Design and Implementation of Intelligent Overtaking System Using Model Predictive Control

Shih-Ting Huang
Department of Electrical Engineering
National Chung Hsing University,
Taichung, 40227 Taiwan
g107064029@smail.nchu.edu.tw

Yu-Chen Lin
Department of Automatic Control Engineering,
Feng Chia University, Taichung, 40724
yuchlin@fcu.edu.tw

Chun-Liang Lin
Department of Electrical Engineering
National Chung Hsing University
Taichung, 40227 Taiwan
chunlin@dragon.nchu.edu.tw

***Abstract*—In this paper, an intelligent overtaking system is developed, which includes overtaking possibility strategy (OPS), autonomous overtaking control scheme, and then successfully implemented on an autonomous vehicle. The OPS is based on the image recognition technology for detecting surrounding vehicles and lane lines, and further calculate the time to lane crossing (TLC) as the basis of overtaking or keep within your lane. Thus, this research can implement two functions, such as lane following and overtake. An autonomous overtaking control scheme using the successive linearization based model predictive control is developed to derive the appropriate throttle, brake and steering angle actuators for a car. This control approach can provide stable and safety overtaking maneuvers effectively. Finally, the proposed system has been incorporated into an electrical golf car and tested in a real-road environment, where the communication of the whole sensors, actuators as well as vehicle control unit (VCU) are used the controller area network (CAN) bus to realize control and data collection. Some of the experimental results demonstrate the feasibility of using the overtaking strategies by considering various traffic situations.**

Keywords—Overtaking possibility strategy, autonomous overtaking, time to lane crossing, lane following, model predictive control

I. INTRODUCTION

In 2018, approximately 24,800 accidents with personal injury on the freeway were registered by the Ministry of Transportation and Communication in Taiwan. The overtaking crashes accounted for 12.46 percent of fatal crashes on freeway [1]. In view of this, the development of advanced driver assistance systems (ADAS) to help prevent accidents plays a key role in the automotive field. However, overtaking control remains one of the most serious challenges in commercial ADAS development. In all of the driver assistance maneuvers, overtaking is the most complicated maneuver because it integrates both lateral and longitudinal controls. Several studies [2-4] have emphasized that the overtaking operation leads to fatal car accidents because of a lack of skills, roadway capacity, and information processing abilities. Nearly 75% of road traffic accidents are caused by lateral maneuvers involve driver failure to identify hazards.

Recently, several researches focus on the overtaking system, Mehmood *et al.* [5] presented a paper that mainly focuses on the control process of vehicle that is able to automatically make the trajectory planning and tracking. They only focused on making lane change decisions, but the control laws of the autonomous vehicle e.g. throttle and steering were not mentioned. Some of the research established the lane change system included control strategy planning but they did not consider the status of preceding vehicle e.g. Zhu *et al.* [6] proposed a single neuron PID tracking control strategy for overtaking. Since their research did not consider the situation of the velocity changing of the preceding vehicle. Their overtaking maneuver had failed when the preceding vehicle speeds up during the overtaking process. Their research did not comprehensively consider the possible scenario during the overtaking maneuver.

In addition, about the control strategy for lane changes or overtaking maneuver, a lot of researches have been proposed in recent years. In [7] the authors addressed the issue of real-time obstacle avoidance on low-friction road surfaces using spatial nonlinear model predictive control. A collision avoidance issue solved with the MPC approach that integrates the artificial potential field method is discussed in [8] where the controller is combined with the feedback linearization in order to manage the control issue of a robot with unicycle kinematics and collision avoidance function. However, in many traffic emergency situations, a collision cannot be prevented by braking alone. In [9] the authors proposed a method based on the nonlinear MPC that simultaneously optimizes steering and brake. In [10] trajectory planning and tracking framework are considered to establish a collision-free path for autonomous vehicles. In particular, to track the planned overtaking trajectory, the proposed controller formulated the tracking task a multi-constrains model predictive control issue and evaluated the steering angle to prevent the vehicle from colliding with a moving vehicle.

