

Lateral Control System for Autonomous Lane Change System on Highways

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ABSTRACT

In this paper, we propose a vision based lateral control scheme for autonomous lane change system on highways. Three main techniques are proposed, to improve the lane keeping/lane change performance, and to reduce the ripple in the yaw rate on highways. First, we propose a model based lane prediction method to cope with the momentary failure of lane detection. Second, we innovate an approach to steering wheel angle control based on torque overlay for the EPS of the lateral control. Finally, the multi-rate lane-keeping control scheme is proposed to improve the lateral control performance and to reduce the ripple in the yaw rate. The performance of the proposed method was experimentally evaluated via test vehicle

CITATION: Kang, C., Sung Gu, Y., Jeon, S., Son, Y. et al., "Lateral Control System for Autonomous Lane Change System on Highways," *SAE Int. J. Passeng. Cars - Mech. Syst.* 9(2):2016, doi:10.4271/2016-01-1641.

I. INTRODUCTION

Autonomous lateral control on highways has become an important issue in the automotive industry. The main objective of lateral control is to keep the vehicle between lanes and to change the lane [1]-[3]. Various lateral control methods have been studied for lane change systems (LXs) and/or lane-keeping systems (LKSs) [4], [5]. The previous vision based lateral control methods have three main problems such as

- Lane information failure: Lane information from a camera sensor is unavailable due to unexpected problems (for examples, complex shadowing, poor lane markings, complex characters, lighting changes and/or malfunction of the camera sensor).
- Asynchronous sampling rate between the processor and the sensors: When many sensors are used with microprocessors, (for example, an inertial measurement unit (IMU) sensor and camera sensor) the overall system for autonomous vehicles becomes a multi-rate system due to the their different and asynchronous sampling rates.
- Electric power steering (EPS) system control: An angle overlay based approaches used in the previous method do not allow the torque combination; therefore it is difficult to use all of the basic functions of the EPS system. Furthermore, it is difficult for the driver to smoothly take over the steering wheel control.

To resolve the problems in the lateral control methods, we propose a lateral control system for autonomous vehicle on highways. The proposed lateral control scheme is the combination of model based lane prediction method, torque overlay based EPS control method, and the multirate lateral control method. First, when a camera sensor has a momentary failure, the predicted lane information using previous captured data and clothoidal constraints can be substituted [6], [7]. As a result, autonomous vehicle can normally operate even when the lane information is momentarily unavailable. Second, we innovate an approach to steering wheel angle control based on torque overlay in order to resolve the problems of the previous methods for the EPS of the LKS [8]. The key idea is that the system function with unknown parameters and external disturbance, and their derivatives are lumped into an augmented state variable to design the nonlinear observer in the absence of Lipschitz conditions. The augmented observer is designed to estimate the full state and disturbance. Finally, the multirate lateral control scheme using a look-ahead distance is proposed to improve the lane-keeping and the lane change performance [9]. Furthermore, to improve the lane-keeping performance on a curved road, we develop a linear quadratic state feedback control using both the lateral offset error at the look-ahead distance and the integral of the look-down lateral offset error. The performance of the proposed method is experimentally evaluated via test vehicle.

II. LATERAL CONTROL SYSTEM

A. Lane Prediction

First, the problem of vision sensor is that both weather and environment strongly influence the performance of lane detection [10]. Although various approaches for lane detection are effective at detecting a lane, they can be used only when the camera sensor operates normally. Thus, we propose a virtual lane prediction method to cope with the momentary failure of lane detection.

1. Predictive Virtual Lane Method

The predictive virtual lane method obtains the lane information using geometric calculation with the relative movements of the vehicle and lanes as well as the longitudinal velocity and the yaw of vehicle at present. designed a virtual lane prediction method The trajectory, $f_v(x)$, is obtained using a parabolic projection with an arc approximation under the assumption that it moves at a constant speed, V_x and at a constant yaw rate, $\dot{\psi}$ [11] as follows

$$f_v(x) = \frac{\rho_v}{2} x^2 = \frac{\dot{\psi}}{2V_x} x^2 \quad (1)$$

where ρ_v is the curvature of a circular road and x is the longitudinal distance. From the lane information, the lane polynomial, $f_L(x)$ is defined as a third order polynomial function of the longitudinal distance, x (see [12], [13])

$$f_L(x) = c_0 + c_1 \cdot x + c_2 \cdot x^2 + c_3 \cdot x^3 \quad (2)$$

where c_0 is the lateral offset, c_1 is the head angle, c_2 is the curvature, and c_3 is the curvature rate.

