7th IFAC Symposium on Advances in Automotive Control
The International Federation of Automatic Control
September 4-7, 2013. Tokyo, Japan

Understanding and Modeling the Human Driver Behavior Based on MPC ⋆⋆

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Abstract: Better understanding driver behavior is essential for autonomous vehicles, as well as simulation, evaluation and optimization of a driver-vehicle closed-loop system. In this paper, the human driver behavior is first discussed in the form of perception, decision, and execution. In the following, the modelling of the driver behavior is proposed based on the preview-follower theory. The driver model includes three parts which are perception module, decision making module and execution module. The decision making module contains longitudinal control using proportional-integral-derivative (PID) controller and lateral control using model predictive control (MPC) method. Moreover, the response of muscle and nerve is modelled in the form of execution module. Typical simulations are carried out using vehicle dynamics software veDYNA and indicate that the proposed driver model is suitable for representative path following at varying vehicle speed.

Keywords: Driver modelling, Human driver behavior, Model predictive control, preview-follower theory, internal vehicle dynamics

1. INTRODUCTION

Vehicles play an important role in the development of the world economy and in society. However, vehicles also cause problem, for example, transport congestion, environmental pollution, traffic accidents, etc. Perhaps the most serious problem among them is accidents. Most of the accidents are caused by the wrong operation of the driver. A better understanding of the driver performance might enable to develop safer and more comfortable road vehicles. Moreover, developing a suitable driver model is significant in the development of autonomous vehicles, as well as simulation, evaluation and optimization of a driver-vehicle closed-loop system.

The topic of understanding the driver behavior has been proposed since 1960s. In the following more than a half century, it has been more and more attractive to researchers from many different disciplines. Among them, a preview-follower theory was put forward by Guo and Fancher (1983) for modelling driver's path following behaviors. The theory describes the driver's behaviors on the basis of the hypothesis that the driver's operation in a path following system is always aimed at minimizing the errors between the desired and actual trajectory of the vehicle.

Based on the preview-follower theory, an analytical method to calculate the driver parameters analytically is introduced by Guo and Ding (2004) where the vehicle lateral dynamics and driver delays are determined. The efforts mentioned above gives the fundamental frame of an analytical driver model. However, the desired path in the former efforts can only be expressed as the function of time. It is not convenient for an arbitrary designated path defined in space domain as vehicle speed is varied. In order to extend the application scope of the driver model, an arbitrary path following method for analytical driver model is discussed by Ding et al. (2007), and in the following Wu et al. (2011) discussed the motorcycle driver modelling based on this approach.

Several artificial neural network driver models have been developed by Lin et al. (2005); Quintero M et al. (2012) to better understand and analyze the driver behavior, which are also based on the preview-follower theory mentioned above. Lin et al. (2005) employed sophisticated artificial neural network architectures for developing models for human drivers in a driver-vehicle-environment system. Quintero M et al. (2012) considered the characterize of the way people drive and developed a driver model based on neural networks. The driver model is applied to driver assistance systems and allowed to identify potential high risk locations on roads and also is able to classify different kinds of drivers with a high degree of reliability.

Besides the method mentioned above about the driver modelling, many other models of the driver have been developed to improve the combined couple of driver and automobile. Based on the control theories, serval kinds of

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⋆⋆This work is supported by the Program for Changjiang Scholars and Innovative Research Team in University (IRT1017), the 863 Program (2012AA11071), and the Open Fund Project of the State Key Laboratory of Automotive Simulation and Control .

driver models have been created, such as the methods of optimization control in Butz and von Stryk (2005), and intelligent control in Hamiltona and Clarke (2005). These methods acquire effective control performance in driver modelling in some extent. However, the characteristics of driver are nonlinear and time variable, and in some aspects, those approaches could not reflect the dynamics of driver behavior, and degrees of driver expertise and knowledge.

Model Predictive Control (MPC) is an algorithm that uses a model to predict the future dynamics of the controlled plant and computes an optimal control sequence by minimizing the difference between a given reference and the predicted output, in the explicit consideration of time-domain constraints on control and output variables Chen and Allgöwer (1998). Previewing the target point is the first step in the process of driving vehicle. Then operates the vehicle running towards the target point. The intrinsic principle of MPC is likely to the driver operating the vehicle. Therefore, MPC is employed to understand the human driver and model their behavior. The time-variant predictive control method is applied to simulate the driver steering skill by Keen and Cole (2012). It uses the multiple linear model to simulate the driver's nonlinear property by linearization the nonlinear model.

