Infrastructure-cooperative algorithm for effective intersection collision avoidance

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A R T I C L E   I N F O

A B S T R A C T

To guarantee the road safety by avoiding collisions at the intersections is one of the major tasks of intelligent transportation systems (ITSs), which contributes to the minimal fatalities and property loss in crashes. This paper proposes an effective algorithm for infrastructure-cooperative intersection accident pre-warning system with the aid of vehicular communications. The proposed algorithm realizes accurate and efficient collision avoidances through five steps, i.e., defining variable, reasoning the vehicles evolution state, verifying safe driving behavior, assessing risk, and making decision. The critical factors are theoretically analyzed, and a vehicle state evolution model based on the Dynamic Bayesian Networks (DBNs) is established. The efficient risk assessment method based on identifying the dangerous driving behavior at intersection and different collision avoidance strategies are proposed according to the actual situation. Finally, extensive simulations are carried out to verify the performance of the proposal, and simulation results show that the proposed algorithm can effectively detect risk and accurately migrate the collision.

1. Introduction

Traffic accident at the intersections is one of the biggest global killers in urban traffic. Intersections are the vital traffic components of traffic networks in which a large volume of vehicles from different directions come together and steer freely at a high speed, making a high possibility for traffic accidents (Lei and Cristofer, 2016; Marchesini and Weijermars, 2010). In 2015, of all police-reported traffic accidents in European Union (EU), accidents occurred at intersections took the total number of fatalities to 26,161 (European Road Safety Observatory (ERSO), 2016; Department for Transport, 2016). In the United States (US), more than 5 million accidents occurred at intersections or intersection related roadways in 2015, accounting for around 47.2% of all accidents, with an estimated economic cost of $114 billion (World Health Organization, 2012; National Highway Traffic Safety Administration, 2016).

For decades, traffic rules and intersection infrastructures (e.g. traffic lights, stop sign and roundabout) have been practically applied to ensure the safety of intersection traffic (Lei and Cristofer, 2016). However, traditional solutions are not working when drivers are at poor health states, encountering illumination changes or bad weather scenarios (e.g. heavy snow, fog and haze) (Yan et al., 2016; Francesco et al., 2015). A recent solution is to install collision warning devices in cars that monitor and predict the surrounding environment, which are mainly based on multi-sensors, to warn the corresponding driver if a potential collision is

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detected. However, such equipment can be very expensive and only affordable by luxury car models, and thus impractical for large-scale commercial use (Francesco et al., 2015; Inman and Davis, 2011). More importantly, the vehicle-mounted sensors are typically of short sensing range and can be easily blocked by buildings or other vehicles; it may be too late for drivers of poor states to take actions based on the sensed information only.

To report and avoid potential risks in a wide range in a scalable yet cost-effective way, the infrastructure-based warning systems under the umbrella of ITSs have recently been proposed. In specific, the ITSs deploy communication devices at the roadside as well as intersections (e.g., on traffic light) and send periodic road information to upcoming vehicles using non-light-of-sight wireless communications. Furthermore, the real-time information exchange enables connection and cooperation between road users, infrastructure and control centers, forming cooperative ITS (C-ITS). Note that most of the traffic accidents happening at intersections result from drivers' misjudgment on the current states, perception failures and faulty operations. The inclement weather can also affect speed control, and brake performance, leading to severe traffic accidents. The ITSs, by incorporating the mobile computing and artificial intelligence to learn the driver's health condition (Yu et al., 2016) and adapting to road and weather conditions, allow upcoming vehicles in a wide range to learn potential hazard. With the aid of vehicle control technologies and vehicle automation, the drivers even the vehicles can adopt appropriate operations in time to avoid accidents (Campos et al., 2017).

With the advancement of the ITSs, extensive works have been carried out, including system design (Misener, 2010; Tan and Huang, 2006), intelligent traffic signal setting (Fayazi and Vahidi, 2016), cooperative intersection scheduling and management (Lio et al., 2017; Colombo and Vecchio, 2015), and collision avoidance algorithm (Xiang et al., 2014; Ba et al., 2017), etc. Among these works, we are attracted by the designing of collision warning/avoidance system. Particularly, the prediction and decision-making algorithms which applied at different components are the core parts of collision warning/avoidance systems (Kim et al., 2015; Brännström et al., 2013). Mathematical theories, mathematical optimization and artificial intelligence have been applied for algorithmic design (Lei and Cristofer, 2016; Xiang et al., 2014; Joseph et al., 2011). Despite previous important works, we notice that two significant problems are not fully addressed: the complex traffic environment and some unpredictable driving behavior.

The design of such algorithms and systems is challenging due to the following issues: (1) *complex road environment*, in that two or more roads cross each other and the road situation as well as sensory observations evolve over time; (2) *dynamic interactions among vehicles*, in which multiple activities have the potential for conflicts resulting in crashes; (3) *noised data*, in that incomplete data acquired from sensors usually exists different degrees of uncertainty due to ambient noise, sensors' systematic errors, and the reliability of data transmission; (4) *immediate actions*, in that decision must be made accurately and quickly. The challenges indicate that the algorithms and systems have high requirements on computational capabilities, communication capacity, reliability, latency. Therefore, it is necessary to develop a cost-effective yet adaptive technology that can simultaneously address all above challenges, which motivates our work.

This paper proposes an collision warning/avoidance algorithm for infrastructure-cooperative accident pre-warning system. We consider an accident scenario where two vehicles in different directions driving on a two-way stop-controlled intersection with traffic lights. In particular, some critical factors are analyzed firstly. We also propose prediction and risk assessment algorithms, and different strategies are implemented to avoid accidents according to the situation. The main contributions of the paper are threefold:

- *Analysis*: The critical factors, i.e. timing factor, communication and positioning factor, are detailed analyzed in this paper. Particularly, we analyse why they occur and how they can affect the performance of collision warning algorithm, which will provide reference for algorithm design.
- *Algorithm*: A prediction algorithm is realized by establishing the vehicle state evolution model which based on Dynamic Bayesian Networks (DBNs). It allows the prediction of the possible states of upcoming vehicles from current and previous states with uncertain contextual information. In addition, we take the human factors and road conditions into account, which makes the model more practical and applicable to real-world scenario.
- *Validation*: The evaluation of a risk situation is based on distinguishing safe behaviors and drivers' intention at the intersection. The risk assessment method can avoid the complex trajectories prediction, which will satisfy the requirements of rapid decision-making.

The remainder of this paper is organized as follows. The related works, including trajectory prediction algorithms and collision avoidance systems, are reviewed in Section 2. Section 3 depicts overall diagram and analyses the effect factors. Section 4 describes the process of realizing the collision avoidance in detail, which contains vehicle state evolution model, risk assessment and collision avoidance algorithm. Section 5 evaluates the performance of proposed algorithm using simulations, and Section 6 concludes the paper.

2. Related works

Driven by the growing user and application requirements, Collision Warning Systems (CWSs) (Córdoba et al., 2017), as an important component of the ITSs, plays an prominent role in traffic safety. Particularly, the collision warning/avoidance algorithm is the core of the CWSs, which has obtained extensive research.

Heretofore, the most popular algorithms for the collision detection and avoidance are based on trajectory prediction and risk assessment. It was observed by researchers in Katrakazas et al. (2015) that the existing methods for vehicle trajectory prediction can be classified into three levels: physics-based motion models, maneuver-based motion models and interaction-aware motion models. In Funke et al. (2017), a new control structure was proposed, which integrates path tracking, vehicle stabilization, and collision

avoidance. Considering collision warning timings, the authors in Xiang et al. (2014) proposed a DSRC-based collision warning system using vehicle kinematics (VK) model for calculating vehicle trajectories. Nevertheless, they are limited to a short-time prediction as well as unable to take into account the driver and environment. In the work presented in Lytrivis et al. (2011), a cooperative path prediction algorithm for safety applications was proposed to calculate all connected vehicles' future paths by gathering their current state information. More recently, a novel method for risk assessment at intersection was implemented in Lefèvre et al. (2012, 2013), where a Dynamic Bayesian Network (DBN) is proposed to model vehicles motion pattern and driver behavior detection.

