COLLISION AVOIDANCE ON WINDING ROADS USING DEDICATED SHORT-RANGE COMMUNICATION

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Abstract. The emergence of wireless communication technologies such as Dedicated Short-Range Communication (DSRC) has promoted the evolution of collision warning from simple ranging-sensor-based systems to cooperative systems. In cooperative systems, path prediction is a promising method for reflecting a driver's intention and estimating the future position of vehicles. In this study, a short-term trajectory-modelling method is proposed to predict vehicle motion behaviour in the cooperative vehicular environment. In addition, a collision detection algorithm for winding roads is presented based on a model for determining the minimum distance of vehicles' future trajectories. The cooperative collision avoidance system's performance is analysed through simulation, providing useful theoretical insights into the effects of DSRC technology on vehicle collision avoidance in a curved road environment.

Keywords: collision detection; dedicated short-range communication; winding roads; cooperative vehicle system; short-term trajectory-modelling.

Introduction

Vehicle and road safety has long been a key issue for communities and governments. Daily, many road accidents occur, especially in curved road environments. On average, roadway curves experience five times more accidents than straight roadways (Lusetti *et al.* 2008). On a curved road, it is difficult for a driver to observe oncoming vehicles, increasing the possibility of opposite collisions. To avoid such collisions, many methods principally based on the exploitation of on-board sensors (Amditis *et al.* 2010; Barth, Franke 2009; Bertolazzi *et al.* 2010; Tian *et al.* 2016) have been developed. However, in light of physical limitations such as limited range and field of view, a standalone sensor or several sensors installed in a vehicle cannot detect potential dangers if they are hidden by hills or other obstructions.

Typical cooperative collision-warning systems were studied by Huang and Lin (2013); Lytrivis *et al.* (2011); Polychronopoulos *et al.* (2007), primarily based on a vehicle's dynamic state obtained from radar tracking, camera-based processing, or a communication device. In the advanced cooperative path-prediction algorithm proposed in (Lytrivis *et al.* 2011), each vehicle can perceive its neighbours' positions, velocities, acceleration, headings, and yaw rate measurements through vehicle ad hoc networks. In addition, drivers can be periodically informed of the present and future statuses of their neighbours. Similarly, (Polychronopoulos *et al.* 2007) proposed a hierarchical-structured algorithm to fuse traffic environment data to accurately predict the trajectory of an ego-vehicle (vehicle equipped with sensors), allowing the active safety system to inform or warn the driver when critical situations occur. All abovementioned studies were based on updating the current state of a vehicle using motion models.

In recent years, inter-vehicle communications based on wireless technologies such as Dedicated Short-Range Communication (DSRC) have paved the way for innovative applications in vehicle collision avoidance (Jaber *et al.* 2015; Liu, Khattak 2016; Tian *et al.* 2016).

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The GM automobile research group proposed the Co-operative Collision Warning (CCW) system (Sengupta *et al.* 2007). In CCW, vehicles exchange information such as time, longitude, latitude, course, and velocity among neighbouring vehicles via wireless communication. For such systems, collision detection is paramount and the exchanged data are used to identify potential dangers. In research by Tu and Huang (2010), each vehicle can adaptively broadcast its own calibrated motion-state information via the DSRC-based protocol. Using this information, collision detection algorithms were designed based on a model of determining the minimum distance of vehicles' future trajectories. A previous study (Lin *et al.* 2000) addressed the on-board prediction of a motor vehicle's path using the numerical integration of a linearized two-degree-of-freedom vehicle-handling model. Another important task of CCW is analysing the time to avoid collision. Tang and Yip (2010) analysed the timing of events and how they influenced collision avoidance strategies. They found that the warning strategies for collision avoidance were constrained by the timing of events such as DSRC communication latency, detection range, road condition and driver reaction and deceleration rate. Using these events, they defined two collision avoidance timings: critical time to avoid collision, and preferred time to avoid collision.

The best way to avoid collision is to predict driver intent and estimate the positions of vehicles in advance. In the vehicular network environment, 360-degree awareness can be implemented using GPS and wireless communications, so there is a strong belief that the improvement of preventive safety applications and the extension of their operative range will be achieved by cooperative vehicular applications. As a driver's intention generally does not change dramatically in a short-time, certain consistencies in the driver's inputs can be assumed. Therefore, path prediction based on the dynamic state of the vehicle can be achieved. Once path prediction is fulfilled, the algorithm can detect potential collisions and trigger different mechanisms to mitigate or avoid collisions.

Aside from viewing the rear end and overtaking and lane-changing situations on a straight road, the view of oncoming vehicles on a curved road is always the worst, as the vision of the driver is always blocked in such situations. Furthermore, unlike a straight road, on which a precise future path is easily obtained, the curvature of a road presents challenges in accurately predicting future trajectories. The main factors that affect the Predicted Minimum Distance (PMD) and Predicted Time to Minimum Distance (PTMD) include the curvature of the road and the dynamic states of vehicles.

In this paper, we will study these factors' effects on the PMD and PTMD on a curved road. The remainder of this paper is organized as follows. In Section 1, the vehicle motion model and collision avoidance algorithm are presented. Simulation experiments to evaluate the performance of the proposed collision avoidance algorithm are described in Section 2. Finally, conclusions and future work are discussed in the last section.

