

Application of Stochastic Model Predictive Control to Modeling Driver Steering Skills

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ABSTRACT

With the development of the advanced driver assistance system and autonomous vehicle techniques, a precise description of the driver's steering behavior with mathematical models has attracted a great attention. However, the driver's steering maneuver demonstrates the stochastic characteristic due to a series of complex and uncertain factors, such as the weather, road, and driver's physiological and psychological limits, generating negative effects on the performance of the vehicle or the driver assistance system. Hence, this paper explores the stochastic characteristic of driver's steering behavior and a novel steering controller considering this stochastic characteristic is proposed based on stochastic model predictive control (SMPC). Firstly, a search algorithm is derived to describe the driver's road preview behavior. Then, the internal vehicle model including driver's knowledge of the vehicle lateral dynamics is derived by a nonlinear 2-DOF model, and a sideslip angle perception model is proposed in the state feedback process to describe the stochastic characteristic of driver's steering behavior, which is characterized by a gauss stochastic variable, whose mean represents the real sideslip angle and variance is associated with driver's steering skills and vehicle lateral dynamics. Moreover, the steering control rule is formulated to generate the trajectory track steering commands according to the trajectory error and steering input. Finally, the proposed SMPC driver model is validated. The results demonstrate the SMPC driver model has an excellent trajectory track capability and describes the stochastic characteristic of driver's steering behavior precisely.

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INTRODUCTION

It is widely recognized that driver's vehicle manipulation behavior demonstrates a critical influence on the driving safety, and the interaction among the driver, vehicle and environment has been widely explored in recent years [1]. Especially, understanding and modeling the steering behavior of a human driver is becoming a popular topic to enable the development of the advanced driver assistance system and autonomous vehicle techniques [2].

Over the past decades, various driver models are developed including the compensation tracking models [3, 4, 5], preview tracking models [6, 7, 8, 9, 10] and adaptive intelligent models [11, 12, 13]. The previous driver modeling mainly focuses on trajectory track capability in the driver-vehicle-environment closed-loop system, but lacks a thorough understanding for the human physiological characteristic. Therefore, many researchers have studied driver modeling based on the neuromuscular dynamics, cognitive processes and the learning behavior [14]. Pick and Cole [15] proposed a method for identifying the arms' dynamic properties of the human driver and developed a model including the neuromuscular dynamics to illustrate the driver's steering behavior [16]. Will and David [17] derived a neuromuscular driver model with the feed-forward and feedback controls simultaneously. Salvucci [18] proposed a driver model based on the cognitive architecture and developed a rapid prototype to evaluate the in-vehicle interfaces [19]. Kim and Cole [20] improved the steering manipulation of a human driver under

constant or varying road frictions through the steering torque feedback control. In addition, tremendous research efforts on driver skills modeling have contributed to a full development of the autonomous driving techniques [21]. Dolgov et al. [22] derived a path-planning algorithm for autonomous vehicles driving in an unknown environment. Liu et al. [23] proposed a real-time trajectory planning framework and developed an integrated local trajectory planning and tracking control approach regarding autonomous vehicles [24].

In recent years, human driver's steering manipulation behavior is widely explored via model predictive control (MPC) [25, 26]. MacAdam [27, 28] derived an optimal preview steering controller based on the MPC theory. Cole et al. [29] developed and compared two optimal linear preview steering controllers with the linear quadratic regulator (LQR) and MPC approaches. Additionally, it is widely accepted that different drivers generally demonstrate different steering manipulation behaviors [14], whereas a driver cannot repeat his steering maneuver on a same road and a set of complex and uncertain factors that include the external disturbance, internal physiological and psychological limits enable the stochastic characteristic of driver's steering behavior, limiting the performance of the vehicle or the driver assistance system. Qu et al. [30] studied the driver's cognition behavior of the uncertain road friction and roughness, modeling the stochastic characteristic of driver's steering behavior via SMPC. Ploechl and Edelmann [31] gave an excellent

review of driver model and pointed out that the human factors including the stochastic characteristic in the vehicle-driver coupled system should be invested more deeply.