The applying of communication technology provide a tremendous opportunity with researchers to study various novel warning model algorithms. Based on V2V communication and control theoretic methods, an efficient decentralized algorithm for intersection collision avoidance was proposed in Hafner et al. (2013). The uncertainty and communication delays are taken into account in their models, whereas the inter-dependencies between vehicles' maneuvers are ignored. Based on inter-vehicle communications and GPS, a future-trajectory-prediction-based cooperative CWS was explored in Tan and Huang (2006), which computed and communicated vehicle states information and predicted future trajectories for collision decision making. Considering collision avoidance timings, Tang and Yip (2010) proposed a DSRC-based collision detection system for calculating vehicle trajectories and providing effective warning to drivers.

In addition, a number of researchers studied collision warning or avoidance models by utilizing some well-known methods in other fields. Considering behavioral and physiological features, a supervised learning model was introduced for crash prediction (Ba et al., 2017). By using enough data to learn models for specific dangerous events, a classification algorithm for identifying dangerous behaviors was proposed in Aoude et al. (2012), where the likelihood of observations is used to match the model which best explains the current state. In Xiang et al. (2014), neural network (NN) was utilized for establishing emergency warning model. In Joseph et al. (2011), a Bayesian nonparametric algorithm was designed to model vehicles mobility pattern.

In order to alleviate the dangerous situation at the intersection, numerous efforts technical approaches have been made. Alessandro and Domitilla Colombo and Vecchio (2015) designed least restrictive supervisors for collision avoidance at traffic intersections. In Alonso et al. (2011), authors studied the collaborative driving strategies among three vehicles and presented two kinds of decision algorithms aiming at resolving the intersection traffic conflicts. However, most of current algorithms are unable to completely satisfy the practice requirements because of the complex road layout and traffic rules of intersections. In addition, few researches thoroughly considered the critical factors, such as timing, communication, and positioning, that provide seriously influence on system performance and practical application. Therefore, this paper takes the research in the aspect of intersection collision avoidance a step further by investigating these factors and their impact on the collision warning/avoidance, which would be helpful for algorithm design and performance evaluation. The goal of collision avoidance is achieved by establishing vehicle state evolution model, verifying safe behavior, risk assessment and collision avoidance algorithm, which are introduced in subsequent sections.

3. Preliminary analysis of algorithm design

In this section, we will first describe the collision scenarios, as shown in Fig. 1. Then we carefully analyse the influencer to initiate the algorithm design.

3.1. Road intersection collision scenario designs

To develop efficient countermeasures, collision scenarios along with the causal factors on intersections need to be studied. Several different scenarios are defined based on traffic lights conditions, vehicle states and driver traffic rule violations. The crash scenarios are illustrated in Fig. 1(b). Each of them involves a two-way stop-controlled intersection layout with traffic lights, a "Subject Vehicle" (SV) and an "Other Vehicle" (OV). The SV's trajectories are shown in red while the OV's trajectories are shown in green. Yellow
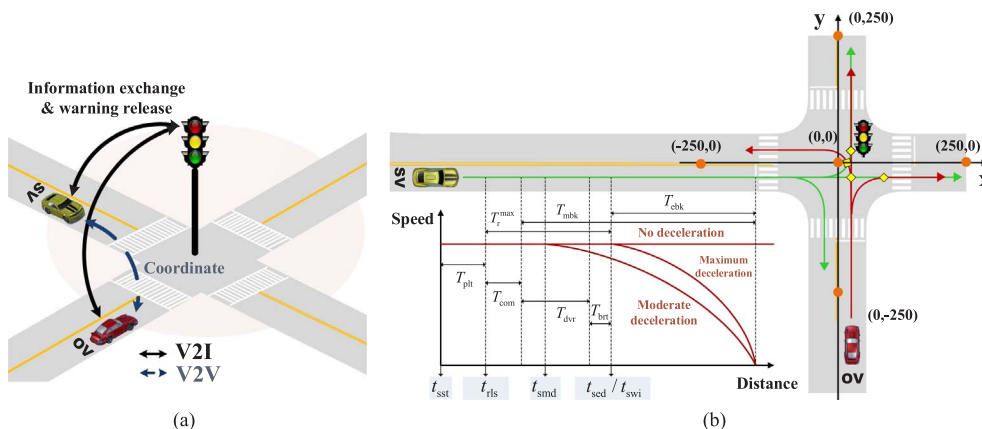

Fig. 1. Collision scenarios at intersection: (a) communication mode; and (b) simulated scenario and critical points for collision avoidance.

Table 1
Description of the important time point.

Symbol	Description
t_{sst}	Time point where the vehicle's state testing is started
t_{rls}	Time point where a warning information is released
t_{smd}	Time point where SV should start moderate decelerating
t_{sed}	The last moment where SV should start emergency decelerating
t_{swi}	Time point where SV ignores the warning, and warning should be sent to OV to avoid collision
T_{plt}	Preliminary test time
T_{com}	Communication time
T_{dvr}	Driver reaction time
T_{brt}	Vehicle brake reaction time
T_r^{max}	Maximum reaction time
T_{mbk}	Deceleration time under moderate braking (with moderate deceleration)
T_{ebk}	Deceleration time under emergency braking (with maximum deceleration)

diamonds represent the collision area. There is no pedestrians jamming, and V2V, V2I communications as well as GPS are available during the entire process. Moreover, the vehicles on the road with green light usually move at relatively high speeds, which means accidents typically resulted from the SV drivers misjudging the speed, distance and available time gaps (i.e. run a red light). Summing up the above analysis, a collision is caused by insufficient response time, which makes it difficult for the driver to avoid an accident in a limited time. Some important time point shown in Fig. 1(b) is defined in Table 1.

3.2. Critical parameter analysis

We analyse the critical factors to enhance prediction and decision-making algorithm in this subsection.

3.2.1. Timing parameters analysis

When vehicles enter the infrastructure's communication range, the preliminary test phase begins. For this phase, vehicles and the infrastructure exchange their status data, and then the potential collision will be detected by calculation and prediction. Therefore, the T_t can be dissected as follows:

$$T_{plt} = T_{com} + T_{cpt}$$
$$= T_{com} + (T_{pdt} + T_{cld} + T_{dmk}) \tag{1}$$

The computation time T_{cpt} depends on real-time performance of the warning system, which mainly consists of prediction time T_{pdt}, collision detection time T_{cld} and decision-making time T_{dmk}. The central control processor utilizes the status information (e.g. vehicle speed, position, traffic light state) to compute and predict whether there is any potential danger. If a potential collision is detected, the corresponding mitigation strategy will be determined quickly. The real-time performance of the system is an important factor as the driver and vehicle need enough time to react to the hazard situation. In fact, the computation process lasts/(does not stop) until the danger is eliminated. It is expected that a computation process completes within 200 ms (Tang and Yip, 2010).

The communication time T_{com} is another important factor that affects the performance of the warning system. Obviously, the higher the communication time is, the less time for the driver to react the hazard situation. In addition, when the status data is exchanged, the vehicles may no longer be their previous state because of the time delay, thus providing erroneous data for the control processor to compute. Generally, the communication time T_{com} includes transmission delay T_{tdl} and propagation delay T_{pdl} and would vary depending on the communications channel condition.

$$T_{com} = T_{tdl} + T_{pdl} \tag{2}$$

The propagation delay can be ignored due to its small value of several microseconds, e.g., transmission range of 300 m and propagation rate of 3×10^8 m/s. For safety-related applications, single-hop communication is widely used for efficient information transmission, which has the expected delay less than 100 ms. In Ghadimi et al. (2011), the authors propose an analytical model to accurately analyse transmission delay in single-hop and multi-hop wireless ad hoc networks. According to the analytical model, the average single-hop transmission delay A_{tdl} is the sum of the average service time A_{ser} and the average queuing delay A_{qdl}:

$$A_{tdl} = A_{ser} + A_{qdl} \tag{3}$$

The driver reaction time T_{dvr}, which consists of the driver perception time T_{dpt} and the driver operation time T_{dot}, can vary depending on the driver's age, gender, status, driving years and so on. In Yan et al. (2015), the authors investigate the different driver reaction conditions and analyse the proper warning timing for avoiding the red-light-running collisions. Generally speaking, warning timing is a critical factor for the driver to avoid a collision, thus the driver's current status should be taken into account in prediction phase and collision avoidance phase. Research shows that most of the driver reaction time is about 1.5–2.5 s (Kuang et al., 2015; Aoude et al., 2012; Rafal and Tomasz, 2014).