In this paper, the modelling of human driver behavior is discussed using the preview-follower theory. The driver model includes three parts which are perception module, decision making module and execution module. The developed human driver has two major functions while controlling the vehicle, which includes longitudinal control and lateral control. In longitudinal control, the setting of the accelerator pedal and brake pedal are determined using proportional-integral-derivative (PID) controller according to the error of longitudinal vehicle velocity. In lateral control case, front steering wheel angle is determined using the MPC controller. Moreover, the muscle response of driver and the execution time of driver's neural reaction is considered during the execution. In order to evaluate the effectiveness of the proposed driver modelling method, representative simulations are carried out based on the commercial software veDYNA on the typical road.

The organization of the paper is as follows: In Section 2 the behavior of the human driver is discussed in the form of perception module, predicted module, making decision and execution module. In Section 3 the human driver is modelled according to the preview-following theory based on MPC. In Section 4 the simulation under the representative conditions are carried out to test the effectiveness of the driver model. Finally, conclusions of this paper are presented in Section 5.

2. UNDERSTANDING HUMAN DRIVER BEHAVIOR

In this section, the driving process is discussed in the form of path following theory. In order to simplify the description of the driving process, three different coordinates are defined which are shown in Figure 1. The ground coordinate (XOY), in which the desired path is defined, the vehicle coordinate ($X_vO_vY_v$) that is fixed with the center of gravity (CoG) of the moving vehicle, and the vehicle reference coordinate (xoy), which shares the same origin with the ground coordinate and has the same axis orientation with vehicle coordinate.

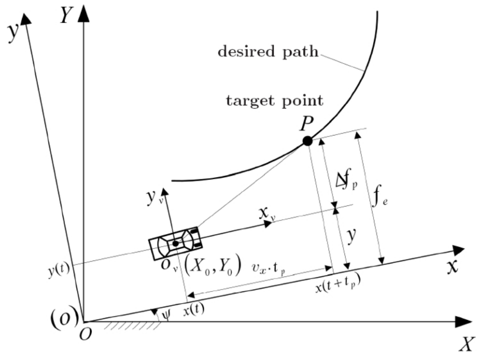

Fig. 1. understanding of the driving process

During the vehicle running in the current position, driver will preview the next vehicle position described as target point, which is marked as P in Figure 1, and this is understood as the perception process. Then the driver makes decision in order to drive the vehicle to the target point by operating the accelerator pedal, brake pedal and steering wheel angle. It is described as decision process of the driver. The decision output of accelerator pedal, brake pedal and steering wheel angle by the driver is executed by the hands and feet of driver after the neural response. Therefore, the neural response and muscle reaction time is considered, which is described as decision making process. These mechanical components have the same time-delay characteristics. The vehicle will be driven to the target point and the driver regulates the steering wheel angle, accelerator pedal and brake pedal real-time according to the vehicle states and road and traffic environment.

Based on the essence of the driver that is described above, the following structure is used to model the driver behavior which is shown in Figure 2. It is composed of three parts Qu et al. (2012), which are perception module, decision module and execution module. The perception module gives the desired path according to the road and traffic information by path previewing. It simulates the driver's behavior to perceive traffic information, preview the road and obtain the desired path. The decision module predicts the vehicle running path according to the internal vehicle dynamics and current vehicle states by trajectory prediction first, and then making decisions to obtain the steering wheel angle, brake pedal and accelerator pedal. Moreover, the neural reaction time for decision of the driver is considered here. In addition, the muscle response time is considered in the execution module.

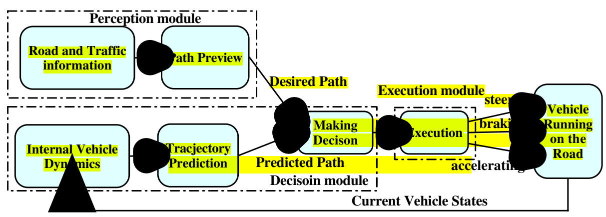

Fig. 2. The structure of driver model

3. MODELLING OF HUMAN DRIVER BEHAVIOR

In this section, the human driver behavior is modeled according to the structure of Figure 2, and the detail modelling process is described in the following subsection.

