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A method for connected vehicle trajectory prediction and collision warning algorithm based on V2V communication

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ABSTRACT

Connected vehicle communication technology is rapidly developing in recent years, and host vehicle (HV) can send or receive the basic safety message (BSM) from the remote vehicles (RVs). However, there are few applications using this information to improve the driving safety. In this paper, we propose a collision warning predicted framework that provides connected automated vehicle and alert driver when time to collision (TTC) is within specified thresholds. After preprocessor RV BSM data, this paper transforms the RV position and calculates the relative position, distance and speed. Then, the RV trajectory is estimated by using Kalman filter algorithm, and the error statistics of the prediction of latitude and longitude are analysed. The prediction results show that it works on straight, corner and the curve road, but the latitude error is higher than the longitude error. At last this paper constructs the relative position radar map for the HV, in which it can show the relative position, speed and TTC information. Vehicle collision can be detected in real time and the vehicle can prevent the potential conflict accordingly by using these information.

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1. Introduction

Driving safety is one of the most important subjects for researchers and developers of automotive industry. An accurate and reliable vehicle future trajectory algorithm can improve driving safety by detecting the potential collision in advance and reducing the risks of vehicle collisions based on vehicle-to-vehicle (V2V) communication. Most of the existing advanced driver assistance systems (ADAS) or typical vehicle collision warning systems (CWSs) are based on the information measured by the host vehicle (HV) via their own sensors, such as camera, radar, LiDAR, acoustic and others [1,6,13,22]. When the warning occurs, there is only limited time left for the driver to react. Therefore, there is still a risk of collision. With the earlier vehicle future trajectory prediction technology, driver can become aware of the nearby vehicle and traffic situation so that they can have enough time to make appropriate decisions to avoid potential collisions and lead to safer and more efficient driving manoeuvres [10,21].

Right now, V2V communication systems is being developed to improve traffic safety, while providing wireless connectivity on the mobility [4,7,8,16,17,19,25]. V2V communications use on-board dedicated short-range communication (DSRC) devices to transmit basic safety message (BSM) to other vehicles and receive the information [14]. A vehicle broadcasts information representative of its status in a BSM at a frequency of 10 Hz. Examples of such information include vehicle's latitude, longitude, speed, acceleration, heading angle, yaw rate, brake status and so on. Using this data, a receiving HV can calculate the remote vehicle (RV) location and future trajectory. Finally, this information can be utilised to detect collision hazards and possibly aid the driver in avoiding a conflict or mitigating its effects [17].

Many researchers and scientists show great interest in predicting the RV trajectory. They have made significant studies such as theory study, algorithm propose, simulation and field test. Tan et al. [13] have explored the engineering feasibility of the cooperative collision warning system, where vehicles are equipped with a differential global position system (DGPS) unit and motion sensors. Yang has defined congestion control policies for emergency warning messages and proposed a vehicular collision warning communication protocol to improve road safety so that a low emergency warning message delivery delay can be achieved and a large number of coexisting abnormal vehicles can be supported [23]. Jin has proposed acceleration-based connected cruise control (CCC) to increase roadway traffic mobility. CCC is designed to

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have access to signals received from multiple vehicles ahead through V2V communication [9]. William has proposed Eigen-based and Markov-based methods to explore the taxi GPS trajectories in real world [12].

It is important and relatively difficult for a vehicle to predict accurately the future location of a vehicle in connected vehicle systems. Barrio et al. [2] have explored four models of the vehicles' behaviours: a vehicle that is not moving, a vehicle travelling at constant velocity (CV), a vehicle travelling with constant acceleration (CA) and a vehicle travelling with a constant jerk (CJ) to predict the vehicle future trajectories. Jihua et al. [15] have explored the feasibility of vehicle future trajectory prediction via vehicle positions and velocities from DGPS-based positioning system and use of the positions and trajectories of nearby vehicles for the construction of the local driving environment. He also analysed the error statistics of the prediction by treating the model-based prediction as an equivalent open-loop Kalman filter (KF) [15].

Groves et al. [11] have proposed a framework for predicting the paths of vehicles which move on a road network. The framework leverages global and local patterns in spatio-temporal data and consists of three parts: the first part provides a graph derived from a GPS location data at the neighbourhood or street level, the second part generates policies obtained from the graph data and the third part predicts the subsequent path of an in-progress trajectory. Yanlei et al. [24] have proposed estimating vehicle position by using three-dimensional (3D) maps and ray-tracing method in order to overcome the problems in urban canyon [24]. Zhu et al. [28] have developed a linear programming formulation for autonomous intersection control (LPAIC) which accounts for traffic dynamics within a connected vehicle environment.

These studies mainly concentrate on specific aspects and cannot evaluate cooperative safety applications under different and challenging testing conditions repetitively. In order to advance this potential initiative, University of Michigan Transportation Research Institute (UMTRI) has evaluated a scaled deployment of V2V technologies in Ann Arbor, including over 3500 equipped vehicles and more than 90 miles of instrumental roadways [5]. The Virginia Tech Transportation Institute (VTTI) has already implemented connected applications, including traveller information, enhanced transit operations, lane closure alerts, work zone and incident management [27]. Sepulcre has presented the implemented cooperative V2V testing platform, including a detailed description of the implemented on-board unit, cooperative applications and testing vehicles and facilities. There are likewise some analysis and discussions about the most significant results of the extensive testing campaign [20]. Tamas et al. [18] have investigated the dynamics of vehicular strings when assuming deterministic packet drops scenarios.