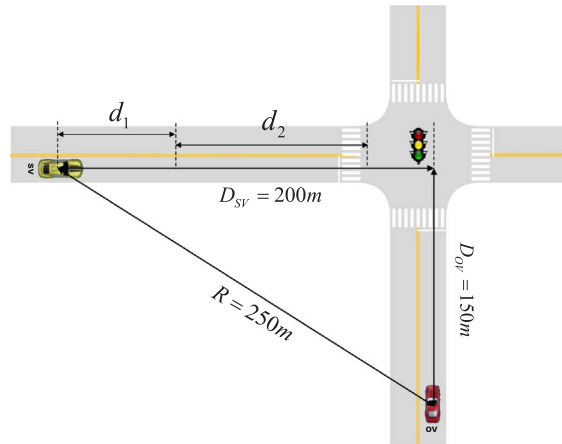$$T_{dvr} = T_{dpt} + T_{dot} \tag{4}$$

Fig. 2. V2V communication and distance analysis.

In addition, the vehicles which are equipped with the ABS have lower sensitive degree on warning timing. In this case, the driver reaction time is absent, and the reaction time of the ABS can be ignored due to its small value.

3.2.2. V2V communication and distance analysis

For intersection collision scenario, the effective braking distance is far less than the vehicle's communication range. Fig. 2 shows an example. Assuming that the vehicle's communication range is 250 m and no obstacles block the vehicle communication, the distance for a vehicle to stop before the intersection (for SV is 200 m, and for OV is 150 m) is less than this distance. Removing the perception time, communication time and reaction time (with the driving distance d_1), there is not nearly enough time for the SV to stop before the intersection (effective braking distance d_2), especially under the condition of high speed as well as the bad weather.

In addition, performance of wireless ad hoc networks is constrained by various kinds of interference (Wang et al., 2012). Authors in Schumacher et al. (2012) find that the reliability and timeliness of V2V communication can drop quite significantly due to environment and the layout of the intersections. Particularly, the channel path loss is strong when the vehicles are far away from the intersection. Because the intersection collision warning system's timeliness demand is rigorous, there are some downsides to relying solely on V2V communication. The higher latency can lead to out-of-date information, and even miss the optimal warning time for the system. Therefore, in order to provide an efficient and real-time intersection collision warning system, V2I communication should be considered for cooperation and extending the communication range.

3.2.3. Positioning error analysis

Positioning service is indispensable in current ITSs (Han et al., 2016). An additional issue is the GPS positioning error which could result in the deviations between the obtained position information and the current real position. A great deal of prior work has been proposed that the GPS positioning data is subject to the zero-mean Gaussian distribution (Miura et al., 2015). Based on the real GPS positioning data, we further adopt Kolmogorov-Smirnov test by Statistical Product and Service Solutions (SPSS) in order to theoretically verify the distribution of GPS positioning data. The results reflect the Gaussian distribution characteristics of the data.

Then we analyze the GPS positioning error D_{err}, which can be decomposed as Eq. (5).

$$D_{\text{err}} = D_{\text{ser}} + D_{\text{rer}} \tag{5}$$

The system errors D_{ser}, which is caused by external interference, contributes same error to every GPS receiver within certain distance range. That is to say, system error is usually a constant, which leads to the same direction with several meters deviations. In addition, the inner noise of the GPS receiver leads to random errors D_{rer} that the GPS points randomly distributed around the actual position. According to Castro et al. (2016), the random errors D_{rer} obey a Gaussian distribution with mean zero, thus the pdf (probability density function) of D_{err} is:

$$f(D_{\text{err}}) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(D_{\text{err}}-\mu)^2}{2\sigma^2}\right) \tag{6}$$

where the μ equals 0, and σ can be calculated.

Let us take the U.S. government's report as an example, real-world data show that the GPS receivers will provide better than accuracy of 4.218 m at a 95% confidence level (Federal Aviation Administration GPS Product Team, 2016). Therefore, we can obtain:

$$\Phi(D_{\text{err}}) = \int_{-\infty}^{D_{er}} \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{x^2}{2\sigma^2}\right)dx$$

$$\Phi(4.218) = 0.975 \tag{7}$$

where the $\Phi(D_{\text{err}})$ represents the distribution function of D_{err}, and $\sigma = 2.152$ can be calculated.

The above timing and positioning analyses provide us a relatively deep and comprehensive understanding on the communication and positioning mechanism, which can help us to design a more reasonable and effective algorithm.

4. Problem formulation

In this section, we describe the process of the proposed collision avoidance algorithm, which includes the data collection, hazard situation detection and collision avoidance strategy. Before the potential hazard situation detection, the vehicles and the infrastructure should acquire its own status information as well as share with surrounding vehicles. In this paper, these information can be acquired directly or indirectly from the system. When the central control processor receives the vehicles status data, the potential danger detection is beginning. As soon as the hazard situation is detected, corresponding measures are used for collision avoidance. Specifically, there are five steps for realizing the collision avoidance, as shown in Framework 1. The detailed process and system implementation are then described in the subsequent subsections.

FRAMEWORK 1: COLLISION AVOIDANCE ALGORITHM
1   Define and represent the data variables:
    ◊ Vehicle state and road condition variables Ps_t^n;
    ◊ Driver behavioral variables Db_t^n;
2   Establish vehicle state evolution model;
3   Verify the safe driving behavior E_t^n;
4   Risk assessment:
    ◊ Compare driver's intention I_t^n and E_t^n;
5   Collision avoidance:
    ◊ Different strategies according to the actual situation
    (deliver warning information, emergency brake).

4.1. Variables definition and representation

4.1.1. Vehicle state and road condition variables

A number of factors such as the vehicle states and the road conditions in different environments based on the vehicles position, speed, acceleration/deceleration rate, heading, turn signal state and the road condition are available in this work, which are gathered by observation and measuring. These data are collected from onboard sensors, radar and cameras, meanwhile, these information are sharing based on V2V and V2I communication. For each vehicle $n \in N$ at time t, a physical state variable is defined as:

$$Ps_t^n = (P_t^n V_t^n A_t^n D_t^n T_t^n C_t^n) \tag{8}$$

- $P_t^n = (X_t^n Y_t^n) \in R^2$: the vehicle position
- $V_t^n \in R$: the velocity of vehicles
- $A_t^n \in R$: the acceleration/deceleration rate
- $D_t^n \in [0,+\infty)$: the distance traveled by the vehicle
- $T_t^n \in \{left,right,none\}$: the turn signal state
- $C_t^n \in \{dry,wet,snow,ice\}$: the road condition, can be used to assist the calculation of the maximum braking deceleration

4.1.2. Driver behavioral variables

In addition to the aforementioned variables, there are some other behavioral variables such as driver's intention and state we are unable to gather by observation. Nevertheless, these variables are closely related to interactions between vehicles as well as some uncertainties. For each vehicle $n \in N$ at time t, a driver behavior variable is defined as:

$$Db_t^n = (M_t^n I_t^n S_t^n E_t^n) \tag{9}$$

- $M_t^n \in \{m_i\}_1^{N_M}$: the maneuver intention of the driver, with N_M the number of possible maneuvers
- $I_t^n \in \{maintainspeed,accelerate,decelerate,stop\}$: the driver's intention maneuver at the intersection
- $S_t^n \in \{concentration,distraction\}$: the driver's state (e.g. distraction means the driver need longer time to react)
- $E_t^n \in \{maintainspeed,accelerate,decelerate,stop\}$: the driver's expectation maneuver at the intersection (i.e. safe behavior at the intersection)

In general, although the driver behavioral variables is considered as the unobservable variables, they can be deduced by capturing some observable variables.

