

A Robust Lane-Keeping ‘Co-Pilot’ System Using LBMPC Method

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ABSTRACT

To provide a feasible transitional solution from all-by-human driving style to fully autonomous driving style, this paper proposed concept and its control algorithm of a robust lane-keeping ‘co-pilot’ system. In this a semi-autonomous system, Learning based Model Predictive Control (LBMPC) theory is employed to improve system's performance in target state tracking accuracy and controller's robustness.

Firstly, an approximate LTI model which describes driver-vehicle-road closed-loop system is set up and real system's deviations from the LTI system resulted by uncertainties in the model are regarded as bounded disturbance. The LTI model and bounded disturbances make up a nominal model. Secondly, a time-varying model which is composed of LTI model and an ‘oracle’ component is designed to observe the possible disturbances numerically and it is online updated using Extended Kalman Filter (EKF). Thirdly, LBMPC method is used to decouple controller's optimal control performance and its robustness. Constraints are applied to states predicted by nominal system, while states predicted by oracle model are used for computation of cost function.

In the end, this paper presents simulation results obtained by Matlab/Simulink. Straight road and curved road are two typical driving conditions used for verification. The results show the conclusion that the EKF algorithm can estimate the un-modeled uncertain dynamics effectively and the proposed lane-keeping copilot based on the oracle model can successfully assist driver to stay in an expected driving zone.

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INTRODUCTION

Lane Keeping Assistance System (LKAS) is one of the typical driving assistance systems and it is proposed at early 2000s. Analysis result from Infiniti research team shows that effective LKAS can help to reduce the total number of traffic accidents by 12%[1]. Car manufacturers, such as Honda, Volkswagen, Nissan, all have this kind of systems on their products, sometimes named as Lane Departure Avoidance system.

In most of the control algorithms, the system is activated when lane departure is detected or predicted, then the system assists driver by steering back into original lane, or by applying a resistant force on steering column. As a unified approach, the control law proposed by A. Grey et al. requires no activation strategy by optimizing a cost function which is composed of only steering and braking inputs, thus can keep the vehicle stay in safe area by using minimum amount of input. If the closed-loop system can satisfy safe constraints without any assistant input, then the system will be at a standby status automatically[2][3].

In recent years, as driving assistance systems show a trend towards more intelligence, more researches are focused on higher level automated driving technologies[4], such as path planning problems aimed at fewer fuel consumptions and hazard risks. Regarding to lane-keeping safety, an example is the combined structure of LKS and ALKAS propose by J. Kim et al. In their system, drivers can choose from options of different level of automation[5].

However, fully autonomous driving is not ready for commercial applications at present. The major reason is that even the most advanced autonomous system cannot ensure absolute safety due to technical limitations such as lane marking detection, therefore, in order to avoid accident, drivers need to be always aware of current driving situation. If drivers are out of the loop, it will become a doubt whether they can response to the system failure and take over the control in time. Besides, when human drivers are out of the loop, the lack of acceptance and trust will make them feel even more nervous than normal driving situation.

Therefore, in this paper, a semi-autonomous lane-keeping ‘co-pilot’ system is proposed. It is designed as a transitional solution which can improve the level of automation, when driver can still stay in loop.

within the driving task. The concept of ‘co-pilot’ which is a constraint-based approach to shared-adaptive control of ground vehicle was firstly introduced by S. Anderson et al.[6]. Using the similar definition, the lane-keeping ‘co-pilot’ proposed in this paper assists driver to keep vehicle stay in the expected lateral driving zone and requires no on/off switch or decision making step. In the meanwhile, this control strategy will bring in a new problem about controller's robustness due to uncertainty in driver behavior. In C. Liu et al.'s research, similar problem in LKAS controller design was dealt by using a unscented transformation based Stochastic MPC[7], while polyhedral-like invariant set as constraints were used by N. M. Enache et al. to ensure system's robustness[8].

As LBMPC method proposed by A. Aswani, et al. can decouple robustness and optimal performance by introducing online learning to traditional tube-MPC and was proved to be safe and robust[9], this method is used for the design of the lane-keeping ‘co-pilot’.