1. Collision Avoidance Algorithm

1.1. Overview of the Algorithm

The main object of the algorithm is to predict vehicles' trajectories from the current state and to calculate the PMD and PTMD in order to determine when a collision may occur. First, the host vehicle continuously scans the surrounding road environment through periodic communication. When the host vehicle detects an oncoming vehicle, path prediction to estimate the future positions of the host and detected vehicle over a discrete fixed-time horizon is triggered. Meanwhile, a collision detection method is run to determine whether the PMD is below a pre-set threshold. It was shown in (Polychronopoulos *et al.* 2009) that the reliable time horizon for path estimation is about 3–4 s in advance. The motion of a vehicle on a road is highly dynamic and estimation is not reliable after a few seconds; therefore, neither predicted trajectory may necessarily extend to the collision area. Correspondingly, it is necessary to update the path-prediction and collision detection processes until the values of both vehicles on the *y*-axis have reached the same value at the same time (Fig. 1).
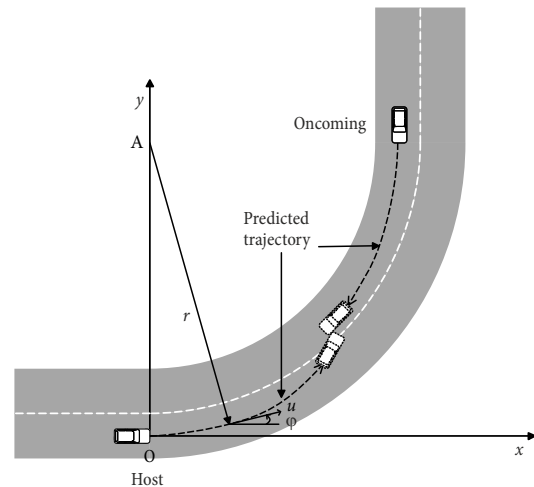

Fig. 1. Scenario of collision on curved road

In the following sub-section, we will discuss the collision avoidance algorithm in detail. The algorithm contains two parts: vehicle motion prediction and collision detection. We assume that the dynamic status of the vehicles has been accurately detected using local sensors (e.g. CAN, GPS) and communication devices.

1.2. Vehicle Motion Prediction

The successful perception of the current environment and accurate prediction of the future are the key issues for collision avoidance. On a curved road, drivers cannot see oncoming vehicles directly in some regions and therefore it would be very helpful if the host vehicle could predict the future evolution of its neighbours on the road. Vehicle motion prediction is based mainly on updating the current state of a vehicle using a vehicle

motion model. The future path can be estimated as:

$$X(k+1) = f(X(k)), \qquad (1)$$

where: $X(k)$, $X(k+1)$ denote the state vectors of a vehicle at time intervals k and $k+1$, respectively. A detailed definition of function f can be found in Eq. (8).

In this paper, three motion models are used to estimate the future path of a vehicle. The first is the Constant Acceleration (CA) model, which assumes that the acceleration of a vehicle is constant on both axes. The second is the Constant Turn Rate (CTR) model (Li, Jilkov 2003), which assumes that the yaw rate and speed of the vehicle remain constant over time. The third model is the CTR and Constant Tangential Acceleration (CTRA) model (Lin *et al.* 2000), which can be considered as a generalization of the other two models. Although the CTRA model describes the true motion of vehicles in a more realistic manner, the amount of computation needed is larger than for the others. Additionally, as drivers will typically maintain a constant velocity and turn rate in the curved road situation, the CTR model is more appropriate for estimating the future path in a curved road situation.

In the following, we will analyse the CTR model to calculate future positions. The coordinate system we use in this paper is shown in Fig. 1. In this system, the y-axis points in the velocity direction and the origin is the initial position when the host vehicle started moving on the curved road. It is assumed that the estimated trajectory has a fixed number of predicted positions, defined as N_{pp}. Without loss of generality, the time step T between two successive predicted scans is fixed and is usually set to 0.1 s. The algorithm is applied at every scan of the data sequence, performing a prediction for the next seconds with respect to the current vehicle coordinate system. So the structure of the path is a set of path points, each of which has position and velocity attributes, and the expression is given as follows:

$$P_{future\_path} = \begin{bmatrix} x_{p\_1} & x_{p\_2} & \cdots & x_{p\_k} & \cdots & x_{p\_n} \\ y_{p\_1} & y_{p\_2} & \cdots & y_{p\_k} & \cdots & y_{p\_n} \\ v_{p\_x_1} & v_{p\_x_2} & \cdots & v_{p\_x_k} & \cdots & v_{p\_x_n} \\ v_{p\_y_1} & v_{p\_y_2} & \cdots & v_{p\_y_k} & \cdots & v_{p\_y_n} \\ \omega & \omega & \cdots & \omega & \cdots & \omega \end{bmatrix}, (2)$$

where: x_{p_i}, $v_{p\_x_i}$ are the position and velocity on the longitudinal axis, respectively; y_{p_i}, $v_{p\_y_i}$ are the position and velocity on the lateral axis; ω is the yaw rate; $k = 1, 2, \ldots, n$, denotes the k-th predicted point; n is the number of path points for each path, which sum to N_{pp}.