4.2. Vehicle state evolution model

In this work, a Dynamic Bayesian Network (DBN) is utilized to model the relations of these variables and the evolution of vehicle
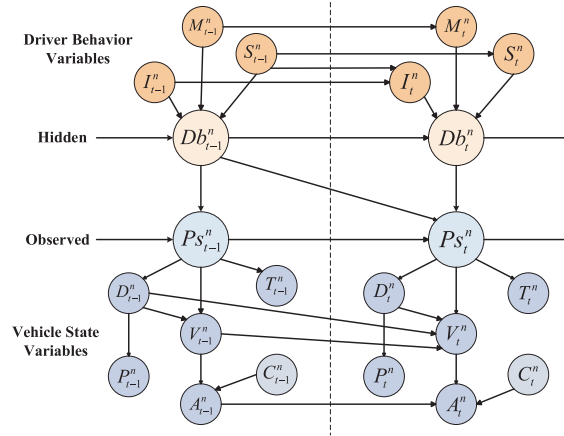
Fig. 3. The DBN structure at time slice $t-1$ and t.

state. A DBN is a way to extend Bayes nets to model probability distributions over semi-infinite collections of random variables, which is defined to be a pair of $(B_1, B_{\longrightarrow})$ (Al-Sultan et al., 2013; Murphy, 2009). Specifically, B_1 represents the initial static Bayesian Network (BN) which defines the prior $P(Z_1)$, and $B_{\longrightarrow}$ is a two-slice temporal Bayes net (2TBN) which defines $P(Z_t|Z_{t-1})$ by means of a directed acyclic graph (DAG). If $P(Z_t|Z_{t-1})$ represents the probability of the any random variable at time slice t under the condition of knowing the variable at time slice $t-1$, we can deduce:

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i|Pa(Z_t^i)) \tag{10}$$

where Z_t^i is the i'th node at time slice t; and $Pa(Z_t^i)$ are the parents of Z_t^i in the graph; and N represents the total number of variables. The parents of Z_t^i (i.e. $Pa(Z_t^i)$) can either be in the same time slice t or in the previous time slice $t-1$. Therefore, the relationship between two time-adjacent slices can be modeled by utilizing the model of first-order hidden Markov with a relaxation of the independence assumptions. The semantics of a DBN can be defined by "unrolling" the 2TBN until we have T time-slices. The resulting joint distribution is then given by:

$$P(Z_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(Z_t^i|Pa(Z_t^i)) \tag{11}$$

It will be of great help for us to take account of some uncertain variables or states to represent the motion pattern in the context of road traffic. The assumption for all the vehicles in the scene are set independent between each other. Fig. 3 depicts the DBN structure at time slice $t-1$ and t as well as the conditional independence between the variables. In addition, the representation of the DBN can be decomposed as:

$$P(Db_{0:T}^n Ps_{0:T}^n) = P(Db_0^n Ps_0^n) \times \prod_{t=1}^{T} \prod_{i=1}^{N} [P(Db_t^n|Db_{t-1}^n) \times P(Ps_t^n|Db_{t-1:t}^n Ps_{t-1}^n)] \tag{12}$$

In addition, with the independence assumptions, the variables can be represented as below (Fu et al., 2016):

- For the vehicle state and road condition variables:

$$\begin{aligned}
&P(Ps_t^n|Db_{t-1:t}^n Ps_{t-1}^n) \\
&= P(V_t^n|V_{t-1}^n D_{t-1:t}^n I_t^n M_t^n S_{t-1}^n) \\
&\quad P(D_t^n|D_{t-1}^n A_{t-1}^n I_{t-1}^n M_{t-1}^n S_{t-1}^n) \\
&\quad P(A_t^n|A_{t-1}^n C_t^n) P(T_t^n|M_{t-1:t}^n) \\
&\quad P(P_t^n|D_t^n M_t^n)
\end{aligned} \tag{13}$$

- For the driver behavioral variables:

$$\begin{aligned}
P(Db_t^n|Db_{t-1}^n) &= P(I_t^n|I_{t-1}^n S_{t-1}^n A_{t-1}^n) \\
&\quad P(S_t^n|S_{t-1}^n) P(M_t^n|M_{t-1}^n)
\end{aligned} \tag{14}$$

Each conditional probability expression is defined as below:

- For the maneuver is assumed as:

$$P(M_t^n|[M_{t-1}^n = m_i]) = \begin{cases} P_{mtM} & if \ M_t^n = m_i \\ \frac{1 - P_{mtM}}{N_M - 1} & otherwise \end{cases}$$

(15)

where P_{mtM} represents the probability that maneuver of drivers at time t maintaining the previous maneuver. In our scenario, there are four possible maneuvers, i.e. straight, turn left, turn right and stop. Therefore, the number of possible maneuvers $N_M = 4$.

- For the distance is defined as follows with the distribution is normal:

$$P(D_t^n|M_{t-1}^n D_{t-1}^n I_{t-1}^n S_{t-1}^n A_{t-1}^n) = N(\mu_D, \delta_D)$$

(16)

where μ_D and δ_D can be extracted from the velocity described in subsequent.

- For the driver's intention to stop model is assumed as:

$$P(I_t^n|[I_{t-1}^n = i_i][S_{t-1}^n = s_i][A_{t-1}^n = a_i]) = \begin{cases} P_{mtI} & if \ I_t^n = i_i \\ \frac{1 - P_{mtI}}{3} & otherwise \end{cases}$$

(17)

where P_{mtI} represents the probability that driver's intention at time t maintaining the previous intention. In our scenario, there are four possible driver's intentions, i.e. maintain speed, accelerate, decelerate, stop. Therefore, the number of possible driver's intention $N_I = 4$.

- For the driver's state is assumed as:

$$P(S_t^n|[S_{t-1}^n = s_i]) = \begin{cases} P_{mtS} & if \ S_t^n = s_i \\ 1 - P_{mtS} & otherwise \end{cases}$$

(18)

where P_{mtS} represents the probability that maneuver of drivers at time t maintaining the previous state. In our scenario, there are two possible driver's state, i.e. concentration, distraction. Therefore, the number of possible driver's state $N_S = 2$.

- For the current position of the vehicle at time t is defined as a bivariate normal distribution of current coordinate (x,y) based on the maneuver M_t^n and the distance traveled by the vehicle away from the stop line:

$$P(P_t^n|[M_t^n = m_i][D_t^n = d]) = N(\mu_x, \mu_y, \sigma_x, \sigma_y, \rho)$$

(19)

where μ_x and μ_y represent the distance d between the current position (x,y) and the position of stop line on the path of maneuver m_i. In addition, σ_x and σ_y are the standard deviation sets for the distance. It is assumed that x and y are independent of each other, therefore $\rho = 0$.

- The acceleration can indicate whether or not the driver wants to stop at the intersection. It is defined as a normal distribution:

$$P(A_t^n|[A_{t-1}^n = a_1][C_t^n = c_1]) = N(\mu_A, \sigma_A)$$

(20)

where μ_D and σ_D are extracted from the velocity described in subsequent sections. In addition, $A_t^n < 0$ means the driver brakes the vehicle, otherwise the driver wants to maintain the speed or speed up.

- The turn signal state of the vehicle can implicate the driver's intention maneuver at the intersection. We assume that:

$$P(T_t^n|[M_{t-1}^n = m_i][M_t^n = m_j])$$

(21)

What's more, the turn signal state can indicate the driver's intention to change the orientation or lanes.

- The velocity can also indicate whether or not the driver intends to stop at the intersection as what the acceleration does. It is assumed that the distribution on V_t^n is normal:

$$\begin{aligned} P(V_t^n|[M_t^n = m_i]&[D_{t-1}^n = d_1][D_t^n = d_2] \\ [I_t^n = i_i]&[S_{t-1}^n = s_1][V_{t-1}^n = v_1]) \\ &= N(\mu_V, \sigma_V) \end{aligned}$$

(22)

where μ_V is the velocity profile that is related to v_1 and velocity profiles $[v_{\min}(d), v_{\max}(d)]$. The relative position of μ_V in $[v_{\min}(d_2), v_{\max}(d_2)]$ is the same as the relative position of v_1 in $[v_{\min}(d_1), v_{\max}(d_1)]$.

