Conflict-Probability-Estimation-Based Overtaking for Intelligent Vehicles

Fenghui Wang, Ming Yang, and Ruqing Yang

***Abstract*—Overtaking is a complex and hazardous driving maneuver for intelligent vehicles. When to initiate overtaking and how to complete overtaking are critical issues for an overtaking intelligent vehicle. We propose an overtaking control method based on the estimation of the conflict probability. This method uses the conflict probability as the safety indicator and completes overtaking by tracking a safe conflict probability. The conflict probability is estimated by the future relative position of intelligent vehicles, and the future relative position is estimated by using the dynamics models of the intelligent vehicles. The proposed method uses model predictive control to track a desired safe conflict probability and synthesizes decision making and control of the overtaking maneuver. The effectiveness of this method has been validated in different experimental configurations, and the effects of some parameters in this control method have also been investigated.**

***Index Terms*—Conflict probability, intelligent vehicles, overtaking.**

I. Introduction

A substantial percentage of traffic fatalities are directly related to overtaking [1]. The development of intelligent vehicles promises to improve the safety of vehicle's operations, including overtaking. An intelligent vehicle may generate an overtaking intention when the preceding vehicle is running with low speed. In a microscopic perspective, overtaking can keep the velocity of the high-speed vehicle; in a macroscopic perspective, overtaking can improve the traffic flow rate by reducing the negative impact generated by low-speed vehicles.

Overtaking performed by an intelligent vehicle is related to a variety of decision-making and control technologies. A considerable number of research projects relative to the cooperative driving and control of automated vehicles have been carried out in the past decades, such as the California PATH project, Demo 2000 in Japan, and the ARCOS project in France [2]–[4]. Most of these research projects emphasize the operation of the platoon, such as Stop&Go, platooning, splitting, merging, lane changing, and obstacle avoidance. Vehicle control technologies, such as adaptive cruise control, automated lane following, and automated lane changing, have extensively been investigated [5]–[7]. However, the control algorithm for overtaking and the relative security issues have somewhat been neglected [8]. An overtaking trajectory planning method that can minimize the energy consumption of an intelligent vehicle has been proposed, but safety issues have not been considered [9]. The determination of a safe intervehicle distance for lane changing uses the vehicular kinematics model and collision-avoidance restrictions; however, the relative position errors caused by road conditions and maneuvers have been ignored [10]. An alternative approach to ensure the safe operation of an intelligent vehicle is to predefine a safety cell around the vehicle, and a warning will be posted if other vehicles enter this cell [11]. Although safety may be ensured by using such an approach, a quantitative criticality, which may help complete overtaking, cannot be presented. Advanced driver-assistance systems can improve the safety of overtaking and assist the driver to complete overtaking, but these systems cannot be applied to directly control an intelligent vehicle [12]. The overtaking maneuver can be completed by two lane-changing maneuvers in the intuitive sense: One is departing from the current lane and passing the overtaken vehicle, and the other is returning to the original lane. However, when to activate these two lane-changing maneuvers and how to perform lane changing in a dynamic environment are issues that need further study. Moreover, decision making and control of the overtaking maneuver are coupled with each other. The motivation of our research is to rethink the overtaking maneuver of an intelligent vehicle and propose a new method for overtaking by considering decision making and controlling together. In this paper, we present a conflict probability-estimation-based overtaking control method for the overtaking maneuver of an intelligent vehicle, which can realize automated overtaking and ensure the safety of this process. The conflict probability is a criterion that has been used in the aviation community to evaluate the safety of flight. The adoption of this conception may help realize effective air traffic management [13]. Here, we use the conflict probability as the safety indicator of overtaking. The proposed method integrates decision making and control of the overtaking maneuver into a tracking control problem, which uses the conflict probability as the safety indicator.

The remaining parts of this paper are organized as follows: Section II describes the solution to the instantaneous conflict probability of the proposed overtaking control method. Section III presents the control algorithm of the overtaking method based on conflict probability estimation. The proposed method is validated in Sections IV and V, and the conclusions are given in Section VI.