3.1 Desired path perception

Generally speaking, detail description of an arbitrary path with mathematical function is very difficult. However, it is easier for us to express the arbitrary path using path data table. Any road can be approximately described using enough discrete points on the path with numbers which designate the direction of the path. The path coordinates at the points in the table are accurate, and the others are obtained by linear interpolation.

As shown in Figure 3, the desired path is described with the path data table, and the current vehicle position in ground coordinate is (X_0, Y_0). Suppose $X(i), Y(i)$ denote the x, y coordinate values of the point with number i in the ground coordinate. The main objective of the desired path perception is to search the target point in path data table. The process of getting the target point mainly contains two steps. One step is to search the nearest point behind the vehicle in the path data table, which is used as the start point for the next searching. The other is to search two closest points to the preview point.

Suppose s_0 is the start point number for current searching process, set by last searching process. Due to the negative longitudinal vehicle velocity is not considered in this paper, $X(s_0)$ must be negative. From point s_0, to search the point behind and nearest to the current vehicle position in path data table satisfying the following equation $X(s)X(s+1) \leq 0$, where s is number of the satisfied point and stored as start point number of next searching process.

The process will continue to search the closest point to the preview point, which satisfies the following in equation:

$$[X(m) - (X_0(k)+V_x * t_p)][X(m+1) - (X_0(k) + V_x * t_p)] \leq 0, \quad (1)$$

where $X_0(k) = X_0(k-1)+V_x*T_s$, T_s is sample interval, t_p is preview time, m is the nearest point behind the target point. That is, the target point P is located in the middle of the point m and $m+1$.

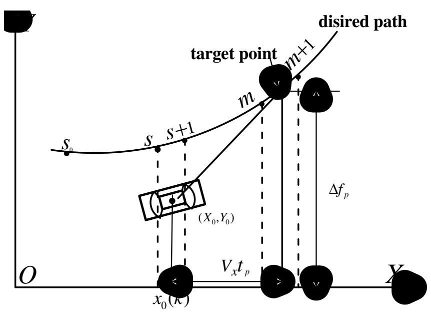

Fig. 3. Searching algorithm for start and target point

3.2 Decision making process

The decision making process includes three parts, which are internal vehicle dynamics, trajectory prediction and making decision.

Internal vehicle dynamics

The human driver keeps the vehicle as near as possible to a target point moving along the given track, as illustrated in Figure 3. The driver model implements this situation by control the longitudinal and lateral vehicle dynamics. Therefore, the internal vehicle dynamics contains the longitudinal dynamics and lateral dynamics.

The longitudinal velocity and longitudinal displacement in the path data are related to the longitudinal control. The longitudinal displacement is used to search the target point, and the longitudinal velocity is employed to obtain the brake pedal and accelerator pedal. Therefore, the longitudinal vehicle dynamics is described as $\dot{v}_x = a_x$.

The steering wheel angle is used to change the direction of the vehicle. Therefore, the lateral part of the driver model operates the steering wheel in order to follow the target point by minimizing the error of lateral displacement. A liner single-track model that contains an 2 degrees of freedom (DOF) is employed to describe the lateral vehicle dynamics, which considers the lateral vehicle velocity and yaw rate. According to the force balance on the lateral direction and torque balance around center of gravity (CoG), the lateral velocity and yaw rate can be described as $M\dot{v}_y = F_{yf}\cos\delta + F_{yr} - v_x r M, J\dot{r} = aF_{yf}\cos\delta - bF_{yr}$, where v_y is the lateral vehicle velocity, r is the yaw rate, δ is the front steering angle, a is the distance from CoG to front axle, b is the distance from CoG to rear axle, M is the mass of vehicle, J is the yaw rate of inertia around the CoG, F_{yr} and F_{yf} are the lateral tire forces of the front and rear wheel, respectively.