From the connected vehicle field test, it can be seen that connected vehicle system delays or drops in wireless communication due to intermittency and packet, the HV may get the RV previous state, which may increase human reaction time [26].

In order to help the HV to detect the RV in advance, this paper aims to explore the RV future trajectory algorithm based on connected vehicle information and to explore a framework of future trajectory prediction for connected vehicle early collision warning prediction. This paper first presents how to pre-process the vehicle BSM, then builds some algorithm to compute the relative position distance and speed for the connected vehicle. The second part provides the state equation of the vehicle and the prediction of the vehicle future trajectory by using KF algorithm. In the final step, the relative position radar map for the HV is built, and the time to collision (TTC) will be used for HV to predict the hazard.

2. Method

After the HV gets the information from the surrounding vehicle, predictions about the trajectory are made mainly including pre-processor RV data, such as GPS, speed, heading and the basic information of the RV.

2.1. GPS data pre-processor

A received GPS data could be missing or erroneous due to the sensor not being able to take measurement (system frequency running faster than the sensor, malfunction or no satellites found for the GPS) from the RV or the device not being able to read from the HVs. When a measurement is absent and the value is needed for the models, the missing or error values are calculated from the previous real measurements.

2.2. RV position transformation

When connected vehicle travel on the road, the HVs will get the BSM from the nearby RV. An RV position transformation algorithm will transform the position and heading direction to the host. Therefore, the HV can scan the RV status and relative safety message.

$$P(t_i) = [\theta(t_i), \varphi(t_i)] \tag{1}$$

$$\Delta d_r(t_i) = \begin{cases} P_r(t_i) - P(t_i), i = 1 \\ P_r'(t_{i+1}) - P(t_i), i > 1 \end{cases} \tag{2}$$

where $[\theta(t_i), \varphi(t_i)]$ are the latitude and longitude coordinates for a vehicle and $P(t_i)$, h, r, $\Delta d_r(t_i)$ represents a

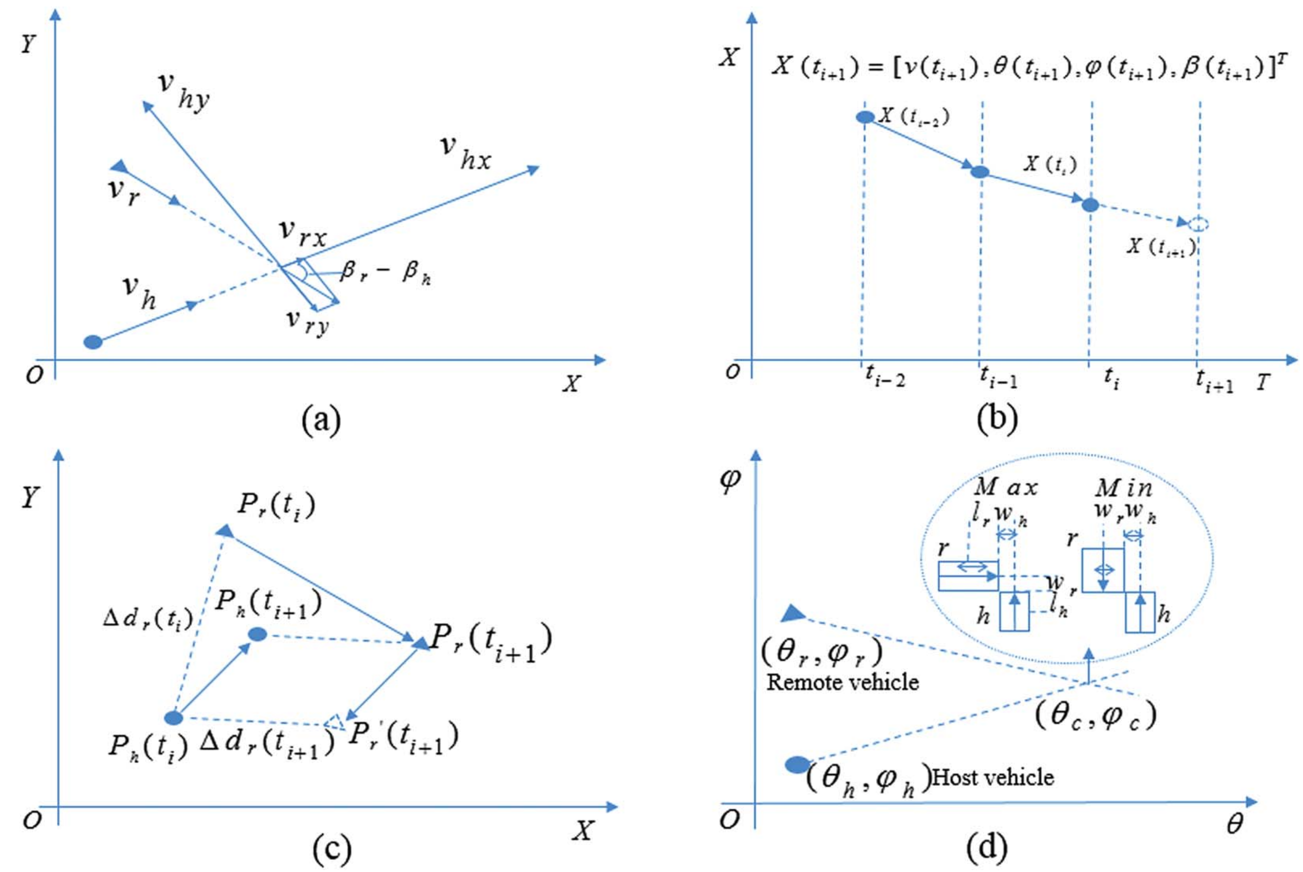

Figure 1. A brief schematic diagram for the algorithm.

vehicle current location, the HV, the RV and the current distance between the HV and RV, respectively (see Figure 1(c)).