In the CTR model, the vehicle is assumed to move with a constant turn rate and maintain constant tangential velocity, as shown in Eq. (3):

$$\omega_{k+1} = \omega_k = \omega;$$
$$v_{k+1} = v_k = v, \qquad (3)$$

where: v_k refers to the velocity of the vehicle in the tangential direction, with constant magnitude but varying direction with time.

Based on the two basic assumptions listed above, the velocity of the vehicle can be analysed in terms of components that are defined from the velocity magnitude v and the heading angle φ as:

$$v_x = v \cdot \cos(\varphi);$$
$$v_y = v \cdot \sin(\varphi), \qquad (4)$$

where: ω can be defined as $\omega = \dfrac{d\phi}{dt}$, and we define $\varphi = 0$, when the vehicle starts to move on the curved road. The location-prediction equations are derived as:

$$\begin{cases} x(k+1) = x(k) + \displaystyle\int_{t_k}^{t_{k+1}} v_x(\tau \mid t_k)d\tau; \\ y(k+1) = y(k) + \displaystyle\int_{t_k}^{t_{k+1}} v_y(\tau \mid t_k)d\tau, \end{cases} \qquad (5)$$

where: $x(k+1)$, $y(k+1)$ is the predicted location of the vehicle at t_{k+1}; $x(k)$, $y(k)$ is the location of the vehicle at t_k; $v_x(\tau \mid t_x)$ is the velocity of the vehicle in x direction at τ ($t_k \le \tau \le t_{k+1}$); $v_y(\tau \mid t_k)$ is the velocity of the vehicle in y direction at τ ($t_k \le \tau \le t_{k+1}$).

The velocity equation is then:

$$\begin{cases} v_x(k+1) = a_1; \\ v_y(k+1) = a_2, \end{cases} \qquad (6)$$

where:

$$a_1 = v \cdot \cos(\varphi + \omega \cdot T) = $$
$$v_x(k) \cdot \cos(\omega \cdot T) - v_y(k) \cdot \sin(\omega \cdot T);$$
$$a_2 = v \cdot \sin(\varphi + \omega \cdot T) = $$
$$v_x(k) \cdot \sin(\omega \cdot T) + v_y(k) \cdot \cos(\omega \cdot T),$$

where: $T = t_{k+1} - t_k$ is the time interval between two sequential scans. The displacements of the host vehicle along the two axes are calculated as:

$$\begin{cases} x(k+1) = a_1; \\ y(k+1) = a_2. \end{cases} \qquad (7)$$

where:

$$a_1 = x(k) + \frac{1}{\omega} \cdot \big(\sin(\omega \cdot T) \cdot v_x(k) - $$
$$\big(1 - \cos(\omega \cdot T)\big) \cdot v_y(k) \big);$$
$$a_2 = y(k) + \frac{1}{\omega} \cdot \big(\big(1 - \cos(\omega \cdot T)\big) \times $$
$$v_x(k) + \sin(\omega \cdot T) \cdot v_y(k) \big).$$

Thus, the solution of the updated equation for this model can be given in the following form:

$$\begin{cases} x(k+1) \\ v_x(k+1) \\ y(k+1) \\ v_y(k+1) \\ \omega(k+1) \end{cases} = \begin{cases} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{cases}, \qquad (8)$$

where:

$$a_1 = x(k) + \big(\sin(\omega \cdot T) \cdot v_x(k) - $$
$$\big(1 - \cos(\omega \cdot T)\big) \cdot v_y(k)\big) \big/ \omega;$$

$$a_2 = v_x(k) \cdot \cos(\omega \cdot T) - v_y(k) \cdot \sin(\omega \cdot T);$$

$$a_3 = y(k) + \big((1 - \cos(\omega \cdot T)) \cdot v_x(k) + \sin(\omega \cdot T) \cdot v_y(k)\big)\big/\omega;$$

$$a_4 = v_x(k) \cdot \sin(\omega \cdot T) + v_y(k) \cdot \cos(\omega \cdot T);$$

$$a_5 = \omega(k).$$

The initial state vector used for the host vehicle can be given as:

$$x_h(0) = 0;$$
$$y_h(0) = 0;$$
$$v_{hx}(0) = v;$$
$$v_{hy}(0) = 0;$$
$$\omega_h(0) = \omega_h. \tag{9}$$

The same motion model can be used for the oncoming vehicle, but with the initial state vector having the following form:

$$x_o(0) = x_{o0};$$
$$y_o(0) = y_{o0};$$
$$v_{ox}(0) = v_{ox_0};$$
$$v_{oy}(0) = v_{oy_0};$$
$$\omega_o(0) = \omega_o. \tag{10}$$