The tire road forces are assumed to be varying in the linear region. In this situation, the lateral tire forces F_{yf} and F_{yr} could be described as a linear function of the side slip angle α_f and α_r, that is to say $F_{yf} = 2C_F\alpha_f, F_{yr} = 2C_R\alpha_r$. Where α_f, α_r are the side slip angle of the front and rear tire, respectively. On the other hand, the side slip angle of the front and rear wheel could be approximated as $\alpha_f = \arctan\left(\frac{v_y+ar}{v_x}\right) - \delta, \alpha_r = \arctan\left(\frac{v_y-br}{v_x}\right)$, where v_x is the longitudinal vehicle velocity. In the case of the vehicle running in the steady-sate condition, the side slip angle is so small that it could be supposed that $\tan\alpha \approx \alpha$. Moreover, the relationship between the steering wheel angle and front steering wheel angle is $\delta = \tilde{\delta}/G$, where $\tilde{\delta}$ is the steering wheel angle, and G is the steering wheel ratio. Therefore, the lateral vehicle velocity and yaw rare could be expressed as

$$\begin{aligned} \dot{v}_y &= \frac{(2C_F + 2C_R)v_y}{Mv_x} + \frac{2(-C_R b + C_F a)r}{Mv_x} - v_x r - \frac{2C_F\tilde{\delta}}{MG}, \\ \dot{r} &= \frac{(-2bC_R + 2aC_F)v_y}{v_x J} + \frac{2(a^2C_F + b^2C_R)r}{Jv_x} - \frac{2aC_F\tilde{\delta}}{JG}. \end{aligned} \quad (2)$$

The lateral displacement Y can be obtained by integration of the following equation

$$\dot{Y} = v_x \sin\psi + v_y \cos\psi, \quad (3)$$

where ψ is the yaw displacement. The yaw displacement is the direction of the longitudinal axis of the vehicle and its rate of change is just the yaw rate r, that is $\dot{\psi} = r$. For synthesizing linear steering controller, small yaw displacement is usually assumed. Moreover, replace

$\dot{Y}$ in (3) with $\dot{y}$. In this event, (3) is approximated to $\dot{y} = v_x r + v_y$. Then the state space form of the lateral dynamics could be expressed as follows

$$\begin{aligned} \dot{x} &= Ax + B\tilde{\delta}, \\ y &= Cx, \end{aligned} \tag{4}$$

where $x = [y\ v_y\ \dot{r}\ r]$, $u = \tilde{\delta}$, y is the output, the coefficient matrix is expressed as follows

$$A = \begin{bmatrix} 0 & 1 & 0 & v_x \\ 0 & \dfrac{2(C_F + C_R)}{v_x M} & \dfrac{2(-bC_R + aC_F)}{v_x M} - v_x & 0 \\ 0 & \dfrac{2(-bC_R + aC_F)}{v_x J} & \dfrac{2(a^2 C_F + b^2 C_R)}{v_x J} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & \dfrac{-2C_F}{mG} & \dfrac{-2aC_F}{JG} & 0 \end{bmatrix}^T, \ C = [\, 1\ \ 0\ \ 0\ \ 0\,].$$

The components of vehicle velocity v_x and v_y, and the vehicle position y are described in vehicle coordinates. By discretization (4) at sample instants T_s, the discrete-time model is consequently given as

$$\begin{aligned} x(k+1) &= A_d x(k) + B_d \tilde{\delta}(k), \\ y(k) &= C_d x(k), \end{aligned} \tag{5}$$

where $A_d = e^{AT_s}$, $B_d = \int_0^{T_s} e^{At} B dt$, and $C_d = C$. Till then, the vehicle dynamics is described by (5), which is the basic model of the MPC controller designed in the next section.

Trajectory prediction

According to the principles of model predictive control, at time k, the coming vehicle lateral displacement is predicted on the basis of model (5). Moreover, the following assumption about longitudinal vehicle velocity is made

Assumption 1. The longitudinal vehicle velocity is invariable in the prediction horizon.

Hence, the prediction function of the lateral displacement is as follows:

$$Y_p(k+1|k) = S_x X(k) + S_u U(k), \tag{6}$$

where

$$Y(k+1|k) \triangleq \begin{bmatrix} y(k+1|k) \\ y(k+2|k) \\ \vdots \\ y(k+p|k) \end{bmatrix}, U(k) \triangleq \begin{bmatrix} \tilde{\delta}(k) \\ \tilde{\delta}(k+1) \\ \vdots \\ \tilde{\delta}(k+m) \end{bmatrix},$$

$$S_u = \begin{bmatrix} C_d B_d & 0 & \cdots & 0 \\ C_d A_d B_d & C_d B_d & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ C_d A_d^{p-1} B_d & C_d A_d^{p-2} B_d & \cdots & \sum_{i=0}^{p-m} C_d A_d^i B_d \end{bmatrix}, \tag{7}$$

$$S_x = \begin{bmatrix} C_d A_d & C_d A_d^2 & \cdots & C_d A_d^p \end{bmatrix}^T.$$

Where m is defined as the control horizon, p is defined as the prediction horizon, $Y(k+1|k)$ is the predict output at time k.