4.3. Safe behavior verification

The expectation of the driver's maneuver at the intersection is resulted from the current context (e.g. traffic light state, traffic rules and other vehicle). It can be expressed as:

$$P(E_t^n|M_t D_t V_t)$$

(23)

We assume that the expectation is the safe behavior. The traffic light state transition time remaining (green light transforms to red light for the SV) is defined as t_R. If t_R is sufficient for the SV crossing the intersection with the current speed, the behavior whether the driver maintain speed or accelerate to go through the intersection is considered as a safe behavior. Whereas if the driver decelerates, an accident may happen.

Next, we discuss the condition that t_R is insufficient. The expectation of the driver's maneuver at the intersection is to stop at the stop line. In this work, we use a probabilistic model to calculate the necessity for a vehicle to stop with the given context. The calculation procedures are as follows:

- For SV heading towards the intersection from d_1 meters away in different scenarios with a constant velocity v_S, and the traffic light maintains green until the vehicle arrives the stop line.
- For OV heading towards the intersection in different scenarios with a constant velocity v_O, and the traffic light maintains red until the vehicle arrives the stop line.
- Calculate the time gap t_S to confirm the condition for the SV to stop at the intersection:

$$t_S = t_R + t_O \tag{24}$$

$$\begin{cases} d_{O_{max}} = \frac{1}{2}\pi\left(\frac{1}{2}w_r + l_a\right) + l_z \Rightarrow \max t_O \\ d_{O_{min}} = \frac{1}{2}w_r + l_a + l_z - \frac{1}{2}w_v \Rightarrow \min t_O \end{cases} \tag{25}$$

then

$$\begin{cases} \max t_S = (d_1 + 2w_r + 2l_a + l_z)/v_S \\ \min t_S = \left(d_1 + \frac{3}{2}w_r + l_a + l_z\right)/v_S \end{cases} \tag{26}$$

where d_O represents the distance traveled by the OV after it passed the intersection; w_r represents the single lane road width; l_a represents the circular arc radius of the intersection; l_z represents length of zebra stripes; v_S and v_O respectively represent the velocity of the SV and the OV; w_v represents the width of vehicles in the scene. Therefore the corresponding $\max t_S$ and $\min t_S$ can be deduced. In addition, the SV needs to stop at the stop line if the time gap t_S satisfies the condition of $\min t_S \leqslant t_S \leqslant \max t_S$.

- Let p_{stp} represents the probability that SV stops at the stop line, where the time gap t_S is not sufficient for this vehicle crossing the intersection. The parameter p_{dec} denotes the probability that SV slows down as it approached the intersection. The expectation motion model is defined as:

$$P(E_t^n|M_t D_t V_t) = \begin{cases} p_{stp} & if \ \min t_S \leqslant t_S \leqslant \max t_S \\ p_{dec} & if \ t_S < \min t_S \\ 1 - p_{stp} - p_{dec} & if \ t_S > \max t_S \end{cases} \tag{27}$$

This reasoning process is of great help to calculate the necessity for the vehicle to stop at the intersection and to wait the next green signal phase despite the current state of traffic light is green.

4.4. Risk assessment

It is possible to deduce whether or not the driver is intended to stop at the intersection as well as the expectation operation from the vehicle's physical state based on the vehicle state evolution model and the safe behavior verification model. As most existing algorithms are calculating collision probability by using trajectory prediction and potential collision detection, this work intends to propose an algorithm which is based on distinguishing dangerous and safe driver behavior. For each vehicle $n \in N$ at time t, it can be expressed as:

$$P([I_t^n = i][E_t^n = j]|Ps_{0:t}) \tag{28}$$

It is assumed that a, b, c and d respectively represent the driver's maneuver at the intersection: to maintain speed, accelerate, decelerate and stop. The result is discussed in different conditions:

For $i = j$, the driver's intention is considered as a safe behavior; for $i \neq j$, various situations are discussed as follows:

- For $j = a, i = b$ or d, the driver's intention is considered as a safe behavior; if $i = c$, the situation may become dangerous;
- For $j = b$, only in the case of $i = d$, the driver's intention can be considered as a safe behavior;
- For $j = c$, any of the maneuvers is safe behavior;
- For $j = d$, none of the maneuvers are safe behavior.

According to the above content, we assess the risk situation via the comparison of safe behavior and the driver's intention at the intersection. In addition, the driver's intention maneuver can be deduced by the vehicle state evolution model. The dangerous situation is defined if and only if the driver's intention is considered as a dangerous behavior. This method can avoid the complex trajectory prediction so that the time complexity and computation complexity can be reduced. What's more, another advantage is its flexibility and convenience to apply for other types of collision.

In some non-dangerous scenarios, a warning for the driver may distract the driver's attention and even cause the tension. Therefore, a warning would be considered as a false alarm under the condition of non-dangerous scenarios.

According to the above definitions, the proposed method is assessed via the simulation study on different collision scenarios, and the performance of this algorithm is evaluated by its accuracy and timeliness for identifying dangerous situation and warning the driver.

4.5. Collision avoidance

This paragraph deals with the collision avoidance strategy (i.e. sending warning and emergency braking) which is based on the Time-To-Collision (*TTC*) and Time-To-Avoidance (*TTA*) matrices. A collision avoidance timing analysis model is established to provide the collision warning information for drivers. *TTC* is the most standard indicator related to the time remaining before the collision occurs at their current speed. This is obtained according to Khondaker and Kattan (2015):

$$TTC = \frac{D_{SO}}{v_S - v_O} \tag{29}$$

where D_{SO} is the distance between two vehicles, v_S and v_O respectively represent the projection of the relative velocity of the two vehicles on the coordinate.

The time that the vehicle needed to stop for avoiding collision is defined subsequently. It is assumed that $\mu \in (0.18, 0.9)$ represents the adhesion coefficient based on the road condition (e.g. $\mu = 0.18$ means the minimum adhesion coefficient of icy pavement and $\mu = 0.9$ means the asphalt pavement); g represents the gravitational acceleration. Therefore the maximum braking deceleration is defined as:

$$a_{\max} = \mu \times g \tag{30}$$

and *TTA* is defined as:

$$TTA = \frac{v_S}{\mu g} + \alpha t_d^{\max} + t_c + t_V \tag{31}$$

where $t_d^{\max} = 2.5$ s represents the maximum driver reaction time; $t_c = 0.2$ s represents the average communication time (transmission time and broadcast latency); $t_V = 0.5$ s represents the average vehicle brake reaction time; $\alpha \in (0, 1)$ and $\alpha \sim N(1/2, 1/6)$. According to the Pauta criterion, numerical distribution in $(\mu - 3\sigma, \mu + 3\sigma)$ has the probability of 99.74%, therefore we assume that these numbers are included in $\alpha \in (0, 1)$. In conclusion, $\mu = 1/2$ and $\sigma = 1/6$ can be calculated.

In the process of driving, the central processor detects the potential risk and compares *TTC* with *TTA* in real time in order to confirm whether to take different collision avoidance measures according to different situations. It is considered an accident is avoidable if it can be perceived earlier than *TTA*. Particularly, vehicles can be controlled by both driver and the Automatic Brake System (ABS) to decelerate, and uniformly retarded motion during the brake process. The collision avoidance strategy is chosen by following illustration.

- For $TTC - TTA > t_d^{\max}$, a warning information delivered to the driver of *SV* is the most efficient strategy. One reason is that the *SV's* intention to across the intersection earlier than the *OV*. Moreover, the warning time is early enough so that the driver can alleviate the current situation via his action, and which guarantees the safety as well as comfort.
- For $t_d^{\max} \geqslant TTC - TTA > 0$, an emergency brake of *SV* is the best solution in case of an unavoidable accident to mitigate the consequences of a collision. In this case, the warning time is insufficient for the driver to respond and execute operation on his own.
- For $TTC = TTA$, it is not possible to avoid collision only by the emergency brake of the *SV* due to the braking time is not allowed. Therefore, actions on *OV* should be taken into account to collaborate to avoid collision. A warning information need to be delivered to the driver of *OV* and let him to wait at the stop line before the *SV* crossed the intersection. The reason is that the *OV* either stops at the intersection or drives with a relatively lower speed as it just started.