1.3. Collision Detection

Timely warning and reacting to a potential collision depend on two categories of information: (1) the space between two vehicles and their relative speed and positions; (2) the time it takes for the driver and the vehicle to avoid the danger (Tang, Yip 2010). We can derive the future trajectories of the host and oncoming vehicles in a discrete time series based on the model defined in the above subsection. In fact, ensuring the accuracy of the path prediction requires that the time span to predict the path cannot be too long. If this time is longer than 4 s, the accuracy will decrease significantly because the estimate will deviate from the actual value dramatically. Therefore, we set $t_{span} = N_{pp} \times T$ as 4 s, which is the fixed interval for detecting a potential collision when the host and oncoming vehicles move towards each other. We assume that at time T_{pre} the host vehicle predicts the future path of both vehicles to determine whether a conflict will occur. The parameters PMD and PTMD reflect the potential danger in space and time. In the detection interval $t_k \in [T_{pre}, T_{pre} + t_{span}]$, the predicted positions of both vehicles are denoted as $p_h(t_k)$ and $p_o(t_k)$, respectively. The condition for repeating the detection process is when y_{p_h} is larger than y_{p_o}. If $y_{p_o} > y_{p_h}$, there is no potential conflict between the vehicles within the next 4 s; therefore, we set $T_{pre} = T_{pre} + 1$ and repeat the above process. If $y_{p_o} \leq y_{p_h}$, there is potential conflict and the detection time is defined as T_{pred}. The problem that must be addressed can be formulated into a minimization problem that calculates the minimum value of the relative distance of the two vehicles, which

can be denoted as:

$$d_{relative}(t_k) = \|p_h(t_k) - p_o(t_k)\|, \tag{11}$$

where: $t_k = k \times T$.

Assuming that time $t_m \in [T_{pred}, T_{pred} + t_{span}]$, we obtain the minimum value of the distance:

$$d_{relative}(t_m) = \min_{k=1,\ldots,N_{pp}} d_{relative}(t_k). \tag{12}$$

Then, the values of the parameters PMD and PTMD are:

$$PMD = d_{relative}(t_m);$$
$$PTMD = t_m - T_{pred}. \tag{13}$$

If *PMD* < *threshold*, the algorithm will warn the driver to take action to avoid it. The detailed process is shown in the pseudo-code of the cooperative collision avoidance algorithm, which includes the following parameters:

- *w* denotes the road width;
- *r*1 denotes the ideal radius the host vehicle will follow;
- *r*2 denotes the ideal radius the oncoming vehicle will follow;
- *X_h(k+1)*, *X_o(k+1)* denote the state of the host and the oncoming vehicle, respectively, at scan *k*+1;
- *X_h(k+1) = f(X_h(k))* refers to the model defined in Eq. (8);
- *isc* is a mark to determine whether a potential collision has been detected.

Algorithm: Cooperative Collision Avoidance

Input: *r, v1, v2, threshold*
Output: warning strategy
Initialization:

```
r1=r+w/2, r2= r−w/2;
x_h(1)=0, y_h(1)=0;
x_o(1)=r1, y_o(1)=r2;
yawrate_h=v1/r1+delta;
yawrate_o=v2/r2;
X_h(1)=(x_h(1), y_(1), v1, 0)^T;
X_o(1)=(x_o(1), y_o(1), 0, v2)^T;
relativeDis(1)=||( x_h(1), y_h(1)),( x_o(1), y_o(1))||;
Npp=40, T=0.1;
Tpre=0, isc=0;
```

Program:

```
Do {
    For k=1:1:Npp−1
    X_h(k+1)=f(X_h(k));
    X_o(k+1)=f(X_o(k));
        relativeDis(k+1)=||(x_h(k), y_h(k)), (x_o(k), y_o(k))||;
    End for
    For m=1:1:Npp
        If (y_h(m)>y_o(m))
isc=1;
        Tpred=Tpre;
        break;
```

```
    else
        Tpre=Tpre+1;
        X_h(1)=X_h(11);
        X_o(1)=X_o(11);
    End if
  End for
} While(isc=0)
For i=1:1:Npp
    PMD=relativeDis(q)=min(relativeDis(i));
    PTMD=Tpred+q*T;
End for
If(PMD<threshold)
    Warn the driver to steer;
End if
```

2. Simulation Experiments

This section describes several experiments performed to validate the proposed algorithm and analyse the influencing factors of the PMD and PTMD. The method is simulated with MATLAB, and the algorithm runs in an *Intel i5* CPU computer. In the simulations, we selected a quarter circle as the curved road situation (Fig. 1). We defined the value of the velocity as positive if its direction was consistent with the positive direction of both coordinate axes. Some initial values are given in Table 1.

Table 1. Initial values

Parameter	Value	
	Host vehicle	Oncoming vehicle
$x(0)$ [m]	0	157.25
$y(0)$ [m]	0	162.50
$v_x(0)$ [m/s]	10	0
$v_y(0)$ [m/s]	0	−10
$\omega(0)$ [rad/s]	0.0645	0.0634

In Fig. 2, we show the ideal situation when vehicles drive on a curved road. The ideal assumption is that both vehicles will maintain a constant tangential velocity v and a constant yaw rate v/r and that they will drive along the curve. Vehicle collisions on a curved road occur when the yaw rate deviates from the ideal trajectory.
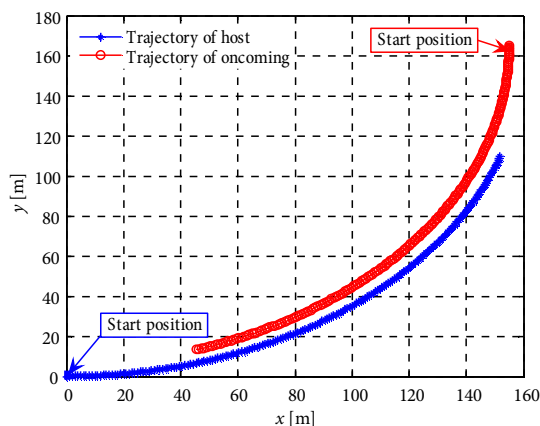