Making decision

As mentioned above, the main control requirement of vehicle following the desired path is divided into velocity tracking in the longitudinal direction and position tracking in the lateral direction, which can be described in Figure 4. The vehicle velocity in the longitudinal direction is mainly

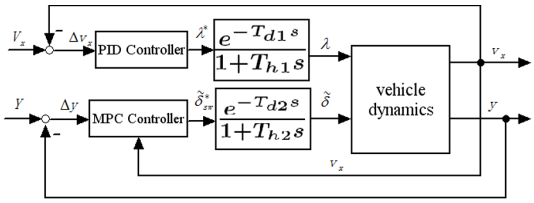

Fig. 4. The decisions in the longitudinal and lateral direction

controlled by the brake and acceleration pedal. Due to the brake and acceleration pedal can not be operated in the same time, the brake and acceleration pedal is regarded as unified pedal in our driver model. In addition, the PID controller is employed to eliminate the error between the desired longitudinal velocity and the actual longitudinal velocity obtained by the internal vehicle dynamics, and the PID controller is expressed as follows

$$\lambda^\star = K_p \cdot \Delta v_x + K_i \int_0^t \Delta v_x dt + K_d \frac{d\Delta v_x}{dt}, \tag{8}$$

where $\lambda^\star$ is the unified pedal, K_p, K_i and K_d is parameters of PID controller, and Δv_x is the error of longitudinal vehicle velocity.

The lateral displacement is mainly controlled by the steering wheel angle. Therefore, the main objective of lateral control is to make decision of steering wheel angle by reducing the lateral displacement error as small as possible. However, Due to the path previewed varies fast during the vehicle running, it is difficult to operate steering wheel to make the vehicle follow the road center. The lateral displacement of vehicle is determined by the predicted equation (6). The reference target points of the road that change to the vehicle coordinate are defined as $R_e(k+1) = [\, Y(k+1)\ Y(k+2)\ \cdots\ Y(k+p)\,]$. The vehicle can track the target point quickly by minimizing the difference between a given lateral displacement and a predicted output in (6), which is usually chosen in a quadratic form. Moreover, the control input $U(k)$ can also be included to penalize control efforts. Then the optimization problem with input and constrained output of the lateral displacement control is described as follows

$$\begin{aligned} &\min_{U(k)} J(y(k), U(k), m, p), \\ &J = ||\Gamma_y(Y_p(k+1|k) - R(k+1))||^2 + ||\Gamma_u U(k)||^2. \end{aligned} \tag{9}$$

where $\Gamma_y = \mathrm{diag}(\tau_{y,1}, \tau_{y,2}, \cdots, \tau_{y,p})$, and $\Gamma_u = \mathrm{diag}(\tau_{u,1}, \tau_{u,2}, \cdots, \tau_{u,m})$ are the weighting matrices.

By solving the optimization problem (9), the optimal control sequences at time k are derived: $U(k) = K_{mpc} E_p(k+1|k), K_{mpc} \triangleq [\, I\ 0 \cdots 0\,](S_u^T \Gamma_y^T \Gamma_y S_u + \Gamma_u^T \Gamma_u)^{-1} S_u^T \Gamma_u^T \Gamma_y, E_p(k+1|k) = R(k+1) - S_x x(k)$. After successful solution of the optimization problem, only the first component of $U(k)$ is effectively used to compute the control signal $u(k)$. Hence the closed-loop control law is defined as $u(k) = [\, 1\ 0 \cdots 0\,] K_{mpc} E_p(k+1|k)$. The above closed-loop control law of MPC is computed as the decision of steering wheel angle and it is applied to the plant, while the procedure will be repeated whenever new measurements are available in the next sampling instance.

3.3 Execution process

Considering the physiological and ergonomic constraints of driver, the neural response of driver is modelled as the delay component, which can be seen as follows $G_1(s) = e^{-T_d s}$. Where T_d is the response time of nerve. Moreover, taking the muscle characteristic of driver, a designed first-order delay model is applied, and its transfer function is given as follows $G_2(s) = \frac{1}{1+T_h s}$, where T_h is the response time of muscle.