In this paper, the driver's perception to vehicle states is investigated and a novel steering controller considering the stochastic characteristic is proposed with structure in Figure 1 based on SMPC. Especially, a sideslip angle perception model described by a gauss stochastic variable is proposed in the state feedback process to characterize the stochastic characteristic of driver's steering behavior, whose mean represents the real sideslip angle and variance characterizes driver's steering skills and vehicle lateral dynamics. The structure of this paper is organized as follow. Section 2 describes the driver's road preview behavior. Section 3 formulates the internal vehicle dynamics model. The steering control rule is derived in Section 4. The proposed SMPC driver model is validated in Section 5. Eventually, the conclusions are drawn in Section 6.

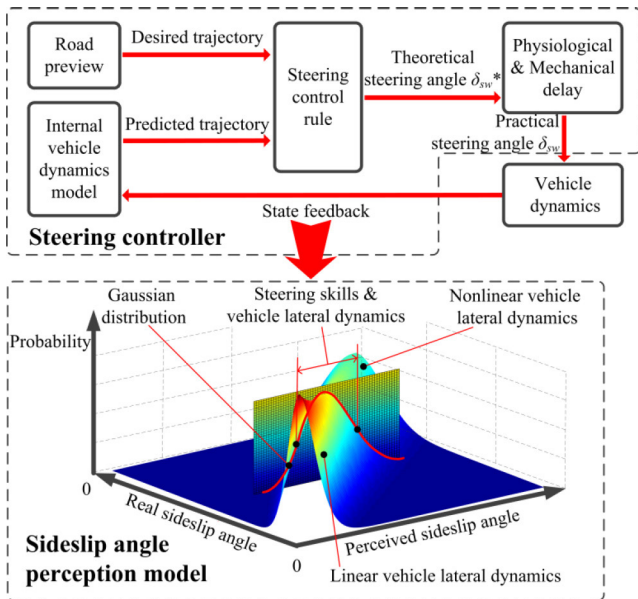


Figure 1. Block diagram of the SMPC driver model

ROAD PREVIEW

The road preview indicates the driver's ability to observe the road conditions ahead of the vehicle [7], and the controller previews the incremental lateral displacement of the desired trajectory with respect to the vehicle frame of reference to generate a steering command. In this paper, the desired trajectory is described with a series of discrete coordinate points as shown in Table 1. In addition, the multiple-point preview assumption is formulated and a search algorithm [32] is adopted here to characterize the driver's preview behavior as shown in Figure 2, whose detailed process is illustrated as follows.

Table 1. Desired trajectory information

Point number	X-coordinate	Y-coordinate
1	X_1	Y_1
2	X_2	Y_2
...	...	...
n	X_n	Y_n

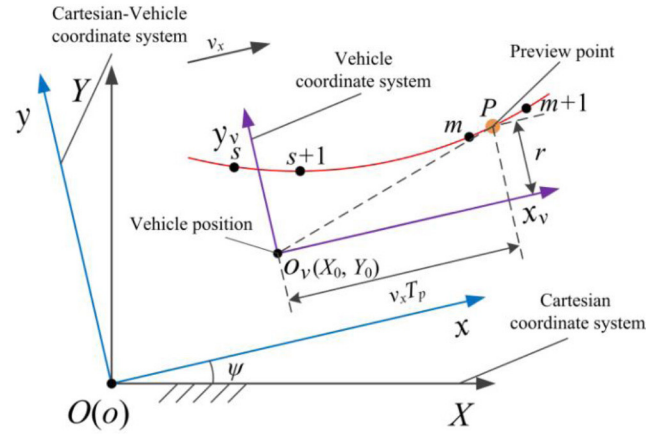


Figure 2. Search process of the preview point

Firstly, the vehicle states including the position $(X_0(k), Y_0(k))$ and the heading angle $\psi(k)$ at the present sample time k are obtained via state feedback, and the transform matrix between the Cartesian coordinate system X - Y and the Vehicle coordinate system x_v - y_v is derived as Equation (1).