For the lane following system, we have to detect the frontal lanes to prevent unintended lane departures; it also called the lane departure prevention (LDP) systems [11]. Several studies outlined the importance of LDP systems for both driver performance evaluation and lane departure characterization [12]. Different from the above researches using lateral offset as LDP indicator, Mammar *et al.* presented research to develop lane departure warning system (LDWs) based on the computation of time to line crossing (TLC) [13]. The TLC can be used as the time duration available for the driver before the lane boundary crossing. It can make an effort to strive for the reaction time to correct the steering wheel before any dangerous driving maneuver. Hence, the TLC information and relative yaw angle are utilized to decide the

XXX-X-XXXX-XXXX-X/XX/$XX.00 ©20XX IEEE

steering angle in this paper.

This paper integrates the advantage and improves the disadvantages in the above researches. We utilize TLC to predict when the vehicle will depart the current lane, then refer it as the condition for lane following control. We can effectively adjust the steering wheel before the lane boundary crossing. On top of that we design the control strategy for overtaking system to predict the optimal steering angle and throttle through successive linearization based model predictive control. We have regarded safety constraint, such as the area for collision-free path to enhance the influence of the controller and comprehensively consider the possible scenario during the overtaking maneuver. Finally, a completely autonomous car with overtaking ability is implemented on an electrical golf car via the controller area network (CAN bus) communication. The results demonstrate that the proposed control approach based on time to lane crossing and model predictive control for the intelligent overtaking system is successfully implemented for guaranteeing driving safety.

II. SYSTEM DESCRIPTION

In this paper, an intelligent overtaking system is developed and implemented on an electrical autonomous car. The proposed an intelligent overtaking system, includes environment sensing, overtaking possibility strategy (OPS) and autonomous overtaking control scheme, is shown in Fig. 1. For the environment sensing, a windshield-mounted camera is used to capture the front view of the scene and to detect the lane lines and surrounding vehicles. In this paper, the canny edge filter and Hough transform scheme are used to identify the lane lines. According to the autonomous vehicle attitude information from the vanishing point and locations of detected lane lines in the images, the time to lane crossing (TLC) can be calculated as the basis for determining whether to lane keeping or change. Similarly, for autonomous overtaking control design, the distance estimation of the front vehicles is also derived; thus, a successive linearization based model predictive control is employed to derive the appropriate throttle, brake and steering angle to actuator for a car.

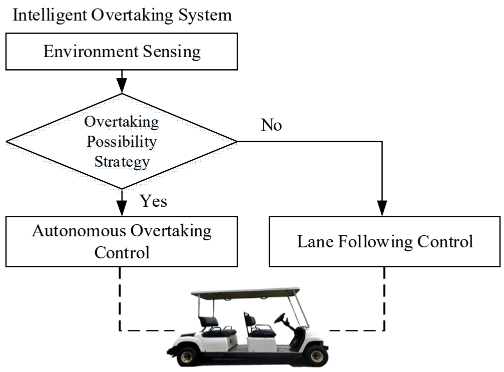


Fig. 1 Control strategy

Based on the results of environment sensing, the OPS can be applied to determine whether the subject vehicle will overtaking and passing another vehicle or stay in the current lane. For example, if a preceding vehicle is detected, the subject vehicle will execute the overtaking maneuver; otherwise it will carry out the lane following maneuver.

III. VEHICLE MODEL

In order to examine as well as analyze the performance of the proposed method, a simple kinematics vehicle model and geometric relationship of vehicle front tire and lane boundary are presented [14], as shown in Fig. 2.

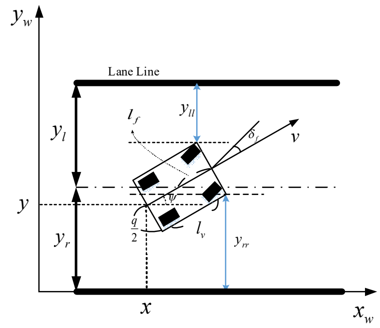


Fig. 2 Kinematics vehicle model and geometric relationship

The nonlinear kinematic vehicle model is described as follows:

$$\begin{cases} \dot{x} = v\cos(\psi) \\ \dot{y} = v\sin(\psi) \\ \dot{\psi} = \frac{v}{l_v}\tan(\delta_f) \\ \dot{v} = a_x \end{cases} \tag{1}$$