4. SIMULATION

In this section, in order to validate the proposed method, simulation results for modelling the driver behavior and the related control algorithm are presented, which are obtained from two representative tests using the vehicle dynamic software veDYNA. The software is a proven and versatile vehicle dynamics simulation tool based on a high-precision vehicle model.

The first simulation is carried out when the vehicle running on the curve road, and the radius of the road is about 400 m. The road path could be seen from Figure 5 (a). The initial position of vehicle is (0 0) in the inertial coordinate system. The preview time of driver has significant influence on the driver-vehicle closed-loop performance. For the human driver, when the road curvature is small, the shorter preview time is chosen to achieve better path following precision. And when the road curvature is large, the larger preview time is selected to achieve relaxing driving. On the other hand, the preview time is influenced by the driving experience, age and disposition of driver. Therefore the prediction time of a driver often belongs to the time internal $[0.5s\ 2s]$ Li et al. (2010). Based on the above analysis, the preview time of the proposed driver model for path preview is chosen as $t_p = 0.8s$ in (1). The parameters of PID controller used for longitudinal vehicle velocity control in (8) are selected as $K_p = 11, K_i = 0.98$, and $K_d = 5$. The actual vehicle velocity compared with the previewed vehicle velocity can be seen in Figure 5 (b), and the error of the vehicle velocity can be seen from Figure 5 (c). Moreover, the computed unified pedal by the PID controller can be seen from Figure 5 (d). The weighting matrices of the cost function in (9) for eliminating the difference of the lateral displacement are chosen to be $\Gamma_u = 0.01\mathrm{I}_4$ and $\Gamma_y = \mathrm{I}_5$, respectively. The predictive horizon is chosen as $p = 5$, and the control horizon is selected as $m = 4$ in (7). The computed control input in lateral direction that is steering wheel angle by optimization problem (9) is shown in Figure 5 (e). The response time of nerve is chosen as $T_d = 0.3$, and the response time of muscle is selected as $T_h = 0.1$. As a result, the error of the lateral displacement that is shown in Figure 5 (f) could be obtained by subtracting the desired lateral displacement from the actual lateral displacement.

From Figure 5 (c), it can be seen that the error of longitudinal vehicle velocity is smaller than $0.15m/s$ in the curve road. On the other hand, from the Figure 5 (f), we can seen that the error of the lateral displacement is smaller than 0.5 m. It is specified that the presented driver model is effective on the curve road. Moreover, the unified pedal in Figure 5 (d) is used as the accelerator and brake pedal in the driver model. Both the accelerator and the brake pedal is between 0 and 1 in veDYNA, and the unified pedal of the driver model seen from Figure 5 (d) is between 0 and 1. It is specified that the longitudinal control of vehicle velocity is effective. The output control of the lateral MPC controller is steering wheel angle that can be seen from Figure 5 (e). The front steering wheel angle is transformed to steering wheel angle by multiply the steering ratio where the steering ratio is 20.5 in the vehicle of veDYNA. It can be seen from Figure 5 (e) and (f), due to the difference between the desired path and predicted path exist, the steering wheel angle regulate the direction of the vehicle.