$$\begin{bmatrix} x_v(i) \\ y_v(i) \end{bmatrix} = \begin{bmatrix} \cos\psi & \sin\psi \\ -\sin\psi & \cos\psi \end{bmatrix} \times \begin{bmatrix} X(i) - X_0 \\ Y(i) - Y_0 \end{bmatrix} \quad (1)$$

Then, the closest point s behind the present vehicle position is searched in the Table 1 according to the constraint condition in Equation (2), which is used for updating the next point.

$$x_v(s) \times x_v(s+1) \leq 0 \quad (2)$$

Finally, the closest two points $m, m+1$ nearby the preview one are obtained based on the constraint condition formulated in Equation (3), and the incremental lateral displacement $r(k)$ of the preview point relative to the present vehicle position is obtained as Equation (4).

$$\left[x_v(m) - v_x \times T_p \right] \times \left[x_v(m+1) - v_x \times T_p \right] \leq 0 \quad (3)$$

$$r(k) = y_v(m) + \frac{y_v(m+1) - y_v(m)}{x_v(m+1) - x_v(m)} \times (v_x \times T_p - x_v(m)) \quad (4)$$

INTERNAL VEHICLE DYNAMICS MODEL

The internal vehicle dynamics model reflects the driver's cognition characteristic to the vehicle lateral dynamics, and generates the predicted trajectory under the present vehicle states. In addition, the driver generally shows more concerns with the vehicle's lateral and yaw motion during the steering process [29], and a 2-DOF vehicle model is adopted as the internal model.

Tire Model

In this paper, it is assumed that the nonlinear characteristic of the 2-DOF vehicle model is mainly from the nonlinear tire performance, which is described by the UniTire model [33] as the [Appendix](#).

Sideslip Angle Perception Model

In this paper, the stochastic characteristic of driver's steering behavior is explored based on the human driver's cognition behavior to the vehicle lateral dynamics, which is regarded as a stochastic process and associated with the driver's steering skills and vehicle lateral dynamics. Generally, a skilled driver shows a more precise perception of the vehicle states, contributing to a better driving performance; a novice driver usually shows a poor perception to the vehicle lateral dynamics, leading to an inferior driving performance. Furthermore, the driver's cognition behavior normally presents a decreasing tendency when the vehicle lateral dynamics transforms from the linear to the nonlinear region.

Based on the discussions above, a detailed cognition process of the nonlinear tire lateral force is studied in this paper and a sideslip angle perception model described by a Gauss stochastic variable Z is proposed as [Equation \(5\)](#), whose mean α_{real} represents the real sideslip angle and the variance σ^2 characterizes the human driver's steering skills and the vehicle lateral dynamics.

$$\begin{aligned} Z &\sim N(\alpha_{real}, \sigma^2) \\ \sigma &= p_1 |\alpha_{real}|^2 + p_2 |\alpha_{real}| \end{aligned} \quad (5)$$

where, p_1 and p_2 are the identified parameters associated with steering skills.

For simplification, the common drivers are categorized into the novice one with less driving experience and the skilled one with abundant driving experience, and their sideslip angle perception characteristic with various real sideslip angles derived as the [Equation \(5\)](#) are presented in [Figure 3](#) respectively.

Regarding the skilled driver, the sideslip angle perception characteristic with various real sideslip angles is derived by a "steep mountain". Considering a small real sideslip angle α' , the perceived sideslip angle demonstrates a Gauss possibility distribution with a small variance nearby its real value, leading to an excellent steering manipulation performance via the accurate perception to the real sideslip angle. Conversely, the sideslip angle perception characteristic of the novice driver is described by a relatively "flat mountain". With the same real sideslip angle α' as the skilled one, the Gauss distribution demonstrates a larger variance, and the perceived sideslip angles are distributed more discretely relative to its real value, which characterizes a poor perception to tire sideslip angle and results in an inferior steering manipulation performance.