Fig. 2. Ideal trajectories of both vehicles

First, we validated the feasibility of the proposed detection method. From Fig. 3a, it is seen that at time 9 s the proposed method predicted that the position on the y-axis would be greater than that of the oncoming vehicle, which implies that the vehicles would collide. For accurate collision warning, it is necessary to predict the most dangerous positions, at which the distance of one or more vehicles is lower than the threshold. In fact, collision occurs when vehicles overlap in both space and time; therefore, time is a crucial factor to be taken into consideration. As such, the intersection point in Fig. 3a does not necessarily denote a collision or dangerous point.
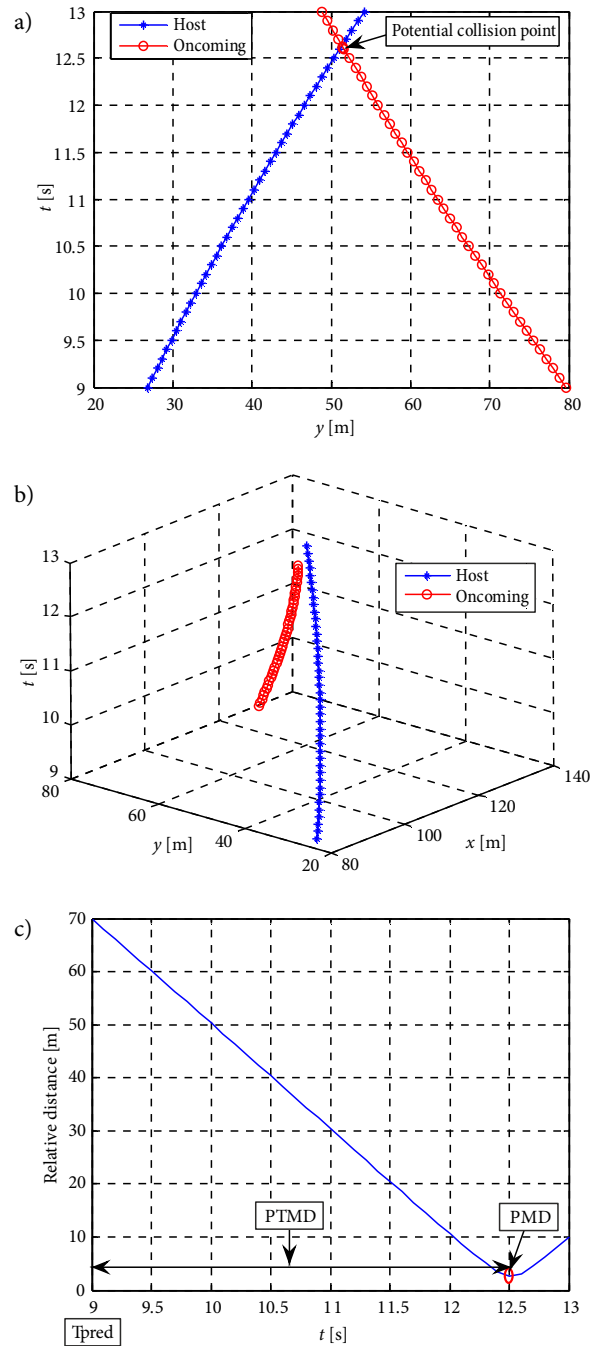

Fig. 3. Collision detection: a – change in position along y-axis with time, b – change in position with time; c – change in relative distance with time

In fact, from Fig. 3b the trajectories of the two vehicles do not intersect, although their distance reaches a minimum value. Fig. 3c shows the variation of the relative distance of the two vehicles. From it we see clearly that the relative distance reaches a minimum value at $t = 12.5$ s, where the position is the PMD and the time is the PTMD.

Fig. 4 shows that the time T_{pre} when the PMD could be detected varied with the speeds of the host and the oncoming vehicles. Assuming that the speed of an oncoming vehicle is constant, T_{pre} starts to decline with the speed of the host vehicle. This means that, by increasing the speed, we can detect the PMD earlier, although the host vehicle will also meet with the oncoming vehicle more quickly.

From Table 2, it is seen that the value of PTMD is maintained at around 3.0 s when the speed changes from 30 to 60 km/h. Considering that the human reaction time τ_{hum} is 0.7–1.5 s (Chang *et al.* 2010), there is sufficient time for the driver to take an action such as steering to avoid the collision. Fig. 5 shows the change
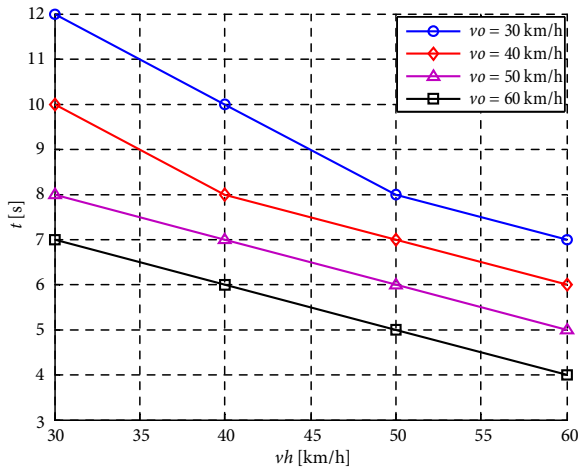
in the PMD with velocity; it is seen from this that the PMD increases with the velocity.