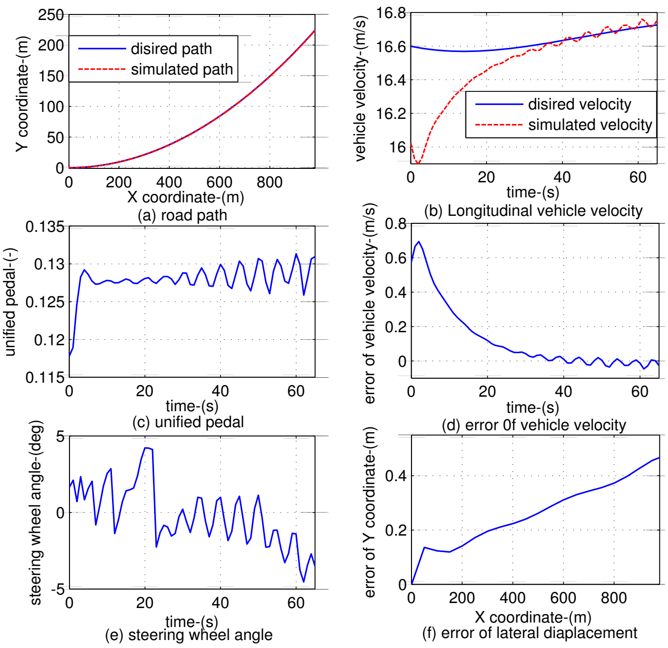

Fig. 5. The simulation results on the curve road

In order to further validate the performance of the modelling schemes of driver behavior, another typical simulation on the sinusoidal path is carried out. The simulation parameters used in the predicted path, making decision, and execution is the same as the first simulation. In order to follow the desired path that is shown in Figure 6 (a), the proposed driver model takes two measures into account, which are longitudinal vehicle velocity control by operating unified pedal and lateral displacement control by optimization the steering wheel angle. The desired longitudinal vehicle velocity and the actual vehicle velocity is shown in Figure 6 (b), the error of longitudinal vehicle velocity is shown in Figure 6 (c) and the output of the PID controller is shown in Figure 6 (d). The parameters of PID controller are the same as the first simulation. The MPC controller is employed to make the lateral error displacement as small as possible. The steering angle considering the muscle execution and driver's neural response time is shown in Figure 6 (e). The error of the lateral displacement could be seen from Figure 6 (f), and the definition of the error of lateral displacement is the same as the first simulation.

It can be seen from the longitudinal velocity in Figure 6 (c) and lateral displacement error in Figure 6 (f), the difference of longitudinal vehicle velocity decreases with time and the error decreases with time increasing, and difference of lateral displacement is less than 0.5m. It is specified that the modelling schemes of driver is effective on the sinusoidal road. Moreover, the unified pedal in Figure 6 (d) and the steering angle in Figure 6 (e) obtained from the longitudinal velocity control and lateral displacement control is satisfied the required value range. On the other hand, it can be deduced from the internal vehicle dynamics that the longitudinal dynamics and the lateral dynamics coupled with each other. Using the assumption 1, the longitudinal vehicle velocity stays invariant in the prediction, and updates in the beginning of the next prediction. It can be concluded that the proposed driver modelling method could be implemented the decoupling of the longitudinal dynamics and lateral dynamics by considering the longitudinal vehicle velocity varying in lateral dynamics. It is one of reasons that the effectiveness the proposed modelling method. Moreover, from the simulation results in Figure 6 (a) (b) (c) and (f), it can be illustrated that the presented modelling method could achieve the effective control performance both in longitudinal and lateral direction in the sinusoidal road.

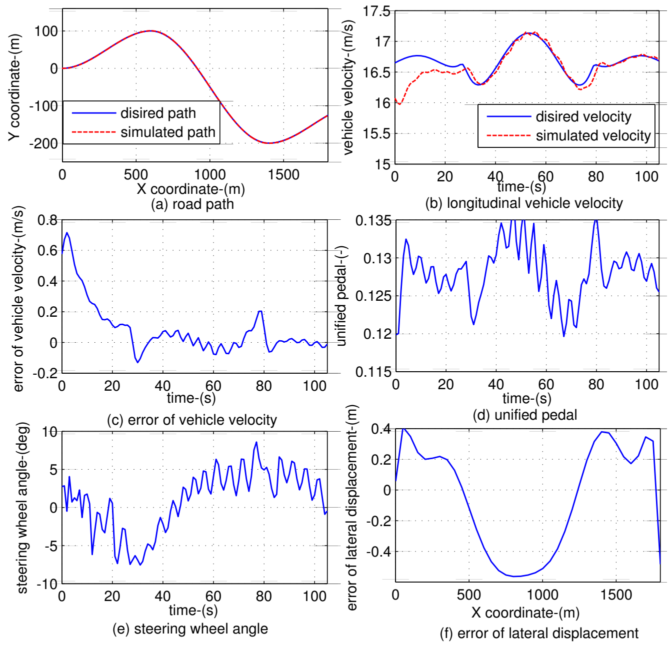

Fig. 6. The simulation results on the sinusoidal road

5. CONCLUSION

The paper presents a driver modelling method based on preview-follower theory. The proposed driver model contains three parts that is perception module, decision making module and execution module. In the perception module, the desired vehicle running path is obtained according to the road and traffic information by path preview. In decision making module, longitudinal control using PID controller and lateral control using MPC control method are proposed in order to follow the desired path. In execution module, the response time and action execution time of driver is considered. The simulation results demonstrate the good performance of the proposed driver modelling method in curve and sinusoidal road.

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