2.3. Relative position distance

The two separate vehicle current distance equation is

$$\Delta d = \arccos(\sin\theta_h \sin\theta_r + \cos\theta_h \cos\theta_r \cos(\varphi_h - \varphi_r)) \quad (3)$$

where (θ_h, φ_h) and (θ_r, φ_r) are the longitude and latitude coordinates for the host and RV locations, respectively, and Δd represents the current distance between the HV and an RV.

2.4. Relative speed

Vehicular relative speed equation is

$$v_{rx} = v_r \cos(\beta_r - \beta_h) \quad (4)$$

$$v_{ry} = v_r \sin(\beta_r - \beta_h) \quad (5)$$

$$\Delta v_{rh} = v_{rx} - v_h \quad (6)$$

where v_r represents the RV current speed, v_h represents the HV current speed, v_{rx} represents the RV current projection speed of HV travelling direction, v_{ry} represents the RV current projection speed of HV travelling vertical direction, β_r represents the RV heading direction degree and β_h represents the HV heading direction degree. A two-vehicle travels simplified model is shown in Figure 1(a).

2.5. Vehicle trajectory estimation and prediction

The discrete-time state equation of the HV and RV is

$$X(t_i) = [x(t_i), y(t_i), v(t_i), \beta(t_i)]^T \quad (7)$$

$$X(t_{i+1}) = \begin{bmatrix} 1 & 0 & \sin(\beta(t_i))dt & 0 \\ 0 & 1 & \cos(\beta(t_i))dt & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(t_i) \\ y(t_i) \\ v(t_i) \\ \beta(t_i) \end{bmatrix} + w(t_i) \quad (8)$$

where $X(t_{i+1})$represents the prediction state of an HV or RV, $X(t_i)$ represents the current state of a vehicle, $x(t_i)$ represents a vehicle west−east position (m) calculated by longitude degree, $y(t_i)$ represents the vehicle south−north position (m) calculated by latitude degree, $v(t_i)$ represents a vehicle speed, $\beta(t_i)$ represents the vehicle traveling direction which degree from north, $t_i$represents time-stamps and $w(t_i)$is a white Gaussian noise. Vehicle travels trajectory estimation simplified model is shown in Figure 1(b).

For this research, KF is the core method chosen to estimate a future trajectory of a vehicle. Usually average human reaction time is 1.5 s to stop a vehicle; this system algorithm will be set up to 3 s later to estimate a future position of a vehicle. Looking at 3 s ahead of time is chosen as a prediction time that is double the reaction time of an average human being [3].

2.6. Current collision detection

The TTC_{hr} for the current collision detection is based on the current relative speed and distance, and the compute equation is

$$TTC_{\mathrm{hr}} = \frac{\Delta d_{\mathrm{r}}}{\Delta v_{\mathrm{rh}}} \tag{9}$$

where Δv_{rh} represents the relative speed of HV and RV, and d_{r} represents the distance between the HV and RV prediction collision point.

2.7. Early collision detection

The hazard of vehicle collision is detected by TTC using vehicle GPS position estimation. TTC in this paper is the early time to collision. The conflict model estimation method diagram is shown in Figure 1(d). Generally, when the collision happened to two vehicles, they are subjected to the following equation:

$$\begin{cases} \theta_h(t_c) = \theta_r(t_c) \\ \varphi_h(t_c) = \varphi_r(t_c) \end{cases} \tag{10}$$

where t_c is the collision time of the two vehicles, and (θ_h, φ_h) and (θ_r, φ_r) are the latitude and longitude coordinates for HV and RV, respectively.

However, vehicle has its size, so that the trim size of the vehicle will be considered in this section to predict the vehicle time to collision.

$$\begin{cases} \theta_r(t_c) + \frac{1}{2}(l_r + w_h) \cdot C_\theta \leq \theta_h(t_c) \ or \ \theta_h(t_c) \leq \theta_r(t_c) - \frac{1}{2}(w_r + w_h) \cdot C_\theta \\ \varphi_r(t_c) + \frac{1}{2}(l_r + w_h) \cdot C_\varphi \leq \varphi_h(t_c) \ or \ \varphi_h(t_c) \leq \varphi_r(t_c) - \frac{1}{2}(w_r + w_h) \cdot C_\varphi \end{cases} \tag{11}$$

where C_θ and C_φ are constants, C_θ represents the length of a degree of longitude in meter of specific latitude, C_φ represents the length of a degree of latitude in meter of specific latitude, l_h represents the HV length, l_r represents the RV length, w_h represents the HV width and w_r represents the RV width.

3. Results

3.1. Vehicle trajectory prediction

3.1.1. Straight and corner scenario

The vehicle trajectory in straight and corner test and the prediction performance shown in Figure 2(a) and (b) are different vehicle test case results.