II. Instantaneous Conflict Probability Estimation

In the actual overtaking process, the changes of road conditions and the control errors of intelligent vehicles may induce relative position errors between the overtaking vehicle and the overtaken vehicle. The uncertainty of the relative position between two objects can be denoted by a probability density function, and the probability of the underlying conflict between two objects can be denoted by the conflict probability [14]. Therefore, the uncertainty of the relative position between vehicles involved in overtaking can be denoted by a probability density function, and the underlying conflict between vehicles can be denoted by the conflict probability.

Referring to Fig. 1, vehicle 1 is the overtaken vehicle, and vehicle 2 is the overtaking vehicle. In the process of overtaking, the longitudinal and lateral position errors of these vehicles are normally distributed with zero means. The ellipses around vehicles are the probability density contour of the position error of vehicles. These ellipses tend to have their major principle axes in the along-track direction and their minor principle axes in the cross-track direction. The conflict probability can be determined by integrating the relative position-error probability density over the conflict area. The relative position-error probability density is determined by the position-error distribution of the overtaken vehicle and that of the overtaking vehicle. The conflict area is a predefined rectangular region around the overtaken vehicle (see Fig. 1).

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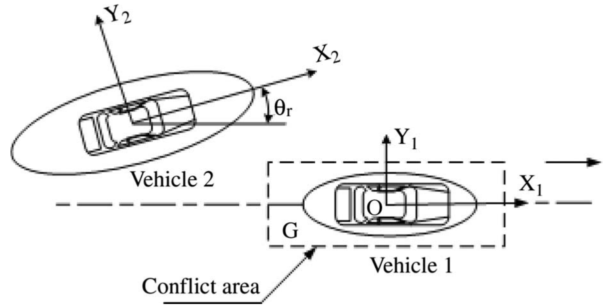

Fig. 1. Relative position between the overtaking vehicle and the overtaken vehicle.

The position-error covariance matrix of the overtaken vehicle and that of the overtaking vehicle in the corresponding vehicle-fixed coordinates are given as

$$\mathbf{C}_1 = \begin{bmatrix} \sigma_{1x}^2 & \\ & \sigma_{1y}^2 \end{bmatrix}$$
$$\mathbf{C}_2 = \begin{bmatrix} \sigma_{2x}^2 & \\ & \sigma_{2y}^2 \end{bmatrix}$$

respectively, where σ_{1x}, σ_{1y}, σ_{2x}, and σ_{2y} are the standard deviations of the longitudinal and lateral position errors of the overtaken and overtaking vehicles, respectively. $\mathbf{C}_1$ and $\mathbf{C}_2$ can be estimated by intelligent vehicles in online or offline way. Assume that θ_r is the relative azimuth angle between the overtaking vehicle and the overtaken vehicle (see Fig. 1) by using coordinate transformation, the position-error covariance matrix of the overtaken vehicle can be converted into

$$\mathbf{C}_1' = \mathbf{R}\mathbf{C}_1\mathbf{R}^T \tag{1}$$

where

$$\mathbf{R} = \begin{bmatrix} \cos\theta_r & -\sin\theta_r \\ \sin\theta_r & \cos\theta_r \end{bmatrix}.$$

The relative position-error covariance matrix can be obtained by combining the position-error covariance of the overtaken vehicle and that of the overtaking vehicle in the coordinate that is fixed on the overtaking vehicle, i.e.,

$$\mathbf{C}_r = \mathbf{C}_1' + \mathbf{C}_2 \tag{2}$$

where $\mathbf{C}_r$ is the relative position-error covariance matrix of the two vehicles. By assigning the relative position error to the overtaking vehicle, the overtaken vehicle can be regarded as having no position uncertainty, and the conflict area can be defined around the overtaken vehicle (see Fig. 1).