Road curvature is another important factor that influences the PMD and PTMD. From Table 3, it is seen that the value of the PMD varies with the radius of curvature R, i.e. it is inversely proportional to R. This is because an increase in R, assuming that other conditions such as velocity and yaw rate remain the same, corresponds to an increase in both the PTMD and T_{pred}.

Table 2. PTMD at various speeds

vh [km/h] vo [km/h]	30	40	50	60
30	3.1	3.0	3.5	3.3
40	3.0	3.4	3.1	3.2
50	3.4	3.1	3.1	3.3
60	3.1	3.1	3.3	3.6

Table 3. PMD, PTMD, and T_{pred} at different curvature radii

R [m]	PMD [s]	T_{pred} [s]	PTMD [s]
100	5.0159	9	3.3
110	4.3986	9	3.3
120	3.9278	9	3.4
130	3.5387	9	3.4
140	3.2096	9	3.5
150	3.0471	9	3.6
160	2.8543	9	3.6
170	2.5920	9	3.7
180	2.4483	9	3.8
190	2.4494	9	3.9
200	2.2705	10	2.9
210	2.1016	10	3

Fig. 4. Change in time T_{pred} with speed (*vo* represents the speed of the oncoming vehicle; *vh* represents the speed of the host vehicle)
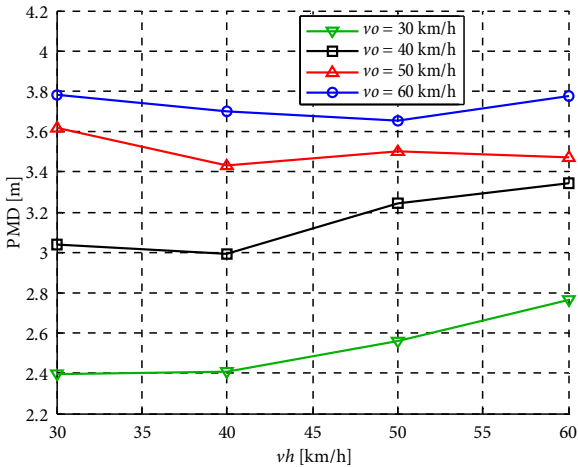

Fig. 5. Change in PMD with speed (*vo* represents the speed of the oncoming vehicle; *vh* represents the speed of the host vehicle)