Figure 2(a) shows that the vehicle conducts a 67-second urban-driving from south to north, which includes straight driving, right turn and its speed varying from 3.3 to 25.5 m/s, and the prediction errors are also recorded. Assuming that the GPS position reading is accurate, this prediction error was calculated when the time stamps between the predicted position and GPS position. The longitude predicted error is -0.34 ± 0.88 m, while the latitude KF predicted error is -0.75 ± 0.90 m as shown in Figure 2(a). Figure 2(b) shows the different test for the same vehicle. This test lasts longer than the previous one whose travel duration is 198 s and includes four straight driving, two left turns, two right turns and its speed varies from 0 to 22.4 m/s. The longitude KF predicted error is -0.14 ± 0.76 m, while the latitude predicted error is -0.53 ± 0.85 m as shown in Figure 2(b).

3.1.2. Curve scenario

Figure 3 shows the vehicle predicted trajectories on the curve road. From its measurement and prediction error curves, it can be seen that the average measurement errors are higher than the prediction errors, and trajectories prediction has a good performance. Figure 3(a) shows that the vehicle travel duration is 41.1 s which includes two curves driving, and its speed varies from 0 to 18.36 m/s. The longitude predicted error is -0.26 ± 0.71 m, while the latitude KF predicted error is -2.44 ± 1.43 m as shown in Figure 3(a). Figure 3(b) shows that the vehicle travel duration is 20.5s which includes one sharp curve and one smooth curve driving, and its speed varies from 0.59 to 14.87 m/s. The longitude predicted error is -0.18 ± 0.68 m, while the latitude KF predicted error is -1.24 ± 1.41 m in Figure 3(b).

The prediction error of curves is similar to straight paths; however, the measured error increased when curves begin. The errors in latitude are higher than longitude both in straight or curve road according to the prediction error, but the latitude position errors curve driving has more error compared with straight driving.

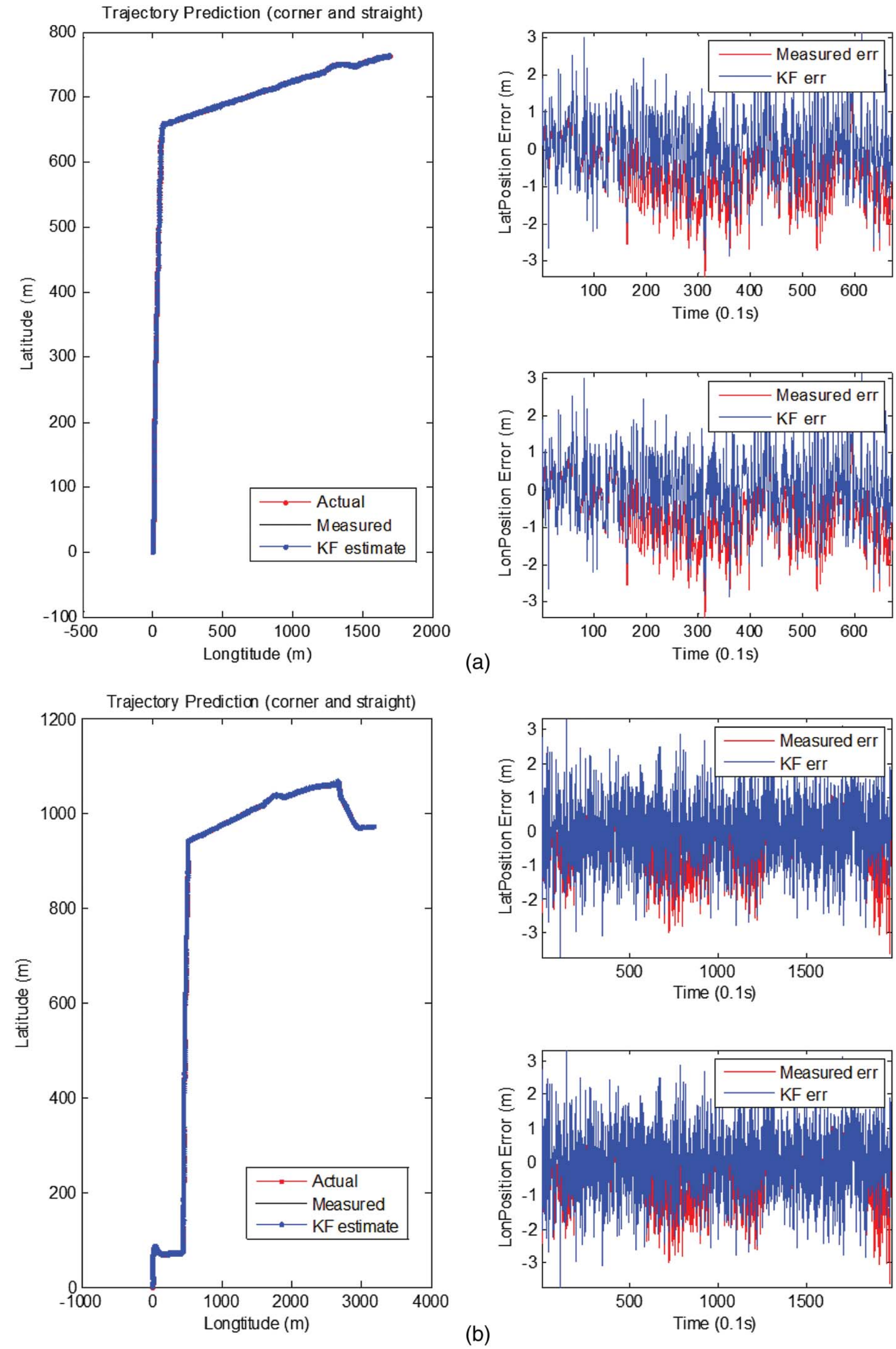

Figure 2. (a) Predicted trajectories of the vehicle on straight and corner road. (b) Predicted trajectories of the vehicle on straight and corner road.