The conflict probability prediction is based on the prediction of the relative position between intelligent vehicles. Via communication, the overtaking vehicle can obtain the position and control input of its own and that of the overtaken vehicle. Then, the future relative position between vehicles can be deduced by using the current positions, the control inputs, and the dynamics models of these two vehicles. Assuming that an instantaneous predictive relative position of the two vehicles is $[s_x, s_y]^T$ in the future moment t, then the corresponding instantaneous conflict probability density function can be expressed as

$$f(s_x, s_y) = \frac{1}{2\pi|\mathbf{C}_r|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{X}-\boldsymbol{\mu})^T\mathbf{C}_r^{-1}(\mathbf{X}-\boldsymbol{\mu})\right\} \tag{3}$$

where $\mathbf{X} = [s_x, s_y]^T$, and $\boldsymbol{\mu} = [0, 0]^T$. Therefore, the corresponding instantaneous conflict probability is

$$P(t) = \iint_G f(s_x, s_y)dxdy \tag{4}$$

where G is the conflict area.

The conflict probability can be used not only as the indicator of collision risk but also as the reference for determining the overtaking maneuver in the process of overtaking. Clearly, the farther the relative distance between vehicles, the smaller the conflict probability, and *vice versa*. Although the conflict probability may be reduced if intelligent vehicles keep a long gap in the process of overtaking, an overlong gap for initiating lane changing and that for returning to the original lane will increase the overtaking time; therefore, a high risk may arise in the bidirectional traffic situation. Thus, the conflict probability in overtaking should be kept at a predefined safe conflict probability P_{cs}, which is between zero and the alert conflict probability P_{ca}.

III. Control Algorithm of Overtaking Based on Conflict Probability Estimation

In a bidirectional traffic situation, an intelligent vehicle has to judge the oncoming traffic before initiating overtaking. We assume that the overtaking intelligent vehicle can correctly judge the situation by using intervehicle communication and can decide whether to initiate overtaking according to the traffic situation.

For the overtaking intelligent vehicle, both current and future conditions should be considered in the process of overtaking; thus, model predictive control can be applied in this process. Model predictive control is an online optimal control method that includes three elements: 1) prediction model; 2) objective function; and 3) obtaining the control law [15]. Model predictive control uses the receding horizon principle. Only the first element of the determined control input sequence is used in the control process. At the next sample, the whole procedure is repeated using the latest measured information.

The prediction model of overtaking control is used to predict the future conflict probability corresponding to the possible control input. This model includes the relative position prediction model and the conflict probability prediction model. The relative position prediction model uses the vehicle dynamics model to predict the future relative position between the overtaking vehicle and the overtaken vehicle. The dynamics models of intelligent vehicles have been described in [16] and [17]. The conflict probability prediction model uses the estimated relative position to predict the future instantaneous conflict probability (see Section II). The predictive model of overtaking control can formally be expressed as

$$P_c(t+j|t) = f(U, t), \qquad j = 1, 2, \ldots, N \tag{5}$$

where $P_c(t+j|t)$ is the estimated conflict probability after j control intervals, $U = [a, \delta_f]$ is the control input, a is the desired acceleration of the vehicle, δ_f is the steer angle of the frontal wheels, and $f(U,t)$ is the integration of the relative position prediction model and the conflict probability prediction model.

The online optimization objective function for determining the control input sequence is

$$J = \sum_{j=N_1}^{N_2} \Gamma_j^p \left[P_c(t+j|t) - P_{cs}\right]^2 + \sum_{j=1}^{N_u} \Gamma_j^u \left[U(t+j-1)\right]^2 \tag{6}$$

where P_{cs} is the predefined safe conflict probability, $P_c(t+j|t)$ is the predictive conflict probability sequence, and $U(t+j-1)$,

$j = 1, \ldots, N_u$ is the control input sequence in the future. N_1 and N_2 are the minimum and maximum cost horizons, respectively, and N_u is the control horizon. Γ_j^p and Γ_j^u are the weight sequences of conflict probability tracking errors and that of the control inputs, respectively. The effects of a and δ_f can be regulated by adjusting the elements of Γ_j^u: These elements of Γ_j^u are initially chosen as near-zero values and should be increased if the corresponding control inputs are too large.