where x and y denote to the longitudinal and lateral coordinate of the rear axle of the vehicle; ψ denotes to the relative yaw angle of the vehicle; l_v denotes the length of the vehicle, v denotes to the velocity of the vehicle; a_x is the acceleration of the center of mass in the same direction as the velocity, and δ_f is the steering angle. The control inputs are the front and rear steering angles δ_f and a_x. In addition, y_{ll} and y_{rr} are the distance between from the front left and right tires to left and right boundary of the lane lines, respectively. Hence, the y_{ll} and y_{rr} are defined as

$$\begin{cases} y_{ll} = y_l - l_f\sin\psi - \frac{q}{2}\cos\psi \\ y_{rr} = y_r + l_f\sin\psi - \frac{q}{2}\cos\psi \end{cases} \tag{2}$$

where y_l and y_r are the lateral distance from the vehicle's center of gravity (CG) to the left and right boundary of the lanes, respectively.

According to (2), we can estimate the distance to lane crossing (DLC), and then the time to lane crossing (TLC) can be derived to correct the steering so that the vehicle keeps entirely within a marked lane, i.e. lane following function. On the other hand, if a preceding vehicle is detected, performing a control of overtaking a preceding vehicle can be considered. In this case, the overtaking control is executed by using the kinematic vehicle model and model predictive control strategy to estimate the suitable steering angle and acceleration commands for the host vehicle that calls autonomous overtaking function. A detailed explanation of them in the next chapters.

IV. Lane Following Function

The lane following function is based on the results of environment sensing, such as vision-based lane lines reorganization. In this paper, the Hough transform scheme is firstly used to detect the lane lines. Next, based on the vehicle attitude information from gyro sensor, such as relative yaw angle, the time to lane crossing (TLC) can be computed to be as a basis for lane following function so that to maintain the vehicle driving in a marked lane and partly adjust the steering angle to improve the stability.

TLC is the most important indicator for lane following function. TLC is defined as the time duration available for the driver prior to any lane boundary crossing and used to predict when the vehicle will depart the current lane. TLC decreasing represents the risk of lane departure is high and increasing represents the risk of lane departure is low. TLC is the indicator of the lane departure in our lane following function but is not used to determine the steering angle of the steering wheel. The steering angle is mainly determined by the relative yaw angle. Since the relative yaw angle occurs when the vehicle is not horizontal with the lane. In other words, the relative yaw angle occurs at every moment. While the steering angle is only determined by the relative yaw angle, the frequent adjustment of the steering wheel leads to discomfort for the passengers. In order to decline in the discomfort for the passengers, we used TLC as the activation condition of steering wheel adjustment. When the risk of lane departure is high, our lane following function adjust the steering wheel immediately to ensure the vehicle follows the lane.

In this paper, the two cases of different road scenario for TLC evaluation are considered, one is in a zero steering angle and the other is constant steering angle on the basis of the established trigonometric formulas.

- *Case 1: Zero Steering Angle*

The first case, zero steering angle, is the steering wheel maintain on the central position, but the vehicle posture is not parallel the lane lines. Figure 3 shows the zero steering angle will affect the vehicle go straight. The vehicle will cross the lane boundary on the left side of the lane. The distance to lane crossing (DLC) is presented as follows

$$DLC = \frac{y_{ll}}{\sin\psi} \tag{3}$$

This formula is valid when the relative yaw angle is positive. If relative yaw angle is negative, it has to replace y_{ll} with y_{rr}. TLC is obtained by dividing distance to lane crossing by velocity. It is given by

$$TLC = \frac{y_{ll}}{v\sin\psi} \tag{4}$$

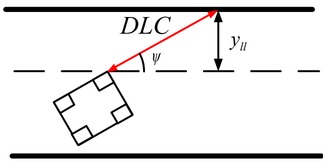


Fig. 3 The zero steering angle scenario.