4.6. Algorithm implementation

Based on wireless communications and computing technologies, the proposed algorithm can be embedded in an infrastructure-cooperated collision pre-warning system through four main steps (i.e. sensing, communications, central control process and collision avoidance). Specifically, the proposed algorithm concentrate mainly on central control process and collision avoidance, as shown in Fig. 4 and described in the following:

The vehicle terminal consists of the GPS module, vehicle condition collection module, wireless communication transmission module, and displays. And the *sensing module* employs vehicle-mounted sensors such as GPS, camera, speed sensor, and distance sensor for vehicle status data collection. Then, the *communication module* utilize V2I and V2V communications to ensure secure and reliable real-time data transmission between vehicles and infrastructure and inter vehicles, respectively. Based on this, the infrastructure periodically broadcasts traffic light status data and warning information to the vehicles running on the road segments within its communication range. Simultaneously, vehicles' and drivers' status data is transmitted to infrastructure as well as other vehicles using. Afterwards, both the traffic light status data and vehicle related status data are input to the *central control process*
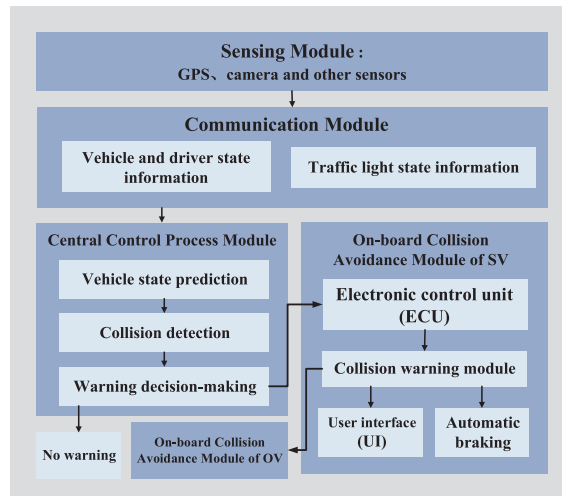
Fig. 4. Proposed strategy for intersection collision.

module for potential dangerous detection, and quick decision will be made for safe driving. Particularly, the vehicle state prediction submodule establishes the vehicle state evolution model based on DBN. Next, the collision detection submodule implements the process of safe behavior verification and risk assessment for detecting the potential dangerous. For the hazard situation, the warning decision-making submodule will send alarm to the *on-board collision avoidance module* of corresponding vehicles in different ways: A warning information with alarm is delivered to user interface (UI) to alert the driver if early enough, and the emergency braking is triggered by Automatic Brake System (ABS) in emergency situation. In order to improve the success rate of the collision avoidance, vehicles could also identify the hazard situation and exchange information to notify the other vehicle to take measures.

5. Simulations and evaluations

To evaluate the performance of our proposals, we conduct extensive simulations in three steps. Firstly, we model and predict the vehicle state and driver behavior using GeNIe (BayesFusion). Whereafter, the performance of risk assessment and collision avoidance are evaluated by MATLAB, which enables to perform computationally intensive tasks fast and convenient.

5.1. Simulation setup

The simulation area is a two-way stop-controlled intersection layout, as shown in Fig. 1. The intersection is managed by traffic lights, and the area for simulation is 500 m×500 m. We only focus on two vehicles to pass the intersection from different orientations. Other conditions, either pedestrians on the road, or different numbers of vehicles, are not suitable for our simulation. The two vehicles' initial positions are randomly distributed between each road edge and the stop lines. We set different velocities and friction coefficient of road surface to generate different simulation scenarios. The possible trajectories of two vehicles are represented with different colors[1] in Fig. 1, in which most of the reasonable conditions are considered. According to our algorithm, the simulation parameters are introduced in Table 2, which are the appropriate values learned from the reality situation.

As introduced in Section 4, the main objective of establishing the DBN model is to predict the vehicle state and driver behavior by inferring the unobserved high-level contextual information from the low-level observed data that is collected by sensors. Although there are many contributory factors that affect the vehicle state, such as the vehicle, driver, road condition and weather, we select the most important factors (as introduced in Section 4) which may lead to more accurate prediction than others.

Based on the predicted vehicle state, the evaluation of the collision avoidance algorithm is carried out in two steps. In the first step, each of the scenarios is performed several times for risk assessment. In the second step, the performance of collision avoidance is evaluated on the proposed algorithm which takes measures on both *SV* and *OV* (i.e. TMSO).

5.2. DBN inference for vehicle state evolution

The vehicle state evolution model combines data about the vehicle, road condition and driver that is collected via sensors for inference process. First, the DBN nodes and the relationships among them are defined, and the DBN graph is shown in Fig. 3. The next step is parameterising the DBN, which means determining the conditional probability table (CPT) for each node and the conditional probability over time. Some of the conditional probability are introduced in Section 4, and the following tables show three samples of the CPT of the proposed DBN. Table 3 shows the prior probability of the road condition node and acceleration node, respectively.

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[1] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.

Table 2
Simulation parameters.

Symbol	Name	Value
w_v	Vehicle width	1.75 m
l_v	Vehicle length	4 m
l_r	Road length	500 m
l_z	Length of zebra stripes	5 m
w_r	Single lane road width	3.5 m
l_a	Circular arc radius of the intersection	3.5 m
μ	Friction coefficient of road surface	0.18–0.9
v_v	Vehicle velocity	25–50 km/h

Table 3
Prior probability for road condition node and acceleration node.

Road condition	Probability	Acceleration	Probability
Dry	0.40079	$a > 0$	0.4687
Wet	0.18236	$a = 0$	0.1573
Snow	0.13334	$a < 0$	0.374
Ice	0.28351		

Table 4
Conditional probability for maneuver node at time t.

| t | $t-1$ | | | |
	Straight	Turn_left	Turn_right	Stop
Straight	0.9	0.033	0.033	0.034
Turn_left	0.033	0.9	0.033	0.033
Turn_right	0.033	0.033	0.9	0.033
Stop	0.034	0.034	0.034	0.9

Table 4 shows the conditional probability for maneuver node at time t. In this paper, the CPTs and the transferred probability are obtained from published papers, reports database and researches (European Road Safety Observatory (ERSO), 2016; Department for Transport, 2016; World Health Organization, 2012; Lefèvre et al., 2012; Al-Sultan et al., 2013; Zeyad, 2014).

According to the parameterised DBN, driver behavior, driver's intention and vehicle state can be inferred. There are eight evidence nodes in this network (driver behavior variables and vehicle state variables except driver's intention), each of which has at least two possible states. Therefore, more than 40,000 evidence combinations are set as the simulation inputs, and corresponding vehicle state and driver behavior can be inferred over time. Because of the large amount of evidence, it is impossible to illustrate all these possible combinations here. After abundant tests, some representative combinations and results are shown in Table 5. The results show that the proposed model can detect different types of driver behavior and vehicle state efficiently, and the vehicle state is consistent with driver's intention.

Table 6 shows the comparison of vehicles' physical state (Ps) and drivers' intention (I) under different combinations of evidences, which can help us further determine the factors that have a stronger impact on driver behaviors and vehicle state. As shown in the table, four kinds of vehicle state are predicted, and each kind of situation is compared in the condition of the same factors except for road condition and driver's state. Driver's state directly affect his/her judgment on the surrounding environment, which will further influence his/her driving intention. Particularly, the relationship between acceleration and road condition is highly dependent due to the different friction coefficient of road surface. For example, it is hard to slow down on slippery roads (i.e. ice surface), even if the driver might step on the brake. In addition, the vehicle will keep the state prior if the driver do not take action due to the inertia. These are the reasons which lead to the gap of probability between vehicle state and driver's intention.