The optimized control input sequence can be determined by minimizing (6). Due to the nonlinear feature of the prediction model of overtaking control, the nonlinear optimal algorithms intrinsically take into account the constraints of the control inputs. An iterative optimization strategy is used in solving this nonlinear optimization problem. The nth iterative step can be expressed as

$$\boldsymbol{U}_{n+1} = \boldsymbol{U}_n + \boldsymbol{\lambda}_n \boldsymbol{d}_n \tag{7}$$

where $\boldsymbol{U}_n$ is the vector of control inputs, $\boldsymbol{d}_n$ is the vector denoting the search direction, and $\boldsymbol{\lambda}_n$ is the vector denoting the step size in the search direction. $\boldsymbol{d}_n$ is determined by the negative gradient of the criterion function J in (6) with respect to $\boldsymbol{U}_n$. $\boldsymbol{\lambda}_n$ is the optimal step size in the search direction. The stop criterion for this optimization problem is that the magnitude of $\boldsymbol{d}_n$ is less than the small positive threshold ε.

IV. Simulation Results

Simulation tests are implemented on the simulation platform The Open Racing Car Simulator (TORCS), which is a validated program including the complete vehicle dynamics model and the road model [18]. The intelligent vehicle model of TORCS includes the programmable decision-making module, control module, sensor model, and communication model. The simulation platform provides a two-lane traffic situation, in which the high-speed vehicle may generate the overtaking intention when it detects the preceding low-speed vehicle. The sizes of the overtaking vehicle and the overtaken vehicle are 4.8 m $\times$ 1.9 m and 5.0 m $\times$ 2.0 m, respectively. The initial intervehicle distances in all the tests are 32 m. We assume that the adjacent lane can be used by the overtaking vehicle in the process of overtaking, that is, the gap until the next opposing vehicle arrives is large enough to perform an overtaking maneuver.

A. Comparison Test

Two different overtaking control methods have been compared in the same scenes. One is the proposed conflict-probability-estimation-based overtaking control method; the other method has been described in [9], which determines an overtaking track for the overtaking vehicle to initiate lane changing and return to the original lane.

Corresponding to different experimental configurations, the desired speed of the overtaken vehicle is kept at 60 km/h, and that of the overtaking vehicle is 80, 85, and 90 km/h, respectively. For the conflict-probability-estimation-based overtaking control method, the predefined safe conflict probability is 1.0×10^{-4}, and the conflict area is Ca $= 25$ m $\times$ 5 m in these tests. Fig. 2 presents the overtaking tracks of the overtaking vehicle corresponding to different overtaking policies in different experimental configurations. One index of the overtaking safety is the closest distance. The closest distance is the shortest distance between two points that belong to the overtaken vehicle and the overtaking vehicle, respectively, and it can be calculated by using the recorded test results. Figs. 3 and 4 present the variations of the closest distance between the two vehicles in the overtaking process, corresponding to different overtaking policies. The overtaking time is denoted by T, and the overtaking time of each overtaking process has also been presented in Figs. 3 and 4.

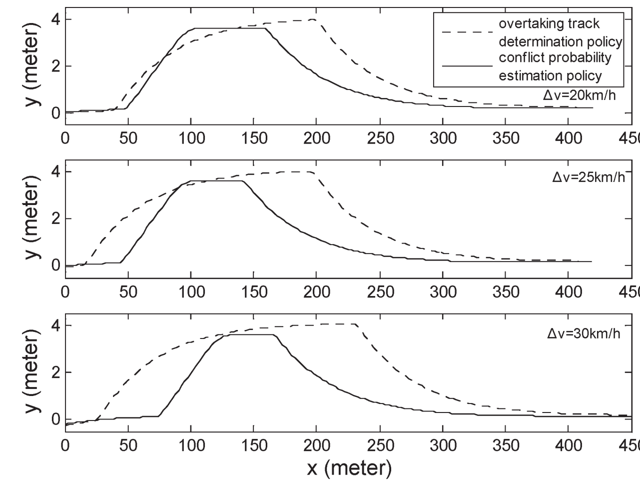

Fig. 2. Overtaking tracks in different situations.

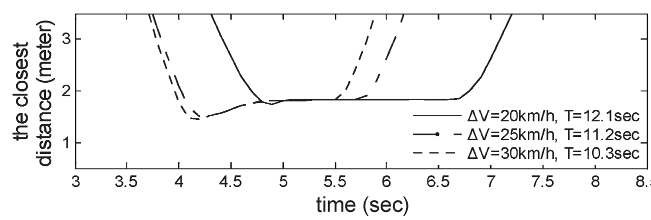

Fig. 3. Variation of the closest distance (conflict probability estimation policy).