- *Case 2 : Constant Steering Angle*

The case 2 considers the constant steering angle, which means the vehicle posture is not parallel the lane lines, as shown in Fig. 4. Thus, the vehicle will cross the lane boundary on the left side of the lane, and the TLC can be described as

$$TLC = \frac{R_{vl}\xi_{ll}}{v} \tag{5}$$

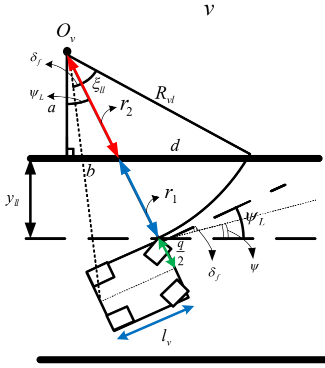


Fig. 4 The constant steering angle scenario

where the radius of the path formula is

$$R_{vl} = \frac{l_f}{\tan\delta_{f0}} - \frac{q}{2} = \frac{v}{\dot{\psi}} - \frac{q}{2} \tag{6}$$

The radian of the circle arc path can be computed from the following process. First, three side lengths of a triangle R_{vl}, r_2, and d are obtained to calculate the radian.

1) Computing $r_1 = y_{ll}/\cos\psi_L$ then we can obtain $r_2 = R_{vl} - r_1$.
2) Using Pythagoras theorem to define the length of a and b in Fig. 4, thus $a = r_2\cos\psi_L$ and $b = r_2\sin\psi_L$.
3) Because of $R_{vl}^2 = a^2 + (b+d)^2$, we can computed the distance d by $d = -r_2\sin\psi_L + \sqrt{R_{vl}^2 - r_2^2\cos^2\psi_L}$.
4) Using Trigonometric to compute the radian such that we can obtain $\xi_{ll} = \cos^{-1}\left(r_2^2 + R_{vl}^2 - d^2 \big/ 2R_{vl}r_2 \right)$.

The steering angle is mainly determined by the relative yaw angle. The steering decision is that if the car is not parallel with the lane lines, and time to lane crossing touches off the threshold at the same time, the steering wheel will be adjusted immediately. In other words, once the risk of lane departure is low even the relative direction of the vehicle head is not parallel with the lane, we keep the steering wheel maintaining on the current steering status.

V. Autonomous Overtaking Function

Secondly, the autonomous overtaking function based on model predictive control is developed. The environment sensing information includes the distance between ego and preceding vehicle φ and the location C_p, width w_p and length l_p of preceding vehicle. The overtaking function is divided into two parts: (1). collision avoidance constraint; (2). model predictive control. Subsequently, a successive linearization based model predictive control is used to deal with the nonlinear vehicle dynamics to overcome the issue in traditional model predictive control. At each time step, we renew the internal plant model used by the MPC with the linear model, our controller handles the vehicle model more effective.

A. Collision-Free Area

MPC is an advanced method of process control that is used to control a process while satisfying a set of constraints. Figure 5 demonstrates the constraints that are computed at each k in the case of left overtaking. In order to define the collision-free area for the ego car, we set up the location constraints for the ego car in each time step are indicated as follows.

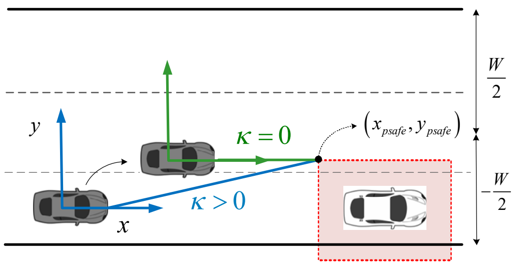


Fig. 5 Constraints in the left overtaking case.