5.3. Risk assessment results analysis

In order to evaluate the warning performance of the proposed algorithm quantitatively, three evaluation indexes are defined: correct warning rate, false warning rate and failure warning rate.

Correct warning is defined as both simulated situation and the predicted situation are consistent. Correct warning rate R_{ctw} is the ratio of the correct warning number and the total number of tests:

$$R_{ctw} = \frac{N_{ctw}}{N_{tot}}$$

(32)

Table 5
The belief of vehicle state and driver's intention by setting different combinations of evidences.

No.	t−1					t					t + 1	
	V (km/h)	A	T	D (m)	P(x,y)	V (km/h)	A	T	D (m)	P(x,y)	P_s (state and belief)	I (state and belief)
	Road condition = Dry, Driver's state = Concentration, Maneuver = {straight, turn_left, turn_right, stop}											
1	40	= 0	none	0–84	$x < 0$	40	= 0	none	0–84	$x < 0$	maintain direction	maintain speed
					$y = 0$					$y = 0$	and speed, 0.983	0.978
2	45	<0	left	167–250	$x < 0$	40	<0	none	250–333	$x = 0$	turn_left	decelerate
					$y = 0$					$y > 0$	and decelerate, 0.958	0.926
3	35	>0	right	167–250	$x < 0$	40	>0	right	250–333	$x = 0$	turn_right	accelerate
					$y = 0$					$y < 0$	and accelerate, 0.975	0.946
	Road condition = Wet, Driver's state = Concentration, Maneuver = {straight, turn_left, turn_right, stop}											
4	10	<0	none	167–250	$x < 0$	5	<0	none	167–250	$x < 0$	stop	stop
					$y = 0$					$y = 0$	0.917	0.915
5	45	<0	none	167–250	$x < 0$	40	<0	none	167–250	$x < 0$	maintain direction	decelerate
					$y = 0$					$y = 0$	and decelerate, 0.987	0.986
6	40	= 0	left	167–250	$x < 0$	50	>0	left	250–333	$x = 0$	turn_left	accelerate
					$y = 0$					$y > 0$	and accelerate, 0.907	0.915
	Road condition = Snow, Driver's state = Distraction, Maneuver = {straight, turn_left, turn_right, stop}											
7	30	= 0	none	84–167	$x < 0$	30	= 0	none	84–167	$x < 0$	maintain direction	maintain speed
					$y = 0$					$y = 0$	and speed, 0.694	0.72
8	5	<0	none	167–250	$x < 0$	0	= 0	none	167–250	$x < 0$	stop	stop
					$y = 0$					$y = 0$	0.753	0.782
9	20	>0	left	167–250	$x < 0$	30	>0	left	250–333	$x = 0$	turn_left	accelerate
					$y = 0$					$y > 0$	and accelerate, 0.815	0.764
	Road condition = Ice, Driver's state = Distraction, Maneuver = {straight, turn_left, turn_right, stop}											
10	20	>0	none	84–167	$x < 0$	30	>0	none	167–250	$x < 0$	maintain direction	accelerate
					$y = 0$					$y = 0$	and accelerate, 0.883	0.734
11	10	<0	none	167–250	$x < 0$	5	<0	none	167–250	$x < 0$	stop	stop
					$y = 0$					$y = 0$	0.691	0.743
12	30	= 0	right	167–250	$x < 0$	25	<0	right	250–333	$x = 0$	turn_right	decelerate
					$y = 0$					$y < 0$	and decelerate, 0.744	0.815

where N_{ctw} is the correct warning number; N_{tot} is the total number of tests.

False warning represents a warning initiating without actual collision. False warning rate $R_{false,w}$ is the ratio of the false warning number and the total number of tests:

$$R_{false,w} = \frac{N_{false,w}}{N_{tot}} \tag{33}$$

where $N_{false,w}$ is the false warning number.

Failure warning means that the actual collision is not detected, which can also be considered as missing alarm. Failure warning rate $R_{failure,w}$ is the ratio of the failure warning number and the total number of tests:

$$R_{failure,w} = \frac{N_{failure,w}}{N_{tot}} \tag{34}$$

where $N_{failure,w}$ is the failure warning number.

The results show a good performance of our risk assessment algorithm, which can be seen in . The main reason is that position error and signal transmission delay have influences on the accuracy of the algorithm.

5.4. Collision avoidance result analysis

Successful collision avoidance means a potential accident was successfully resolved, and successful collision avoidance rate R_{sca} is the ratio of the number of successful collision avoidance and the total number of collision avoidance tests. Instead, R_{fla} represents the failure avoidance rate, which means the probability of the accident eventually happen:

$$R_{sca} = \frac{N_{sca}}{N_{tca}}$$
$$R_{fla} = 1 - \frac{N_{sca}}{N_{tca}} \tag{35}$$

where N_{sca} is the number of successful collision avoidance, and N_{tca} is the total number of collision avoidance tests.

The performance of the proposed algorithm for intersection collision avoidance under different road conditions is evaluated, and the results are listed in . For dangerous situations, our algorithm maintains good performance. Specifically, we use different

Table 6
Comparison of P_s and I under different combinations of evidences.

No.			$t-1,t$				$t+1$			
	V (km/h)	A	T	D (m)	P(x,y)	C	S = Concentration		S = Distraction	
							P_s	I	P_s	I
						Maneuver = {straight, turn_left, turn_right, stop}				
1	40	= 0	none	167–250	(x < 0,y = 0)	Dry	maintain direction	maintain speed	maintain direction	maintain speed
	40	= 0	none	167–250	(x < 0,y = 0)	Dry	and accelerate, 0.987	0.985	and accelerate, 0.868	0.839
2	40	= 0	none	167–250	(x < 0,y = 0)	Wet	maintain direction	maintain speed	maintain direction	maintain speed
	40	= 0	none	167–250	(x < 0,y = 0)	Wet	and accelerate, 0.963	0.976	and accelerate, 0.771	0.803
3	40	= 0	none	167–250	(x < 0,y = 0)	Snow	maintain direction	maintain speed	maintain direction	maintain speed
	40	= 0	none	167–250	(x < 0,y = 0)	Snow	and accelerate, 0.909	0.931	and accelerate, 0.708	0.731
4	40	= 0	none	167–250	(x < 0,y = 0)	Ice	maintain direction	maintain speed	maintain direction	maintain speed
	40	= 0	none	167–250	(x < 0,y = 0)	Ice	and accelerate, 0.890	0.901	and accelerate, 0.682	0.714
5	35	>0	left	167–250	(x < 0,y = 0)	Dry	turn_left and	accelerate	turn_left and	accelerate
	40	>0	left	250–333	(x = 0,y > 0)	Dry	accelerate, 0.975	0.966	accelerate, 0.851	0.814
6	35	>0	left	167–250	(x < 0,y = 0)	Wet	turn_left and	accelerate	turn_left and	accelerate
	40	>0	left	250–333	(x = 0,y > 0)	Wet	accelerate, 0.953	0.958	accelerate, 0.824	0.795
7	35	>0	left	167–250	(x < 0,y = 0)	Snow	turn_left and	accelerate	turn_left and	accelerate
	40	>0	left	250–333	(x = 0,y > 0)	Snow	accelerate, 0.934	0.925	accelerate, 0.817	0.766
8	35	>0	left	167–250	(x < 0,y = 0)	Ice	turn_left and	accelerate	turn_left and	accelerate
	40	>0	left	250–333	(x = 0,y > 0)	Ice	accelerate, 0.892	0.905	accelerate, 0.797	0.743
9	40	<0	right	167–250	(x < 0,y = 0)	Dry	turn_right and	decelerate	turn_right and	decelerate
	35	<0	right	250–333	(x = 0,y < 0)	Dry	decelerate, 0.958	0.926	decelerate, 0.795	0.819
10	40	<0	right	167–250	(x < 0,y = 0)	Wet	turn_right and	decelerate	turn_right and	decelerate
	35	<0	right	250–333	(x = 0,y < 0)	Wet	decelerate, 0.935	0.911	decelerate, 0.786	0.812
11	40	<0	right	167–250	(x < 0,y = 0)	Snow	turn_right and	decelerate	turn_right and	decelerate
	35	<0	right	250–333	(x = 0,y < 0)	Snow	decelerate, 0.916	0.908	decelerate, 0.754	0.804
12	40	<0	right	167–250	(x < 0,y = 0)	Ice	turn_right and	decelerate	turn_right and	decelerate
	35	<0	right	250–333	(x = 0,y < 0)	Ice	decelerate, 0.906	0.902	decelerate, 0.734	0.795
13	10	<0	none	167–250	(x < 0,y = 0)	Dry	stop	stop	stop	stop
	5	<0	none	167–250	(x < 0,y = 0)	Dry	0.983	0.989	0.806	0.813
14	10	<0	none	167--250	(x < 0,y = 0)	Wet	stop	stop	stop	stop
	5	<0	none	167–250	(x < 0,y = 0)	Wet	0.955	0.978	0.775	0.797
15	10	<0	none	167–250	(x < 0,y = 0)	Snow	stop	stop	stop	stop
	5	<0	none	167–250	(x < 0,y = 0)	Snow	0.909	0.931	0.728	0.761
16	10	<0	none	167–250	(x < 0,y = 0)	Ice	stop	stop	stop	stop
	5	<0	none	167–250	(x < 0,y = 0)	Ice	0.885	0.927	0.691	0.743