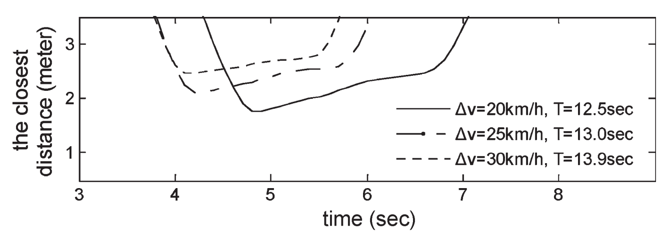

Fig. 4. Variation of the closest distance (overtaking track determination policy).

The results in Fig. 2 indicate that the overtaking track determination policy may extend the overtaking track with the increase in the relative speed, but the conflict probability estimation policy does not perform the same way. The results in Figs. 3 and 4 indicate that the conflict probability estimation policy can keep a nearly constant closest distance between vehicles in spite of the variation of the relative speed, and the overtaking track determination policy cannot keep the closest distance in different situations. The variation of the overtaking time in Fig. 3 indicates another advantage of the conflict-probability estimation policy: The higher the relative speed, the shorter the overtaking time.

B. Effect of the Conflict Area

To investigate the effect of the conflict area on the overtaking maneuver, different conflict areas have been tested in the same overtaking situation, where the desired velocity of the overtaken vehicle is 60 and that of the overtaking vehicle is 85 km/h. The predefined safe conflict probability P_{cs} is 1.0×10^{-4} in these tests. Fig. 5 presents the variation of the closest distances and the overtaking time of the overtaking processes with different conflict areas, namely, $\mathrm{Ca}_1 = 20$ m $\times$ 5 m, $\mathrm{Ca}_2 = 25$ m $\times$ 5 m, and $\mathrm{Ca}_3 = 30$ m $\times$ 5 m.

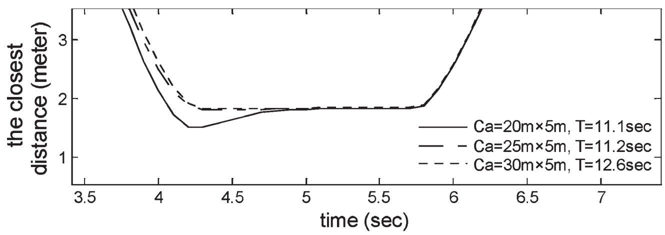

Fig. 5. Variation of the closest distance (scenarios with different conflict areas).

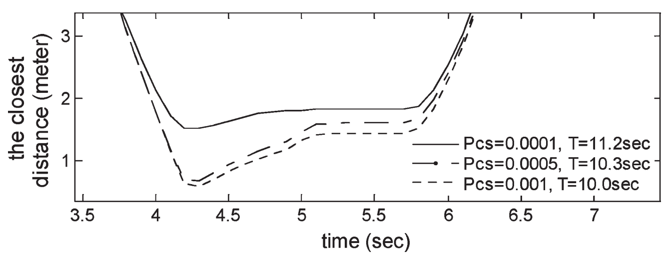

Fig. 6. Variation of the closest distance (scenarios with different safe conflict probabilities).

The results in Fig. 5 show that with the increase in the conflict area, the closest distance has not remarkably decreased. Therefore, the variation of the conflict area in a certain scope does not significantly affect the safety of overtaking. The variation of the overtaking time indicates that the overtaking time increases with the increase in the conflict area.

C. *Effect of the Safe Conflict Probability*

The safe conflict probability is a critical factor that may affect the performance of the overtaking control method. Different safe conflict probabilities have been tested in the same overtaking situation. The desired velocity of the overtaken vehicle is 60 km/h, and that of the overtaking vehicle is 85 km/h. The conflict area is $\mathrm{Ca} = 25\ \mathrm{m} \times 5\ \mathrm{m}$ in these tests. Fig. 6 presents the variation of the closest distances and the corresponding overtaking time of the overtaking processes with different safe conflict probabilities.