$$-\frac{W}{2} \le n_{2,1}(k) \le \frac{W}{2}, \quad k = 1,2,\cdots,N_p \tag{7}$$

$$\kappa n_{1,1}(k) - n_{2,1}(k) \le \tau, \quad k = 1,2,\cdots,N_p \tag{8}$$

$$\kappa = \left(\frac{y_{psafe} - y}{x_{psafe} - x} \right) \tag{9}$$

where N_p is the number of the prediction steps, W denotes the width of the road, and κ is the slop of the overtaking constrained area. y_{psafe} is the lateral location of the preceding vehicle collision avoidance area. y_{psafe} is set as half of the width of the preceding vehicle. x_{psafe} is the longitudinal location of the preceding vehicle collision avoidance area. x_{psafe} is set as half of the length of the preceding vehicle. We can use the radar to sense the distance between the ego and preceding vehicle, and use image detection to recognize the vehicle type to obtain the length and width of the preceding vehicle. If ego vehicle have not overtaken the preceding vehicle, τ is set as $-y_{psafe} + \kappa x_p$. If the ego vehicle had overtaken the preceding vehicle, τ is set as $-W/2$. According to the driving safety constraint, the ego vehicle can avoid the collision of the preceding vehicle when overtaking the preceding vehicle.

B. Model Predictive Control

The controller deal with a nonlinear system is based on linearization. In successive linearization based MPC, a linear model is computed on the fly as the operating conditions change. At each time step, successive The state-space of the vehicle system dynamics (1) can be represented as

$$\dot{m} = f(m,u), \quad n = p(m,u) \tag{10}$$

Since MPC is based on the discrete-time and linear system formula; hence, the nonlinear system (10) needs to transfer an linear discrete-time system by linearization method. Thus, (10) can be expressed as

$$\begin{aligned} \tilde{m}(k+1) &= A(k)\tilde{m}(k) + B(k)\tilde{u}(k) \\ \tilde{n}(k) &= C(k)\tilde{m}(k) \end{aligned} \tag{11}$$

where $\tilde{m}(k) = m(k) - \overline{m}(k)$ and $\tilde{u}(k) = u(k) - \overline{u}(k)$ where $\overline{m}$ is nominal state and u is the control input, i.e., $m = [x \quad y \quad \psi \quad v]^T$ and $u = [a_x \quad \delta_f]^T$. In addition, $\overline{u}$ is expected value of the control command. $\tilde{n}(k)$ is the system output. $A(k)$, $B(k)$, $C(k)$ are the linearized matrices at current time k, i.e. the Jacobian matrices of the system.

According to (11), the predicted output can be formed as follows

$$\tilde{Y}(k) = \Psi_k \sigma(k) + \Phi_k \Delta U(k) \tag{12}$$

where $\tilde{Y}(k) = \left[\tilde{n}(k+1) \quad \tilde{n}(k+1) \quad \cdots \quad \tilde{n}(k+N_p) \right]^T$; $\sigma(k) = \left[\tilde{m}(k) \quad \tilde{u}(k-1) \right]^T$, $\Delta U(k) = \left[\Delta u(k) \quad \Delta u(k+1) \quad \cdots \quad \Delta u(k+N_c-1) \right]^T$, $\Psi_k = \left[\tilde{C}_k \tilde{A}_k \quad \tilde{C}_k \tilde{A}_k^2 \quad \cdots \quad \tilde{C}_k \tilde{A}_k^{N_p} \right]^T$, and

$$\Phi_k = \begin{bmatrix} \tilde{C}_k \tilde{B}_k & 0 & \cdots & 0 \\ \tilde{C}_k A_k \tilde{B}_k & \tilde{C}_k \tilde{B}_k & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{C}_k A_k^{N_p-1} \tilde{B}_k & \tilde{C}_k A_k^{N_p-2} \tilde{B}_k & \cdots & \tilde{C}_k A_k^{N_p-N_c} \tilde{B}_k \end{bmatrix}.$$

where,

$$\tilde{A}_k = \begin{bmatrix} A_k & B_k \\ 0_{2\times 4} & I_2 \end{bmatrix}; \tilde{B} = \begin{bmatrix} B_k \\ I_2 \end{bmatrix}; \; \tilde{C}_k = \begin{bmatrix} C_k & 0_{2\times 2} \end{bmatrix}$$

and $\Delta u(k+i) = u(k+i) - u(k+i-1)$ for $0 \le i \le N_c - 1$.