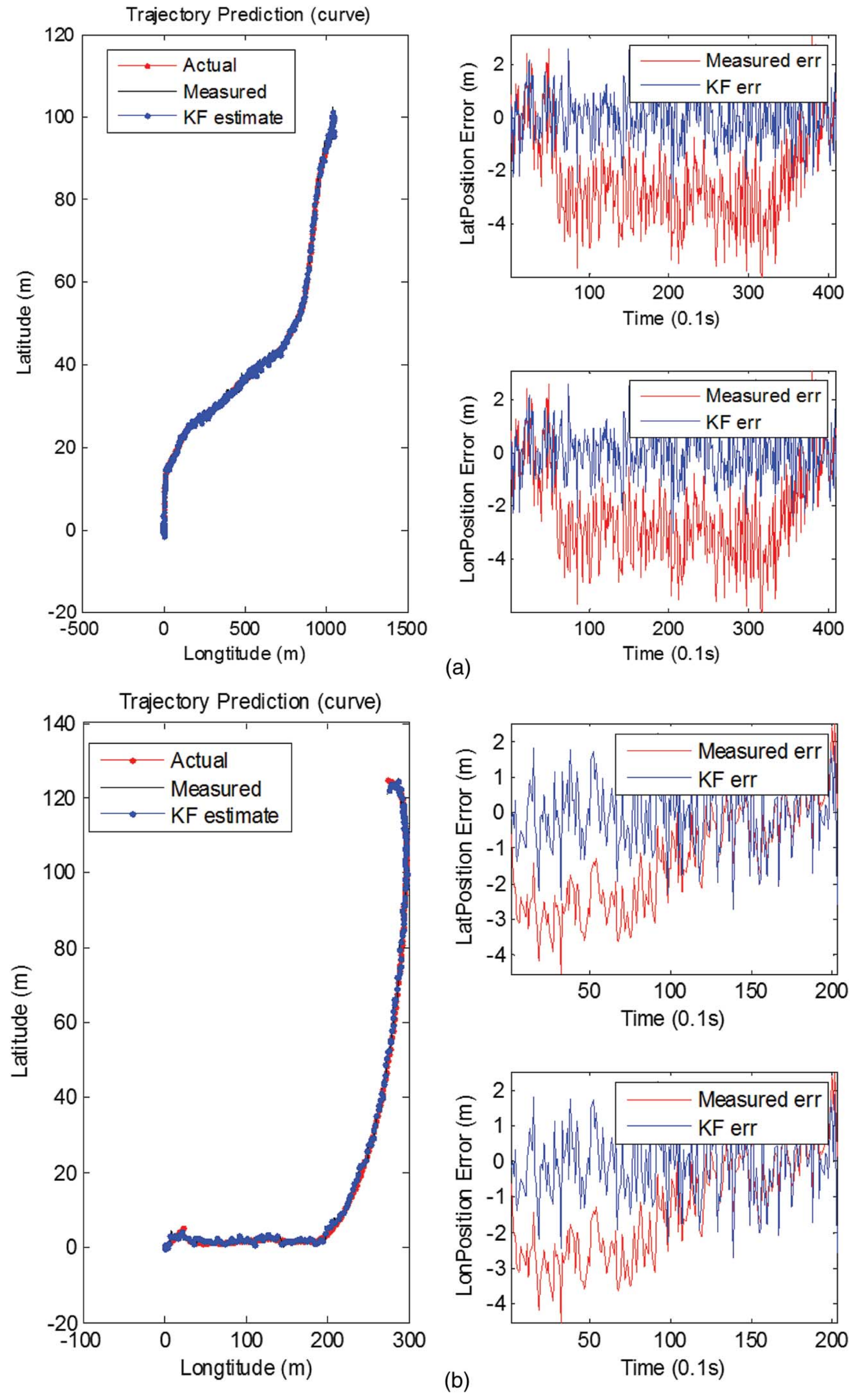

Figure 3. (a) Predicted trajectories of the vehicle on curve road. (b) Predicted trajectories of the vehicle on curve road.

