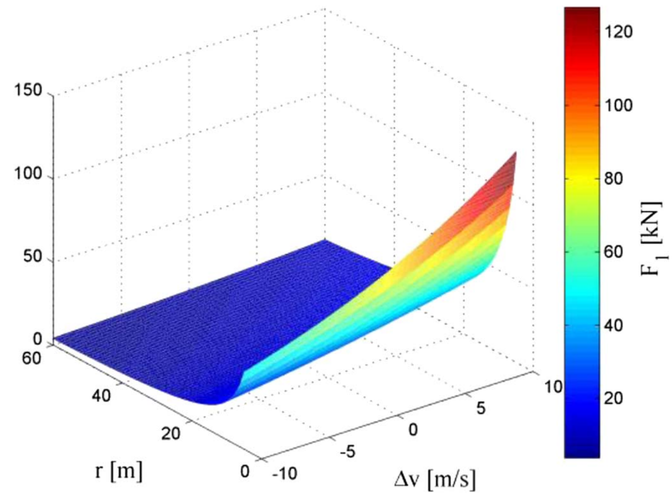

Fig. 10. Field force of the driving safety field formed by vehicle 2 acting on vehicle 1. The range of r is [5, 60] m, and $\Delta v = v_1 - v_2$.

For the purpose of illustration, we chose the following set of parameters: $G = 0.001$, $k_1 = 1$, $k_3 = 0.05$, $M_1 = 4000$ kg, $M_2 = 5000$ kg, $DR_1 = 0.2$, $DR_2 = 0.6$, and $R_1 = R_2 = 1$. Therefore, F_1, calculated according to (13) is shown in Fig. 10.

As shown in the figure, the field force on vehicle 1 increases as the distance decreases and the relative velocity increases, which indicates that the driving risk of vehicle 1 also increases. Therefore, the results meet the objectives of this study.

In this scenario, compared with existing driving safety evaluation methods, the driving safety field model considers not only the relative velocity and distance, but also vehicle attributes (which are associated with the potential severity of a collision, and are denoted as the virtual mass in the model), road conditions, and driver characteristics. Hence, for example, when the weather changes from fine to rainy, the driving safety field model can amend its risk evaluation to reflect greater risk while most existing methods cannot.

VI. Discussions And Conclusion

A. Discussions

Three main issues must be discussed in this paper.

1) Information Access: As described previously, a considerable amount of information is involved in the driving safety field model. The model considers not only the vehicle information, but also the information concerning road conditions, nonmoving objects, moving objects in addition to vehicles, and driver characteristics. Hence, access to this information is fundamental to the model's application. The difficulty of accessing this information may appear to make the application of this model doubtful. However, owing to the development of sensor and communication technologies, the information is either presently available or will be available in the near future. Considerable research has been conducted regarding V2X communication, including vehicle-to-vehicle (V2V) communication, vehicle-to-road (V2R) communication, and vehicle-to-infrastructure (V2I) communication, and V2X communication has been verified to enhance driving safety [22]–[29]. With these technologies, we can obtain the required information regarding vehicles, road conditions, and infrastructure. However, the information regarding drivers must also be accommodated. Fortunately, the body sensor network (BSN) has been used to detect a driver's physiological state [30]–[33]. For example, a detector for human emotions has been proposed [30], of which tiredness and stress (tension) can be related to traffic accidents. Above all, it is certainly possible that the information required for the driving safety field model will be available in the future. Of course, an increasing amount of information provides a higher accuracy for the evaluation of driving risk.

2) Model Calibration: The basic ideas and methods of model calibration were proposed in Section V, and the possible difficulties associated with calibration were analyzed. Most of the foreseen difficulties are related to evaluation standards, which can be solved by further research.

3) Model Validation: Qualitative validation of the model was provided by the explanations given in Section III and the car following example given in Section V. Moreover, methods for quantitative validation were discussed in Section IV, which are presently underway.

Although further research is needed to fully establish the concept and model of the driving safety field, the field theory based method provides a new foundation for the evaluation of driver-vehicle-road-influenced driving safety in complex scenarios.

B. Conclusion

In this paper, the influencing factors of driving safety and the mechanisms by which they function were analyzed. Analysis of the driving risk and its connection with field theory revealed similarities between the driving risk caused by traffic factors and the concept of a field. On the basis of field theory, a new method for evaluating driving safety was proposed. The main results of this study are summarized in the following points.

1) The concept of the driving safety field was proposed for the first time. The risks to moving vehicles caused by drivers, vehicles, roads, and other traffic factors are represented by this field. The field strength vector of the driving safety field denotes the influence of the traffic factors on driving safety. The field force acting on a vehicle denotes the vehicle's current driving risk.
2) A unified model of the driving safety field was developed, which includes three parts: i) the potential field, which is determined by nonmoving objects on roads; ii) the kinetic field, which is determined the moving objects on roads; and iii) the behavior field, which is determined by the individual characteristics of drivers.
3) Methods for the model calibration were proposed, including the virtual mass, road condition influencing factor, driver risk factor, and so on.
4) The model's applications were proposed, including the calculation of the field strength distribution, the real-time evaluation and prediction of driving risk, dynamic path planning, driving safety decisions and active safety controls, and so on. An example of a typical car-following scenario was provided. The results demonstrate the effectiveness of the model.

Compared with existing driving safety evaluation methods, the driving safety field model incorporates a greater number of traffic factors and is not limited to specific scenarios such as car following and lane changing. Moreover, the driving safety field model is applicable to highly complex scenarios, and can provide a new foundation for investigation of intelligent driver assistance systems.

Future work will focus on further study of methods to determine the parameters of the model, and the development of vehicle safety assistance and intelligent control methods based on the driving safety field model.

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