The cost function in quadratic form at sample time k is defined as follows

$$\begin{aligned} J(k) = &\left[R_s(k) - \tilde{Y}(k) \right]^T Q \left[R_s(k) - \tilde{Y}(k) \right] \\ &+ \Delta U(k)^T R \Delta U(k) \end{aligned} \tag{13}$$

where $R_s(k)$ is the matrix of reference $\left[x_{ref} \quad y_{ref} \quad \psi_{ref} \quad v_{ref} \right]^T$. To minimize the cost function, the optimal control law is derived by first element of vector $\Delta U(k)$. Finally, we transmits the predictive steering angle, throttle, and brake commands with CAN bus signal to VCU, and then the intelligent overtaking function will implement in an electric golf car.

VI. EXPERIMENT RESULTS

A. Autonomous Vehicle Implementation

Finally, an electric golf car is used to implement the proposed intelligent overtaking system. The configuration of this car is illustrated in Fig. 6.

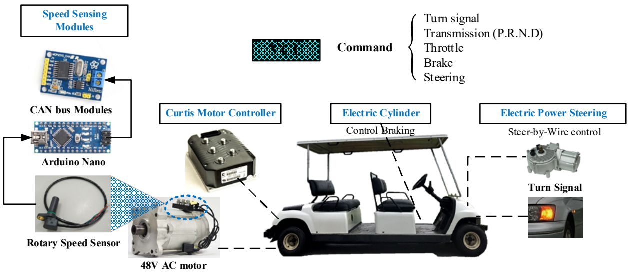


Fig 6. System architecture of the intelligent overtaking system with the testbed vehicle

The core of the hardware in this car is a vehicle control unit (VCU) which is used to command turn signal, transmission, throttle, brake, and steering. There is an electric cylinder used to control the brake pedal, and an electric power steering motor used to control the steering wheel. The electric cylinder and electric power steering motor are connected with VCU by CAN bus, they are not only receiving the command from VCU but also transmit each status of the motors to VCU. In the part of the throttle control, there is a Curtis motor controller installed beside the AC motor which is used to control the car go forward or reverse.

B. Experimental of Lane Following Function

The experiment environment is a 3.7 meters wide and 80 meters long single lane with a T-junction. The vehicle velocity is restricted to 2 meters per second. The lane line detection processing marks the lines are shown in Fig. 7.

Fig. 7 Results of lane line detection processing.

The comparison of lane following control based on the different conditions in this paper: (1). based on relative yaw angle, (2). based on vehicle posture, (3). based on time to lane crossing. In the first case, the relative heading direction so-called relative yaw angle exists in every moment. The adjustment extension of the steering wheel is corresponding to the extension of the relative yaw angle. However, this method for the steering wheel lastingly adjusted would cause uncomfortable feeling. In the second case, we design the method that if the relative yaw angle exists, we will consider the distance between tires and lines as the condition of adjustment, simultaneously. In the third case, we design the method that if the car is not perfectly parallel with the lane lines, and time to lane crossing is within 15 seconds, it is indispensable to adjust the steering wheel. The potential risk of crossing lane boundary is significantly reduced and the comfort for the passengers is effectively enhanced. Figure 8(a)-(f) illustrates the steering wheel status and TLC results of the lane following control based on these three cases. Figure 8(a)-(b) are the results in the case based on relative yaw angle. Figure 8 (c)-(d) are the results in the case based on vehicle posture. Figure 8 (e)-(f) are the results in the case based on time to lane crossing.