This paper is organized into the following parts: firstly, a nominal system composed of a LTI system model and bounded disturbances is built to simulate the closed-loop of ‘driver-vehicle-road’ system. Secondly, an oracle is designed to learn the un-modeled part of real system and an oracle model is built to be composed of the LTI model and the oracle. Thirdly, a LBMPC control law is introduced using the two models, constraints and cost function are designed for both safety and a quick and close response to designed trajectory. In the end, simulations are conducted to test the function of the ‘co-pilot’ system and to compare the performance of the LBMPC-based controller with the result of the traditional tube-MPC method. Two scenarios are used in simulations, and it is shown that the LBMPC-based ‘co-pilot’ system is able to obtain satisfying results in each scenario.

NOMINAL SYSTEM MODELING

In the LBMPC theory, the nominal model is an approximate linear time-invariant model with bounds on its modeling error. The linear dynamics and the bound of un-modeled uncertainties will be used to compute invariant sets which can give a certificate that system states can converge to the tube around the states generated by the LTI model safely.

For state prediction over the preceding horizon, a closed-loop ‘driver-vehicle- road’ system is composed of a vehicle model, a ‘vehicle-road’ kinematic model and a driver model.

LTI System Model

The LTI model can be simplified to simulate the linear dynamics of the system basically.

‘Vehicle-Road’ Model

Using a linear two DOF bicycle model as one part of the vehicle-road dynamic system, the ‘vehicle-road’ model can be described by (1). The diagrammatic sketch of the vehicle-road dynamic system is shown by Figure 1.

The system state x is made up of vehicle's yaw rate $\dot{\psi}$, relative yaw angle e_ψ , relative lateral speed v_{yr} and relative lateral offset e_y . System input u is steering angle of front wheel δ . The curvature ρ is regarded as external input.

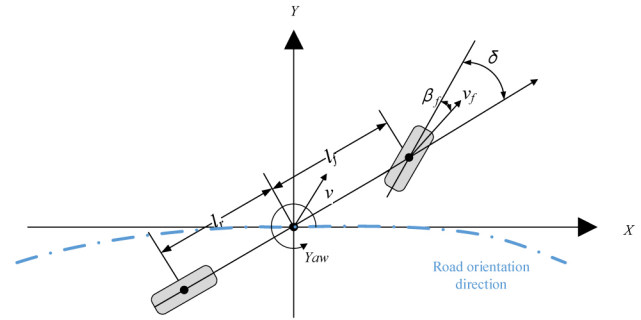


Figure1. vehicle-road system

$$\dot{x} = Ax + Bu + E\rho$$

$$x = \begin{bmatrix} \dot{\psi} \\ e_\psi \\ v_{yr} \\ e_y \end{bmatrix}; A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & 0 \\ 1 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}; B = \begin{bmatrix} b_1 \\ 0 \\ b_3 \\ 0 \end{bmatrix}; u = \delta; E = \begin{bmatrix} 0 \\ -v \\ -v^2 \\ 0 \end{bmatrix} \quad (1)$$

In the matrixes,

$$a_{11} = -\frac{2C_f l_f^2 + 2C_r l_r^2}{I_z v}; a_{12} = \frac{2C_f l_f - 2C_r l_r}{I_z};$$

$$a_{13} = -\frac{2C_f l_f - 2C_r l_r}{I_z v}; a_{31} = -\frac{2C_f l_f - 2C_r l_r}{mv};$$

$$a_{32} = \frac{2C_f + 2C_r}{m}; a_{33} = -\frac{2C_f + 2C_r}{mv};$$

$$b_1 = 2C_f l_f / I_z; b_3 = 2C_f / m$$

Where,

$l_f(l_r)$: distance from front(rear) axle center to mass center

$C_f(C_r)$: cornering stiffness of front(rear) tire

m : vehicle's mass

I_z : vehicle's moment of inertia

v : vehicle's longitudinal speed

Simplified Driver Model

A simplified driver model (2) is used by assuming that drivers adjust their steering input according to lateral offset error, yaw angle error at current position and yaw angle error at preview point. These factors are shown in Figure 2.