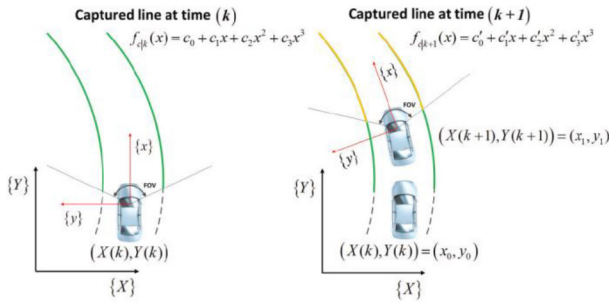


Figure 1. Vehicle trajectory and lane polynomial

Let us assume that at time k , the reliable lane information is obtained from the vision sensor. Now, we can estimate the lane coefficients at time $k+1$ using the yaw rate $\dot{\psi}$ and the longitudinal velocity V_x which are always obtained with the same sampling rate of control. More details are described in [9].

2. Model Based Lane Prediction

Second lane prediction method uses vehicle lateral motion model and the clothoidal cubic polynomial curve road model. This method makes use of prediction to obtain lane coefficients $\bar{c}_i(k, i)$. About 40m/\$\sim\$50m lane information is captured during processing period of the vision sensor. One can use a prior sample time curvature rate and curvature as a substitute when vision has failure under clothoidal constraints.

Clothoidal constraint is that every lane of highway should have slowly varying continuous curvature [14], [15]. The clothoid is defined to be a spiral whose curvature is a linear function of its arc length. Clothoid spirals are curves that are used for smooth transition from one curvature value to another. The curvature of clothoidal curve at arc length, s , is described as follows

$$\kappa = 6c_3s + 2c_2 \quad (3)$$

where $2c_2$ is the road curvature at $s = 0$ and $6c_3$ is its rate. Integration of this equation twice with respect to s leads to a clothoidal cubic polynomial curve road model:

$$f_c(s) = c_0 + c_1s + c_2s^2 + c_3s^3 \quad (4)$$

For small curvature, the arc length s can be approximated by down range distance x . With assumption that there is no rapid change of curvature ($= 3c_2(\cdot)$) and curvature rate ($= 6c_3(\cdot)$) we can obtain the predicted lane coefficients $\bar{c}_i(k, i)$.

$$\bar{c}_3(k, i) = c_3(k, i - 1)$$

$$\bar{c}_2(k, i) = \kappa(k, i - 1) / 2$$

where $\kappa(\cdot) = 2c_2(\cdot)$ Other coefficients c_1 and c_0 , are computed from predicted heading angle error and lateral offset as follows

$$\bar{c}_1(k, i) = \bar{e}_\psi(k, i)$$

$$\bar{c}_0(k, i) = \bar{e}_{yL}(k, i) - \bar{c}_1L - \bar{c}_2L^2 - \bar{c}_3L^3 \quad (5)$$

where predicted heading angle error, $\bar{e}_\psi(k, i)$ and lateral offset, $\bar{e}_{yL}(k, i)$ are obtained from the state of each model.

Using these predicted road coefficients, we can estimate the lane polynomial as follows

$$\bar{f}_c(L) = \bar{c}_0 + \bar{c}_1L + \bar{c}_2L^2 + \bar{c}_3L^3 \quad (6)$$

Now, we can use $\bar{f}_c$ as a substitute for f_c in lateral control even at the existence of vision malfunction while the vehicle travels forward 40m~50m. Furthermore, $\bar{f}_c$ is synchronously provided at every ECU update instance. More details are described in [6], [7].

B. Torque Overlay-Based Control Method

In this section, we design the EPS controller for the lateral control based on torque overlay. The block diagram of the EPS control system for the lateral control is shown in Fig. 2. In the lateral control, the main role of the EPS system is to make the steering wheel angle θ_h track the desired steering wheel angle θ_{hd} derived by the lateral control method. In the torque overlay based method, since the EPS system can be used for steering wheel angle control, still, a modification of the EPS, the torque integration with basic functions of the EPS is available for the driver's convenience [16] Thus, the

driver can smoothly and comfortably assume steering wheel control from the LKS [17]. Unfortunately, in the torque overlay based method, the driver torque could affect the disturbance input to the steering wheel angle control, resulting in a decrease in control performance. The unsymmetrical hysteresis behavior, which occurs on account of the structure and friction of the EPS system, is also activated as the disturbance. Furthermore, the parameter uncertainties of the EPS model make control more difficult. We design the torque overlay based steering wheel angle control to guarantee the semi-global uniform ultimate boundedness of the steering wheel angle tracking error using only steering wheel angle feedback with the robustness of the parameter uncertainties [18]. The proposed method consists of an augmented observer and a nonlinear damping controller. The key idea of this approach is that the system functions with unknown parameters and external disturbances, as well as their derivatives, are combined in an augmented state variable for designing the nonlinear observer in the absence of Lipschitz conditions [19]. The mathematical model of the EPS is