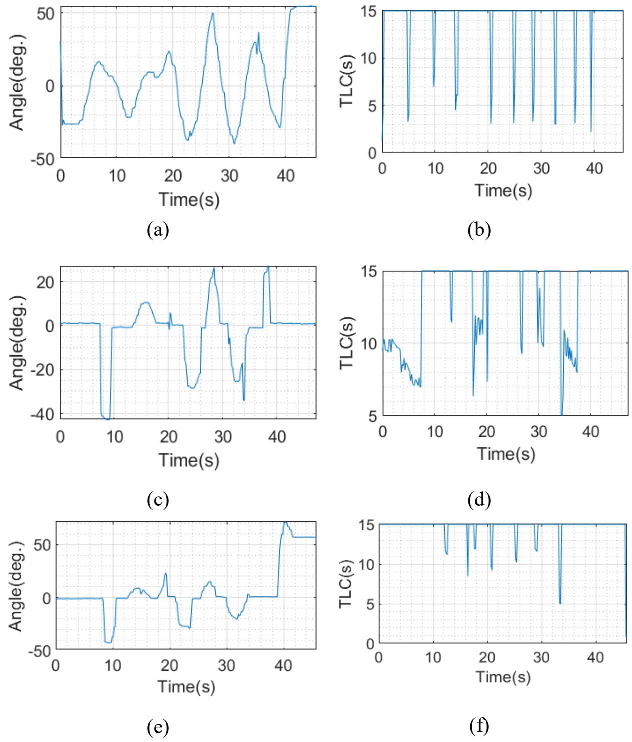


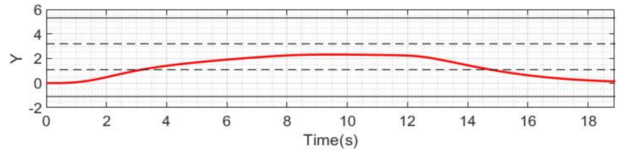
Fig. 8 Steering wheel status and time to lane crossing results of the lane following control based on these three cases.

C. Experimental of Overtaking Function

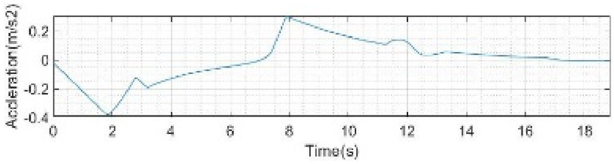
The experiment environment is a 2.2 meters wide and 80 meters long dual lanes road. The lane line detection processing marks the lines are shown in Fig. 9.

Fig. 9 The overtaking experiment environment.

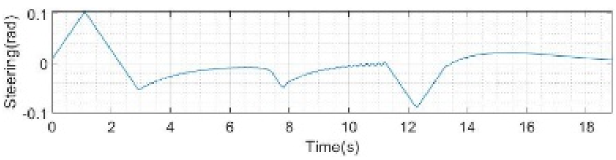
The scenarios of overtaking control in this paper: (1). preceding vehicle moves with zero lateral velocity; (2). preceding vehicle moves with lateral velocity; (3). preceding vehicle moves with drastically lateral velocity. In the first scenario, the preceding vehicle velocity is set as 0.36 km/hr. In the second scenario, the preceding vehicle goes forward with lateral speed 0.36 km/hr. Figure 10-11 show the overtaking trajectory, predicted throttle and predicted steering angle in three scenarios, respectively. We accomplish in three overtaking scenarios by the electric golf car.



(a)

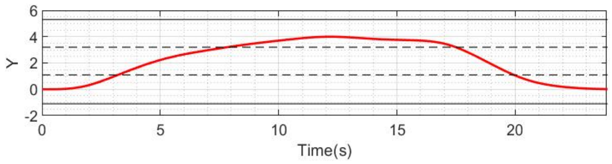


(b)

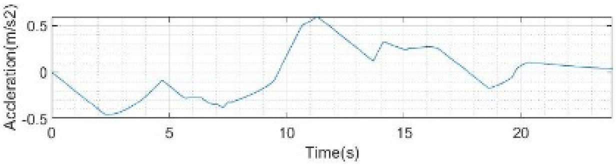


(c)

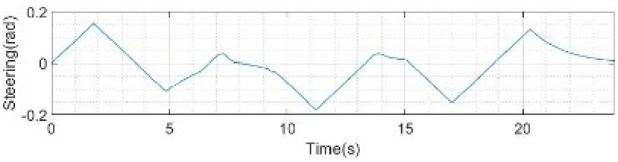
Fig. 10 The overtaking scenario is the preceding vehicle with zero lateral velocity (a) Overtaking trajectory of ego vehicle; (b) Acceleration; (c) Steering angle.



(a)



(b)



(c)

Fig. 11 The overtaking scenario is the preceding vehicle with lateral velocity 0.36km/hr. (a) Overtaking trajectory of ego vehicle; (b) Acceleration; (c) Steering angle.