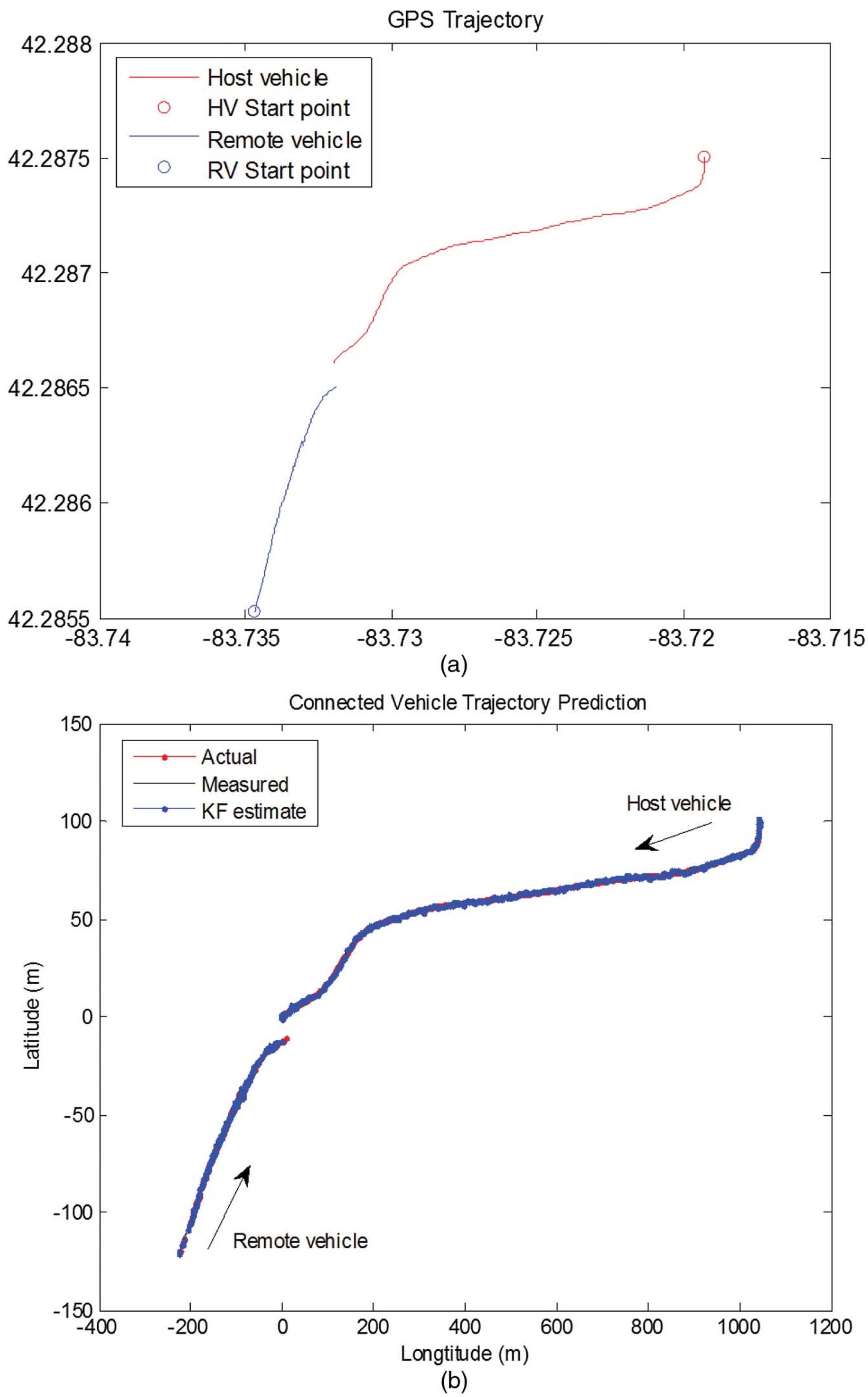

Figure 4. (a) Vehicle GPS trajectories and predicted trajectories. (b) Vehicle GPS trajectories and predicted trajectories.

3.2. Trajectory prediction of connected vehicle

Data from connected vehicle test are combined to simulate two vehicles trajectory prediction simultaneously. The HV moves on northeast to southeast, while the RV comes from southeast to northeast. Figure 4(a) sketches the actual vehicle GPS readings position. Figure 4(b) sketches the actual vehicle GPS trajectories with the predicted trajectories.

3.3. Connected vehicle relative position detection

Connected vehicle communicate data of four cases were used to calculate the relative position in this paper. In the four cases, vehicle starts communication range from 597 to 857 m, and time duration is from 8.8 to 67 s. The host and remote connected vehicle position trajectories are shown in Figure 5.

Figure 6 shows the relative position between the HV and the RV. This position radar map shows the surrounding RV current position and direction related to the HV. In case 1 and case 3, the RV s were located in the left-front direction based on the HV, whose relative distance was between 800 and 1100 m. In case 2, the RVs were located in the front direction, whose relative distance was between 500 and 800 m. In case 3, the RV was located in the left side, whose relative distance was about 800 m from the HV. With this connected vehicle radar map, the RV relative distance, relative speed and TTC can be shown.

3.4. Time to collision

TTC between the connected vehicles of Figure 4 case is computed according to the collision detection algorithm shown in Figure 7. As shown in Figure 7, red dots show the current TTC according to the V2V communication data, and the blue dots show the future predicted TTC. From the current TTC, the vehicle driver will know the current time to collision. However, future TTC prediction methods allow the vehicle gets the information 3 s in advance. Vehicle can have more time to analyse whether the hazard by combining the future TTC with current TTC. Therefore, it will improve the connected automated vehicle driving safety in the future.