Table 7
Performance evaluation of risk assessment.

Correct warning rate (R_{ctw})	False warning rate ($R_{false.w}$)	Failure warning rate ($R_{failure.w}$)
97.8%	1.25%	0.95%

Table 8
Performance evaluation of collision avoidance under different road conditions.

Collision avoidance rate (R_{sca})	Failure avoidance rate (R_{fla})	Road condition
98.99%	1.01%	$0.63 \leqslant \mu \leq 0.9$
97.86%	2.14%	$0.4 \leqslant \mu < 0.63$
96.65%	3.35%	$0.18 \leqslant \mu < 0.4$

values of adhesion coefficient (μ) to represent different road conditions. As mentioned in Section 4.5, $0.63 \leqslant \mu \leq 0.9, 0.4 \leqslant \mu < 0.63$ and $0.18 \leqslant \mu < 0.4$ can represent the good road condition, normal road condition and bad road conditions, respectively.

In view of the common practice of the current algorithms for collision avoidance are only taking measures on *SV* (i.e. TMS) or *OV* (i.e. TMO), the performance of collision avoidance is evaluated by comparing our algorithm (i.e. TMSO) with TMS and TMO. Fig. 5 illustrates the evaluation results. For the sake of showing, the results which less than 0.6 are set as 0.6. The results show a good performance of our algorithm for the success avoidance rate maintains at a high level in spite of the driver reaction time is changing. For TMS, the success avoidance rate decreases with the increase of the driver reaction time. The main reason is that for some
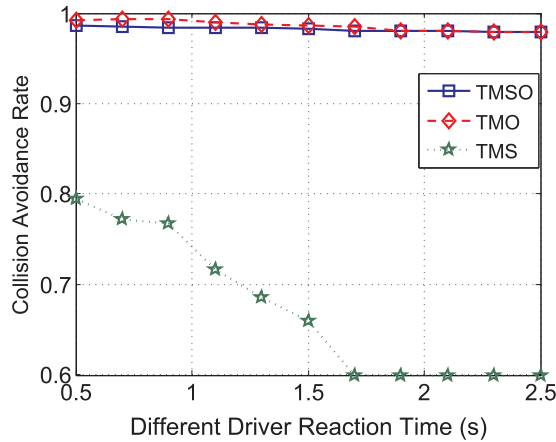
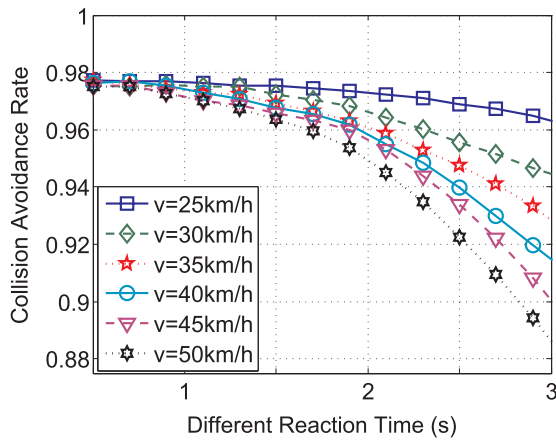**Fig. 5.** Performance evaluation for different collision avoidance strategies.

Fig. 6. Performance evaluation for different vehicular speeds and different reaction time.

emergency situations (e.g. bad state of the driver, insufficient reaction time), the collision can't be avoided by only taking actions on *SV*. In other words, actions on *OV* should be taken into account to collaborate to avoid collision. The accident cannot be avoided due to errors of location, signal transmission delay, drivers' response time and road condition estimation. For TMO, additional waiting times will be added, although the performance is good. The main reason is that the *SV* need to wait the *OV* passing through the intersection with a lower speed under any circumstances.

Subsequently, the performances of the algorithm is evaluated with different reaction time. Fig. 6 shows the successful collision avoidance rate of the vehicles at the intersection. Observe from the figure that more collisions will occur, when there is a longer reaction time as well as higher vehicular speed. However, the collision avoidance algorithm improves the attainable performance, regardless of the specific situation. Nearly 94% of the potential collisions is avoided, when the vehicular speed is 40 km/h and the reaction time is 2.5 s at the intersection.

Fig. 7 shows the successful collision avoidance rate by setting different vehicular speeds and different friction coefficient of road surface. The total reaction time is set at 2 s. The results show that the performance reduce with the increase of the vehicle speed as well as the deterioration of road condition. Particularly, the worse the road conditions is, the earlier the performance declines substantially. For example, when $\mu = 0.4$, the performance begin to decrease substantially at $v = 45$ km/h. Whereas the drop point appear at $v = 32.5$ km/h when $\mu = 0.18$. The main reason is that for slippery roads, the vehicle takes more time to slow down.

6. Conclusion

This paper addressed the problem of intersection collision by proposing an effective collision warning/avoidance algorithm for infrastructure-cooperative accident pre-warning system based on V2V and V2I communications. Some critical factors were explained and analyzed in this paper at first. Next, the vehicle state evolution was analyzed with the help of DBN, which is used to model a temporal stochastic process. Then a warning algorithm for intersection collision avoidance was designed using the vehicles state information, inter-vehicle communication and so forth. The evaluation of risk situation was based on distinguishing dangerous and
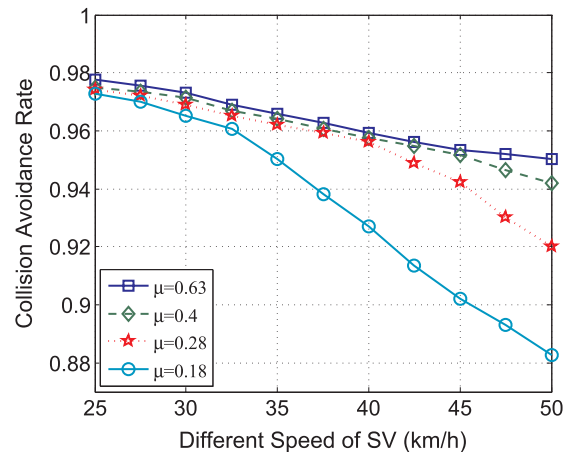
Fig. 7. Performance evaluation for different vehicular speeds and different friction coefficient of road surface. In addition, $\mu = 0.63, 0.4, 0.28$ and 0.18 represent normal road, wet road, snowy road and icy road, respectively.

safe driver behaviors. After that, different collision avoidance strategies were proposed to cope with the potential danger. The algorithm was evaluated in simulation, and the results indicated the ability of the algorithm to issue a warning to the driver when a potential dangerous situation is detected and to avoid the accident. It can be seen from the results that the maximum accuracy of risk assessment and collision avoidance algorithm reach up to 97.8% and 98.99%, respectively, which proves that the proposed algorithms can assist to improve vehicles safety at intersections.

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