VII. CONCLUSION

We develop an intelligent overtaking system by model predictive control scheme, which not only enhance driving safety for overtaking maneuver but also effectively decline in the unnecessary acceleration and the urgent steering. By exploiting the application of the model predictive control, preceding vehicle states obtained via radar sensor, and the road geometry information including lane lines detection and vanish point via camera, a successive linearization model of ego vehicle is generated to predict the future state of ego vehicle. The vehicle is able to predict the acceleration and steering angle for overtaking maneuvers and also brake to avoid collisions against the preceding vehicle. In addition, we utilize TLC as the time duration available for the driver, then refer TLC as the condition for lane following control. TLC enables the vehicle to accurately adjust the steering wheel prior to any lane boundary crossing and implement to lane following function. The experiment results perform that the proposed scheme fully meets the desired objectives including safety.

ACKNOWLEDGMENT

Research supported by Ministry of Science and Technology, Taiwan, R.O.C., under the contract No.: MOST 109-2628-E-035-001-MY3.

REFERENCES

[1] Taiwan Freeway Bureau , freeway traffic accident statistics and characteristic analysis in 2008 [Online]. (Available:https://www.freeway.gov.tw/Publish.aspx?cnid=516&p=2849)

[2] H. Tehrani, Q. H. Do, M. Egawa, K. Muto, K. Yoneda, and S. Mita, "General behavior and motion model for automated lane change," *IEEE Intelligent Vehicles Symposium*, pp. 1154-1159, 2015.

[3] T. Richter, S. Ruhl., J. Ortlepp, and E. Bakaba, "Prevention of overtaking accidents on two-lane rural roads," *Transportation Research Procedia,* vol. 14, pp.4140-4149, 2016.

[4] D. Clarke, J. ward, and J. Jones, "Overtaking road-accident: differences in maneuvers as a function of driver age," *Accident analysis and prevention,* vol. 30, pp.445-467, 1998.

[5] A. M ehmood, M. Liaquat, A. I. Bhatti, and E. Rasool, "Trajectory Planning andControl for Lane-Change of Autonomous Vehicle," *2019 5th International Conference on Control, Automation and Robotics*, pp. 331-335, 2019.

[6] Y. Z hu, M. Feng, X. Wang, and X. Xu, "Research on intelligent vehicle autonomous overtaking based on single neuron PID control," *2012 IEEE 2nd International Conference on Cloud Computing and Intelligence Systems*, Hangzhou, pp. 1192-1195, 2012.

[7] J. V. Frasch, A. Gray, M. Zanon, H. J. Ferreau, S. Sager, F. Borrelli, and M. Diehl, "An auto generated nonlinear mpc algorithm or real-time obstacle avoidance of ground vehicles," *European Control Conference*, pp. 4136-4141, 2013.

[8] M. F. Manzoor and Q. Wu, "Control and obstacle avoidance of wheeled mobile robot," *International Conference on Computational Intelligence, Communication Systems and Networks*, pp. 235-240, 2015.

[9] M. Werling and D. Liccardo, "Automatic collision avoidance using model-predictive online optimization," *IEEE Conference on Decision and Control*, pp. 6309-6314, 2012.

[10] J. Ji, A. Khajepour, W. W.Melek, and Y. Huang, "Path planning and tracking for vehicle collision avoidance based on model predictive control with multi-constraints," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 2, pp. 952-964, 2017.

[11] M. Ali, P. Falcone, C. Olsson, and J. Sjoberg, "Predictive prevention of loss of vehicle control for roadway departure avoidance," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 56-68, 2013.

[12] C. F. Lin and A. G. Ulsoy, "Time to lane crossing calculation and characterization of its associated uncertainty," *Journal of Intelligent Transportation Systems*, vol. 3, no. 2, pp. 85-98, 1996.

[13] S. Mammar, S. Glaser, and M. Netto, "Time to line crossing for lane departure avoidance: a theoretical study and an experimental setting," *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 2, pp. 226-241, 2006.

[14] J. Kong, M. Pfeiffer, G. Schildbach, and F. Borrelli, "Kinematic and dynamic vehicle models for autonomous driving control design," *IEEE Intelligent Vehicles Symposium (IV)*, pp. 1094-1099, 2015.