Figs 6–8 show the relative distances of the vehicles, the velocity of the host vehicle along the *x*- and *y*-axes, and the trajectories of the host and oncoming vehicles, respectively. We will analyse the effect of communication (e.g. DSRC) on cooperative collision avoidance. The trajectories of the host and oncoming vehicles are shown in Fig. 6. In this group of pictures, we define P_{pred} as the position at which the future potential danger is detected and P_{act} as the position at which the action (e.g. steering) to change the driving state comes into effect. To demonstrate the influence of communication, we assume here that the oncoming vehicle drives at the ideal trajectory from Fig. 2. The ideal trajectory of the host vehicle is drawn as a purple line. Actually, at position P_{pred} the real trajectory of the host vehicle is offset from the ideal trajectory. A vehicle equipped with a DSRC device enters a changed driving state, as the DSRC is used to forecast potential danger, resulting in a moderating action that tends to steer the trajectory towards the ideal trajectory.
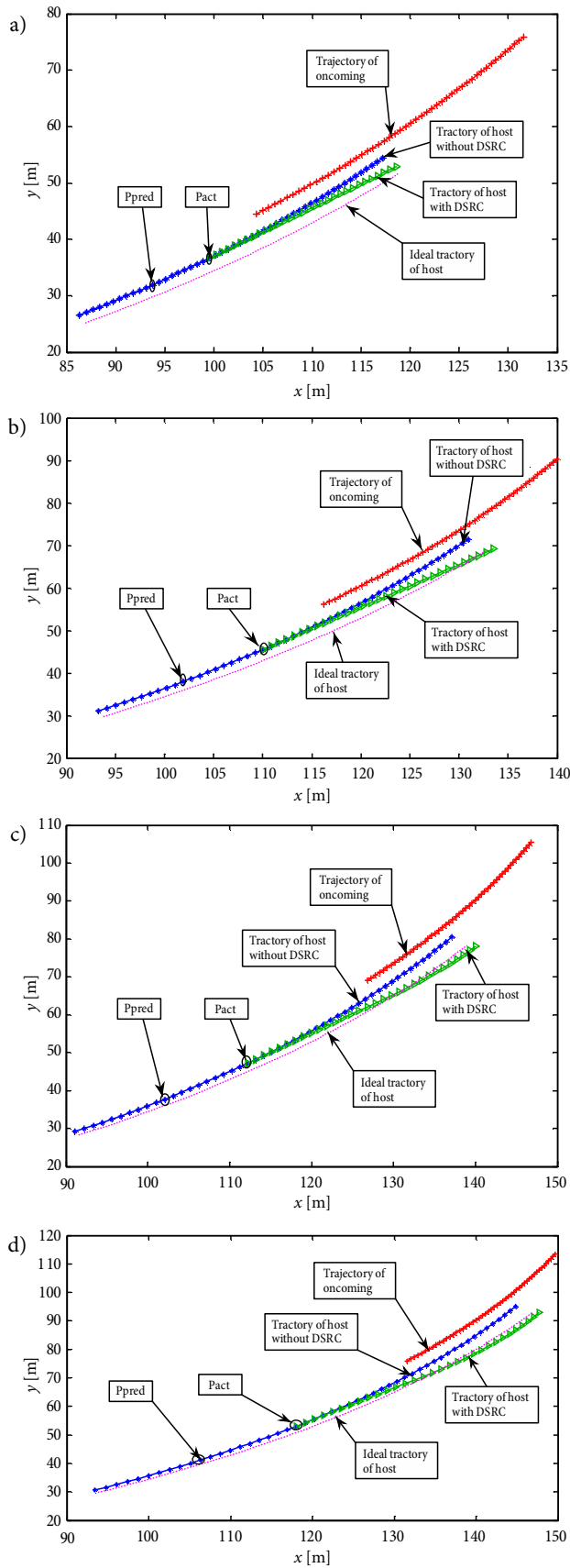
Fig. 6 Trajectories of the host and oncoming vehicles:
a – v_{host} = 30 km/h; b – v_{host} = 40 km/h;
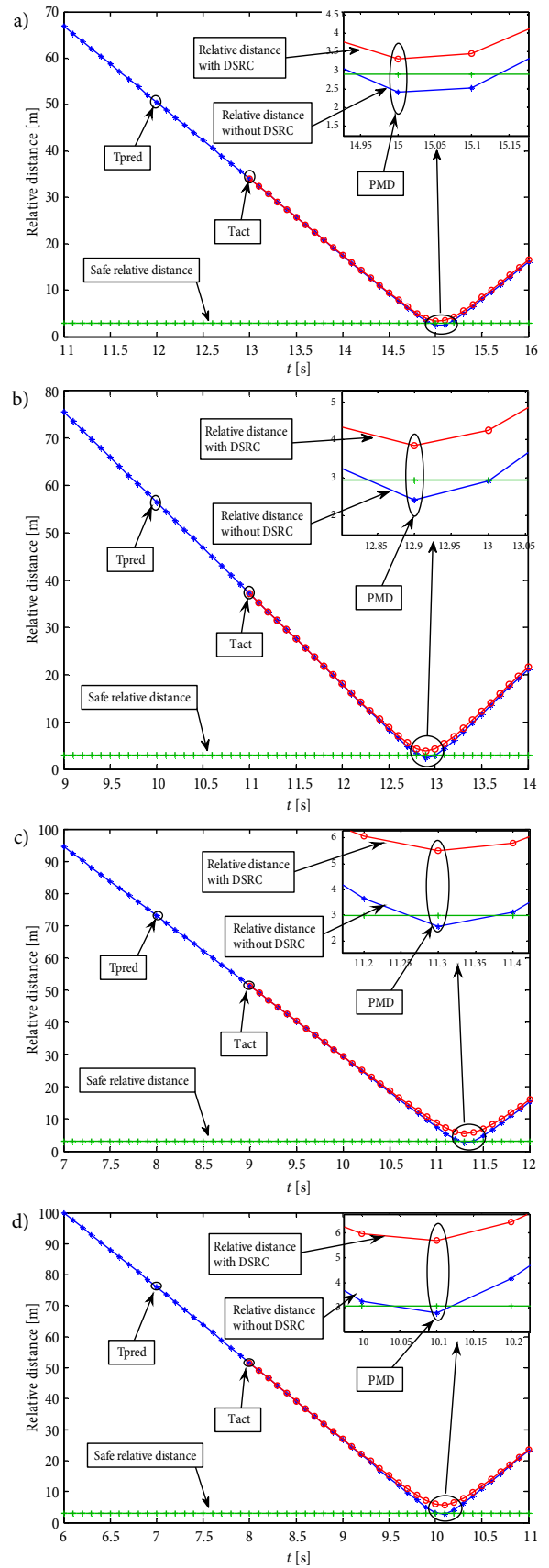c – v_{host} = 50 km/h; d – v_{host} = 60 km/h