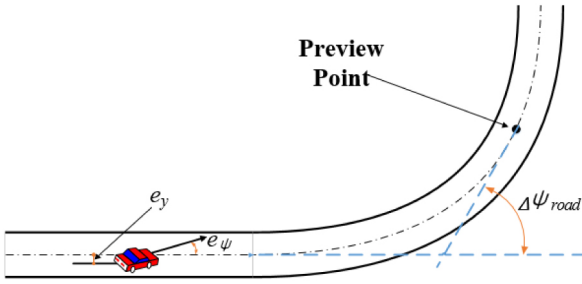


Figure 2. three important factors in a simplified driver model

$$\begin{aligned}\delta_d &= k_y e_y + k_{\psi,1} e_\psi + k_{\psi,2} \Delta\psi_{road} \\ &= \begin{bmatrix} 0 & k_{\psi,1} & 0 & k_y \end{bmatrix} x + k_{\psi,2} \Delta\psi_{road}\end{aligned}\quad (2)$$

Where,

δ_d : driver's input angle on steering wheel

$\Delta\psi_{road}$: the change of road orientation angle at preview point

k_y : gain coefficient on current lateral offset error

$k_{\psi,1}$: gain coefficient on current yaw angle error

$k_{\psi,2}$: gain coefficient on change of road orientation angle

Closed-Loop System Model

The closed-loop system is built by combining (1) and (2). Assistant control input angle δ_c is then regarded as the only input.

$$\dot{x} = (A + BG_{sw/fw}G_d)x + BG_{sw/fw}\delta_c + E\rho + E_d\quad (3)$$

Where,

$$G_d = [0 \ k_{\psi,1} \ 0 \ k_y]$$

$$E_d = BG_{sw/fw}k_{\psi,2}\Delta\psi_{road}$$

δ_c : assistant control input angle on steering wheel

$G_{sw/fw}$: transfer ratio from steering wheel angle to front wheel angle

For prediction and control usage, equation (4) is obtained by discretization of (3). Therefore, the nominal system can be modeled by (5) considering bounded disturbances.

$$\begin{aligned}x_{k+1} &= A_{DVR}x_k + B_{DVR}u_k + E_{DVR} \\ A_{DVR} &= e^{(A + BG_{sw/fw}G_d)T} \\ B_{DVR} &= \left(\int_0^T e^{(A_k + B_k G_{sw/fw}G_d)t} dt \right) B \\ E_{DVR} &= \left(\int_0^T e^{(A_k + B_k G_{sw/fw}G_d)t} dt \right) (E\rho + E_d)\end{aligned}\quad (4)$$

It is worth noting that larger disturbances will bring in more conservativeness, which will result in a smaller range to find a feasible solution. Therefore, in order to properly diminish the range of disturbances, three options of LTI models using different nominal vehicle longitudinal speed are provided as (6) shows.

$$\begin{aligned}x_{k+1} &= A_{DVR}x_k + B_{DVR}u_k + E_{DVR} + d_k \\ x_{k+1} &= A_{DVR,i}x_k + B_{DVR}u_k + E_{DVR} + d_k\end{aligned}\quad (5)$$

if $v_{real} < 80$, then $i = 1, v = 70$
else if $v_{real} < 100$, then $i = 2, v = 90$
else $v_{real} < 120$, then $i = 3, v = 110$

(6)

Bounded Disturbance Analysis

In the process of simplification during approximate LTI system modeling, the un-modeled dynamics include unmeasurable vehicle parameters, indeterminate tire characteristics, stochastic driver behaviors and environment recognition errors. Bounds are estimated and summed up using Minkowski sum of disturbances which are resulted from three kinds of sources, as is shown by (7).

$$D_{DVR} = D_{DVR_d} \oplus D_{DVR_v} \oplus D_{DVR_r}\quad (7)$$

Where,

D_{DVR_d} : disturbances generated by driver modeling error

D_{DVR_v} : disturbances generated by vehicle modeling error

D_{DVR_r} : disturbances generated by road recognition error

ORACLE DESIGN AND LEARNING

In this paper, a parametric oracle is introduced to learn the un-modeled system dynamics online. The motivation of the oracle is to obtain a model which is closer to real system than the nominal one through real-time learning method. The LTI model and the oracle together made up a complete model which is called oracle model in this paper.

As long as the oracle's algebra value lies within the bounds of disturbances which is previously calculated, and states predicted by nominal model satisfy robust invariant-set constraints, the optimal solution which can minimize cost function of states predicted by oracle model is feasible. In the meanwhile, as oracle model is more close to real system, the optimal control input can lead to a better control performance, ideally a better performance should be observed as faster and closer convergence to target states, which is target trajectory in a lane-keeping task.