In addition, the distribution variance presents an increasing tendency with the real sideslip angle's increase, in other words, the perception accuracy is decreasing when the vehicle lateral dynamics transforms from the linear to the nonlinear region, causing a decreasing steering manipulation performance.

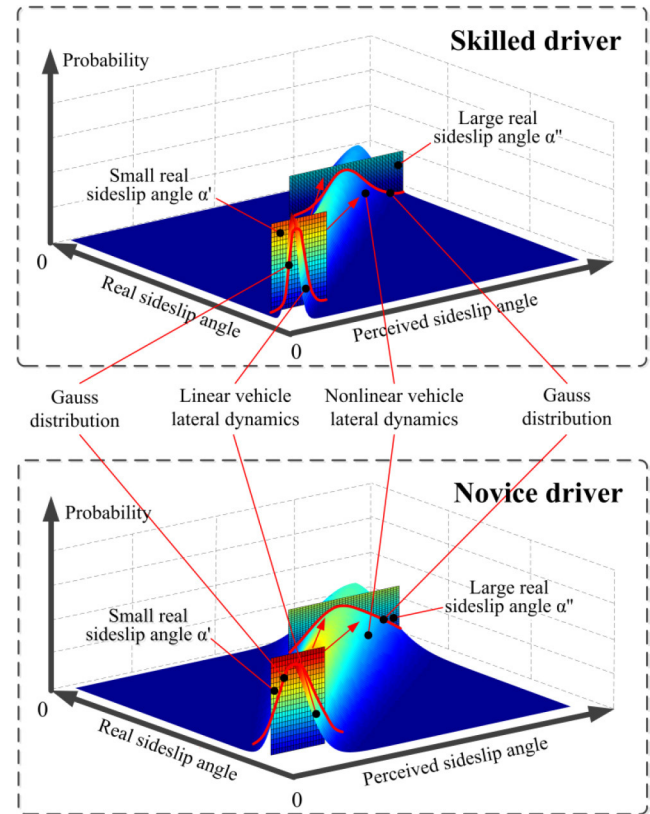


Figure 3. Sideslip angle perception model

Vehicle Model

In general, the dynamics equation of a typical 2-DOF bicycle model as shown in [Figure 4](#) can be derived as [Equation \(6\)](#) with a small steering angle assumption.

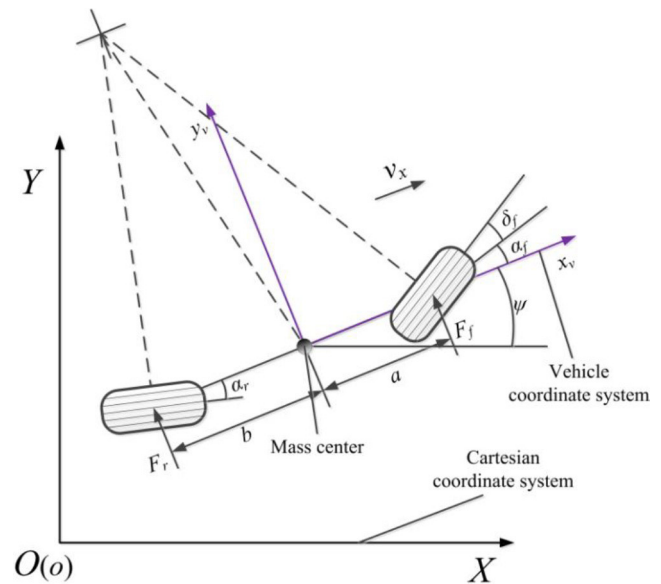


Figure 4. Schematic diagram of the 2-DOF bicycle model

$$\begin{aligned} m\ddot{y} &= -mv_x\dot{\psi} + 2F_{yf} + 2F_{yr} \\ I\ddot{\psi} &= 2aF_{yf} - 2bF_{yr} \end{aligned}$$