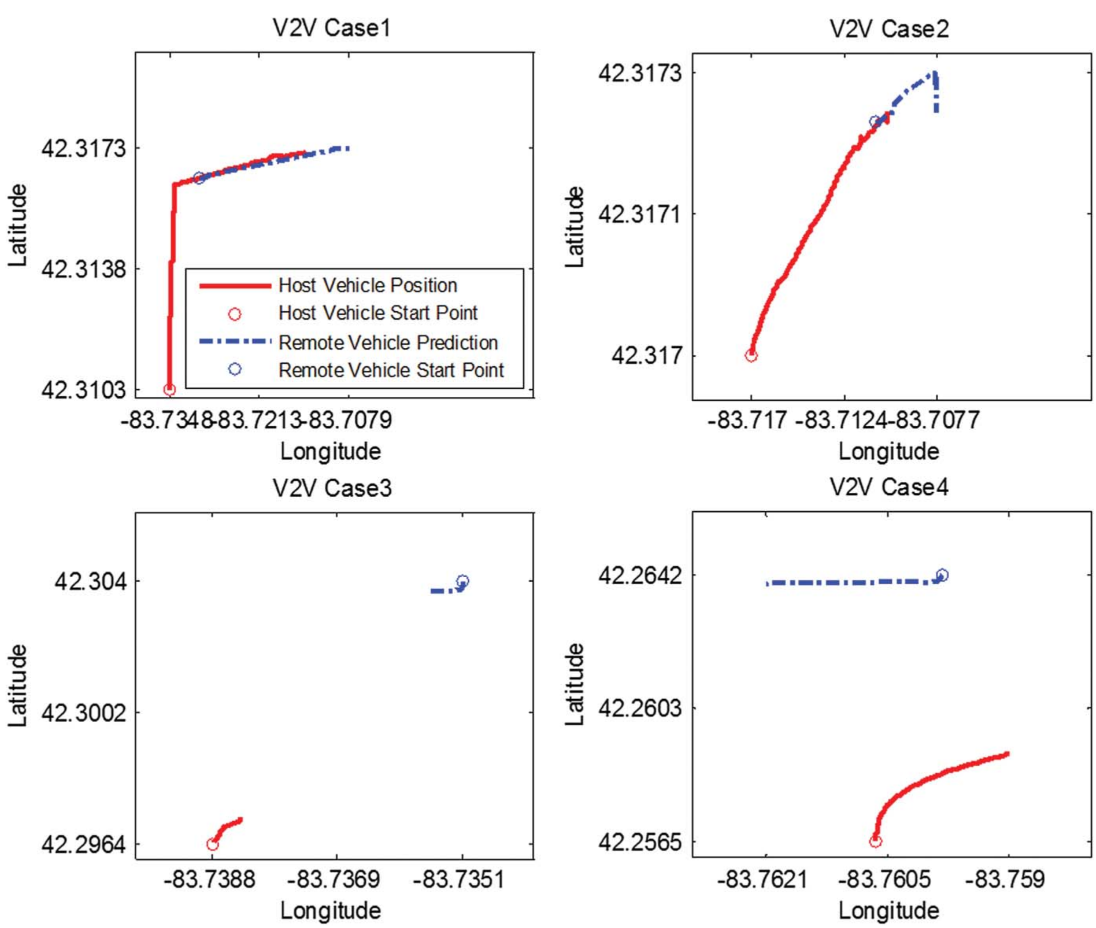

Figure 5. Host and remote connected vehicle position trajectories.

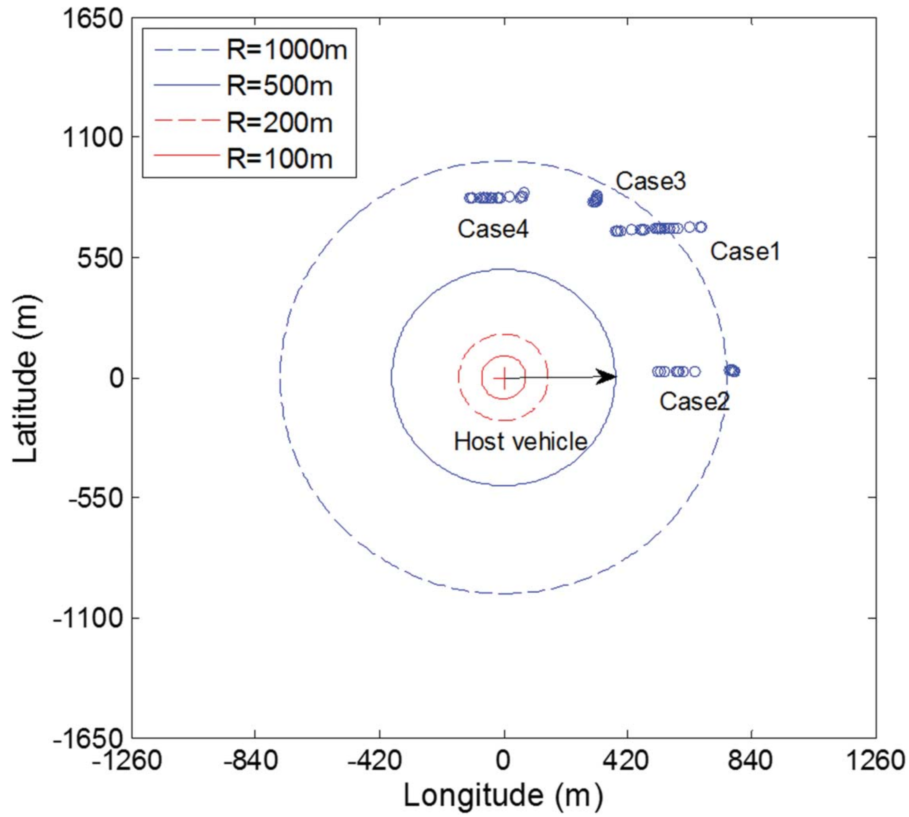

Figure 6. Host and remote vehicle relative position radar map.