Fig. 7. Change in relative distance between the host and
the oncoming vehicle over time: a – v_{host} = 30 km/h;
b – v_{host} = 40 km/h; c – v_{host} = 50 km/h; d – v_{host} = 60 km/h
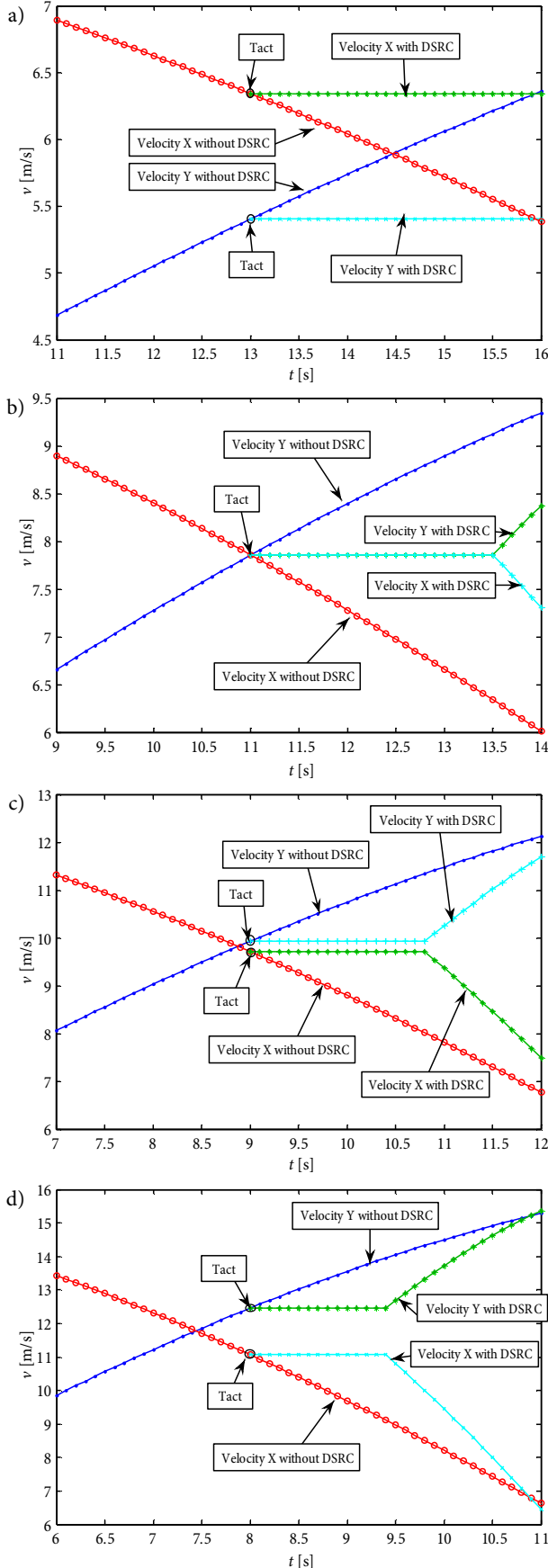
Fig. 8. Change in the velocity of the host vehicle in both axes over time: a – v_{host} = 30 km/h; b – v_{host} = 40 km/h; c – v_{host} = 50 km/h; d – v_{host} = 60 km/h

In the experiments, we set a threshold to detect collision: namely, the safe relative distance, which is calculated as $d_{safe} = 0.94 + \dfrac{v_h - 40}{200}$, where v_h is the velocity of the host [km/h]. From Fig. 6 it is seen that a vehicle with DSRC can identify a potential danger at the time T_{pred} and then take action to avoid it (e.g. steering). Considering the reaction time of the driver and the response time of the vehicle, the state of the vehicle changes at time T_{act}. However, the time PTMD is still enough to mitigate the danger because the value of the PMD is above the safe relative distance curve, as can be seen from the partial enlarged view of each picture in Fig. 6.

The time needed to pull the vehicle to the ideal trajectory is seen in Fig. 7. This time, which is the time from T_{act} to the time when the red line splits from the blue line, is about 1.5 s. Thus, when the driver sees the danger, a moderate alteration will not be effective, resulting in the adoption of hard actions such as emergency steering, which is dangerous, especially on a curved road.

The change in velocity of the host vehicle with time is shown in Fig. 8. At time T_{act}, the velocities along both axes of the vehicle equipped with DSRC are modified from the previous curve for that the vehicle comes to change its trajectory to the ideal one to avoid the collision. In terms of the coordinate system used in this paper, an increase of velocity along the y-axis means that the host vehicle is moving towards the oncoming vehicle while the velocity along the x-axis decreases to maintain a constant total velocity. To avoid a detected potential collision, it is necessary to pull the trajectory towards the ideal. Therefore, a strategy of allowing the vehicle to move in the tangential direction will keep the velocity along both axes constant for a while. With an increase in speed, the car moves more quickly towards the ideal trajectory, as seen in Fig. 7. However, if the vehicle crosses the ideal trajectory, other dangers, such as collision with the road boundary, will occur; in this case, the velocity along the y-axis will increase and the velocity along the x-axis will decrease (Fig. 8b–d) to allow the trajectory of the host to approach the ideal trajectory.

Conclusions

On winding roads, it is difficult for a driver to observe oncoming vehicles, and the sensors installed in a vehicle cannot detect potential dangers if they are hidden by obstructions. Wireless communication technologies have made vehicle-to-vehicle communication possible. Thus, active vehicle safety systems need not rely only on on-board sensors but also on communication with other vehicles via DSRC. This paper analysed collision detection on a curved road using a cooperative vehicle motion model, which considers the curvature of the road and the dynamic states of vehicles. Based on the model, we derive the future trajectories of the host and oncoming vehicles in a discrete time series, and present the cooperative collision avoidance algorithm. In several experiments, we analysed the effects of velocity and road

curvature on the PMD and PTMD. The results showed that the DSRC technology could help to warn a driver to avoid collisions earlier. In future work, we will take more parameters (e.g. GPS error, driver's behaviour, etc.) into account, and analyse the performance based on the CTRA model.

Contribution

Daxin Tian, Yong Yuan and Jian Wang (ORCID: 0000-0002-2900-2275) designed and performed the DSRC model research, Haiying Xia and Jian Wang (ORCID: 0000-0002-7701-8511) analysed the experimental results.

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Disclosure Statement

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