The results in Fig. 6 show that the closest distance decreases with the increase in the safe conflict probability. When the safe conflict probability increases to $P_{\mathrm{cs}} = 1.0 \times 10^{-3}$, the safety of overtaking cannot be ensured. The variation of the overtaking time indicates that the overtaking time has no notable variation with the increase in safe conflict probability.

D. *Discussion on the Overtaking Time*

The overtaking time is an important indicator of overtaking, particularly in the bidirectional traffic situation. The results in Figs. 3–6 show that the reduction of the overtaking time relies on the reduction of the conflict area Ca, as well as the increase of the safe conflict probability P_{cs} or the relative speed Δv, and *vice versa*. However, the regulation of Ca, P_{cs}, and Δv should ensure the safety of the vehicles.

V. Experimental Results

To validate the proposed overtaking control method, a number of field experiments have been implemented. The intelligent vehicles used in the tests are Cybercars, which are low-speed electric intelligent vehicles used in the Cybernetic Transportation System [19]. The Cybernetic Transportation System is a branch of Intelligent Transportation Systems, which can provide transportation services for special areas, such as the university campus, industrial park, and central business district. In the long term, Cybercars could autonomously run at high speeds and complement mass transportation [20]. Because we have only two experimental intelligent vehicles, one is chosen as the overtaking vehicle, and the other is chosen as the overtaken vehicle. To establish a bidirectional traffic situation, we replace the oncoming vehicle by a mathematical model of an intelligent vehicle running on a laptop, which can communicate with the onboard computers of the two experimental vehicles, and the positions and velocities of these vehicles can be shared in the wireless local area network. Two Cybercars equipped with real-time kinematic global positioning system receivers with a sampling rate of 5 Hz are used in the field experiments. The normal speeds of these vehicles are between 20 and 30 km/h. The initial distance between the tested vehicles is 10 m. The overtaken vehicle tracks a desired speed of 20 km/h, and the overtaking vehicle tracks a desired speed of 30 km/h in the test. The intelligent vehicle with an overtaking intention can initiate the overtaking maneuver only if the preconditions for overtaking are satisfied. Intelligent vehicles can determine these preconditions by communications.

Fig. 7. Overtaking experimental scenes.

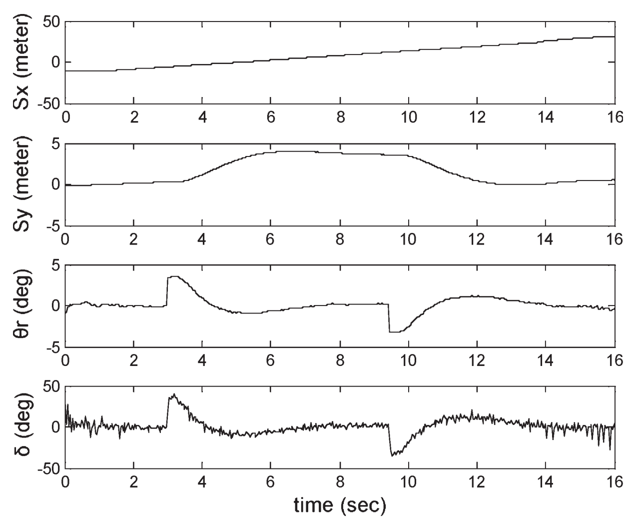

Fig. 8. Experiment results of overtaking.

The experimental scenes of one test are shown in Fig. 7. The corresponding variations of the relative position between the two vehicles and the steer control input of the overtaking vehicle are presented in Fig. 8. The results in Figs. 7 and 8 show that the proposed overtaking control method can induce safe overtaking.

VI. Conclusion

A conflict-probability-estimation-based overtaking control method for the intelligent vehicle has been presented. The introduction of the conflict probability has presented a quantitative indicator for the safety of the overtaking vehicle, and tracking a safe conflict probability can ensure the safety of overtaking. Issues involved in the overtaking control method, including when to initiate the overtaking maneuver and how to overtake, have been translated into a conflict-probability tracking problem. An advantage of the proposed overtaking control method is that the predefinition of the gaps between vehicles for overtaking is not needed. Simulation tests and experiments in different experimental configurations have validated the effectiveness of the proposed overtaking control method.

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