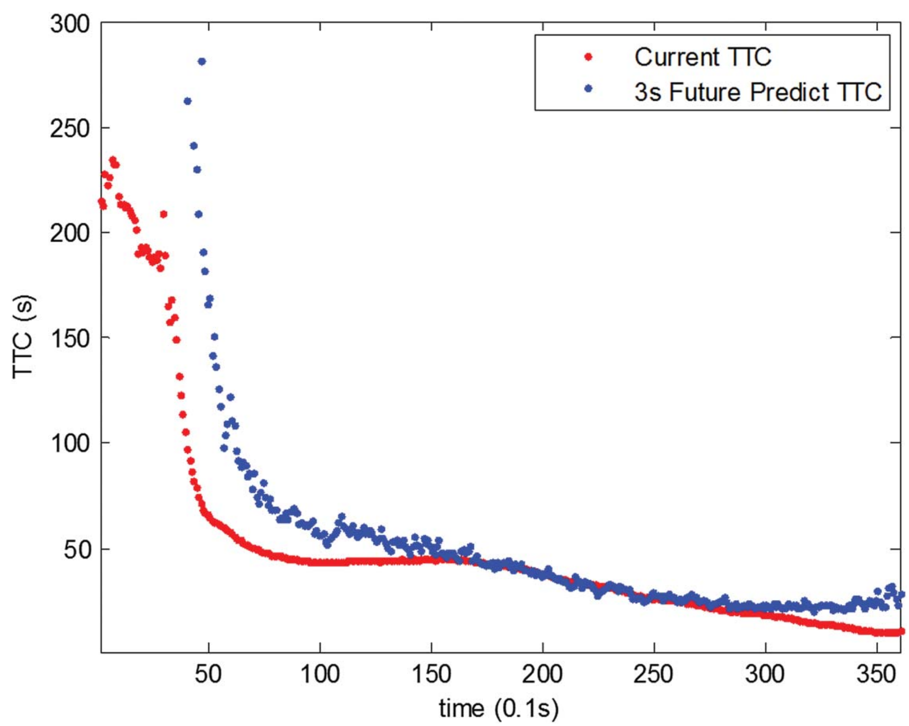

Figure 7. Time to collision. (The colour version is available online)

4. Discussion

The connected vehicle may lose the RV's safety information sometimes; according to the previous RV GPS location, velocity and heading information to predict the RV future trajectories can be used to improve the HV driving safety.

Each vehicle can estimate its current states based on a KF-based algorithm by the method proposed in this paper; in the connected vehicle system, the HV not only transfers its current states but also delivers the advanced time status to the RV. Upon receiving these state estimates, the HV then can determine the potential collision. First, the RV s that may result in a collision within the specified time horizon are pre-selected and then the future trajectories for those vehicles are computed or retrieved. Second, comparing the distance between RV and the HV within 3 s, the early time to collision, the location and vehicle ID when the respective future TTC is within certain threshold is identified. Third, the persistency of the occurrences and associated probability are calculated, and potential conflict is determined accordingly. In addition, it can combine the autonomous vehicle research with development, providing the hazard information and time to collision for autonomous vehicle to help the vehicle to avoid accidents.

Discrepancies between the input assumptions and the actual driver input are inevitable in practice. When the vehicle is driven along a straight line or in its steady on curves, both the yaw rate and the steering angle are always constant. When the vehicle is in a manoeuvre where the yaw rate or the steering angle varies, the yaw acceleration insertion has been shown to help predict a more realistic yaw rate profile. However, there are cases where even the current yaw acceleration does not reveal the intention of the driver, e.g. the straight line driving right before a curve or rather abrupt exit out of a curve. In such cases, large deviations occur. Moreover, this is the main reason which makes it very difficult to verify the predicted trajectory. Acceleration and human turning intention are not considered in this paper when TTC is calculated. In the future, acceleration, turning direction, road map, traffic condition and the speed limit should be considered in the RV trajectory prediction. For example, in order to improve the accuracy and normalising of the model, vehicle acceleration vector needs to be added to the discrete-time state equation, and the covariance matrix also changes in the algorithm. The vehicle yaw rate can be used to forecast the driver reaction.

5. Conclusions

This paper has explored a framework of connected vehicle future trajectory prediction. The goals of this paper are to provide a new method to demonstrate an early collision warning prediction of connected vehicle and improve driving safety.

A detailed algorithm of future trajectory prediction and early time to collision detection has been provided in this paper. By choosing this method, the HV can create its surrounding safety radar map and make appropriate decisions based on both itself and nearby RV's positions and the predicted trajectories as well.

Use of the position and trajectories of nearby vehicles for the construction of the local driving environment. Results demonstrate that the trajectory prediction achieves sufficient accuracy for the application. Therefore, connected vehicle can send its future trajectory or receive RV future trajectory. The longer detection distance allows vehicles to perceive some threats sooner than sensors, radar or cameras can do, and provide warning signals to alert their drivers accordingly.

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