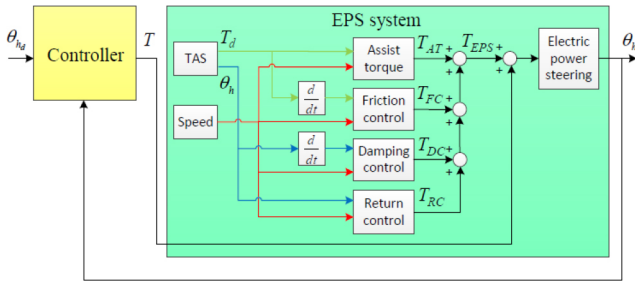


Figure 2. Block diagram of the EPS control system for the lateral control

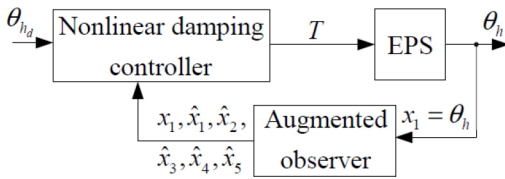


Figure 3. Block diagram of the proposed method

$$\begin{aligned}\dot{\theta}_h &= \omega_h \\ \dot{\omega}_h &= a_{21}\theta_h + a_{22}\omega_h + a_{23}\theta_m + d_1 \\ \dot{\theta}_m &= \omega_m \\ \dot{\omega}_m &= a_{41}\theta_h + a_{43}\theta_m + a_{44}\omega_m + b_4T + d_2\end{aligned}$$

where $J_{eq} = J_m + \frac{R_p^2}{N^2}M_r$, $K_N = \frac{K_c + K_r R_p^2}{N^2}$ and $B_{eq} = B_m + \frac{R_p^2}{N^2}B_r$.

$$\begin{aligned}a_{21} &= -\frac{K_c}{J_c}, \quad a_{22} = -\frac{B_c}{J_c}, \quad a_{23} = \frac{K_c}{J_c N}, \quad d_1 = \frac{1}{J_c}(T_d - T_f), \\ a_{41} &= \frac{K_c}{J_{eq} N}, \quad a_{43} = -\frac{K_N}{J_{eq}}, \quad a_{44} = -\frac{B_{eq}}{J_{eq}}, \quad b_4 = \frac{1}{J_{eq}} \quad \text{and} \\ d_2 &= -\frac{R_p}{J_{eq} N}T_r + T_{EPS}.\end{aligned}$$

With the definition of the vector x

$$x = [x_1 \quad x_2 \quad x_3 \quad x_4]^T = [\theta_h \quad \omega_h \quad \theta_m \quad \omega_m]^T$$

(7)

(8)

we obtain the dynamic of x_4 as

$$\begin{aligned}\dot{x}_4 &= \omega_h^{(3)} \\ &= f(x) + gu + d_{ext}(d_1, \dot{d}_1, \ddot{d}_1, d_2)\end{aligned}\quad (9)$$

where $u = T, f, g$, and d_{ext} are the system function, input gain, and external disturbance, respectively, such that

$$\begin{aligned}f &= (a_{23}a_{41} - a_{21}a_{43})x_1 + (a_{21}(a_{22} - a_{21} - a_{43}) - a_{22}a_{43})x_2 \\ &\quad + (a_{21} + a_{43} - a_{21}a_{22} - a_{22}a_{43})x_3 + (a_{22} + a_{44})x_4 \\ g &= a_{23}b_4 \\ d_{ext} &= -(a_{21} + a_{43})\dot{d}_1 - (a_{22} + a_{44})\ddot{d}_1 + a_{23}d_2.\end{aligned}$$

Let us define disturbance d as

$$d = f(x) + \Delta gu + d_{ext}(d_1, \dot{d}_1, \ddot{d}_1, d_2).\quad (10)$$

The dynamics of x are obtained as

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= x_3 \\ \dot{x}_3 &= x_4 \\ \dot{x}_4 &= g_0 u + d.\end{aligned}\quad (11)$$

where g_0 and Δg are nominal value and uncertainty of g , and $f(x) + \Delta gu + d_{ext}(d_1, \dot{d}_1, \ddot{d}_1, d_2)$. Let us define x_5 as

$$x_5 = d.\quad (12)$$

To estimate the full state and disturbance in (11), the augmented observer is designed as

$$\dot{\hat{x}}_a = A_o \hat{x}_a + B_o u + L(x_1 - \hat{x}_1)\quad (13)$$

where $\hat{x}_a$ is the estimated state of $x_a = [x^T, d]^T$,

$$\begin{aligned}A_o &= \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\ B_o &= [0 \quad 0 \quad 0 \quad g_o \quad 0]^T \\ L &= [l_1 \quad l_2 \quad l_3 \quad l_4 \quad l_5]^T\end{aligned}$$

L is the observer gain matrix. In order to suppress the angle tracking error using the input-to-state stability (ISS) property, the nonlinear damping controller is developed via backstepping as follows