System Identification and Controller Design for Lateral Control of an Unmanned Vehicle

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Abstract: In this paper, we get the lateral dynamic model of an unmanned vehicle by using system identification methods and design a lateral controller. The system input is the steering wheel angle of the vehicle with constant speed and the output is the yaw of the vehicle. With system identification for a basis, to achieve a control objective, we design a PID controller using the model equation. And we compare the PID control performance designed by using system identification with it of the physically modeled system.

Keywords: System identification, Lateral control, PID controller, GPS

I. INTRODUCTION

Recently, a developed country performed research of ITS (Intelligent Transportation System) and IVHS (Intelligent Vehicle Highway System) actively based on electric and electronic engineering, communication engineering, automatic control, and traffic engineering (Broggi *et al.* [1] and Shladover [2]). When driving a car, in order to realize autonomous technology for the control of auto cruising, which greatly prefers to be leading longitudinal and lateral control to be performed (Chen, C. *et al.* [3]). Longitudinal control is that regulate the vehicle's distance suitable for vehicle's velocity regulation. Lateral control need for change the lane and along the lane. As for lateral control use measured lateral distance error that reference line or lane with measured data using sensor. In this paper, use system identification to get a system model equation for lateral control and design a PID controller achieve the control objective. Also we compare the performance of system identification model with two bicycle model using simulation. We estimate and validate the system identification model that applied real system.

II. Modeling

1. System Identification

Discrete time subspace system identification methods have attracted much attention during the past few years due to ability of identifying multivariable linear processes directly from the input-output data. Compared with the classical PEM and IVM, these subspace methods do not suffer from a parameterization and nonlinear optimization. Also, their properties and common features have been analyzed well (Van Overshee *et al.* [4]) and their extensions to closed-loop process data have been developed (Chou *et al.* [5], and Ljung *et al.* [6]). The objective of discrete-time subspace system identification methods is identifying the system matrices as well as the process order of the discrete-time state space model.

In general, linear time invariant system represented

$$x(t+1) = Ax(t) + Bu(t) \tag{1}$$

$$y(t) = Cx(t) + Du(t) + v(t) \tag{2}$$

System identification tool is used discrete state-space model. Discrete state-space equation is

$$x(kT+T) = Ax(kT) + Bu(kT) + Ke(kT) \tag{3}$$

$$y(kT) = Cx(kT) + Du(kT) + e(kT) \tag{4}$$

$$x(0) = x_0 \tag{5}$$

In order to design a PID controller, equ. (2), (3), and (4) is transformed the continuous state space equation

$$\dot{x}(t) = Fx(t) + Gu(t) + \bar{K}\, w(t) \tag{6}$$

$$y(t) = Hx(t) + Du(t) + w(t) \tag{7}$$

$$x(0) = x_0 \tag{8}$$

The relation discrete time state matrices A, B, C, D have relation with continuous time state matrices F, G, H, D

$$A = e^{FT} \tag{9}$$

$$B = \int_0^T e^{F\tau} G d\tau \tag{10}$$

$$C = H \tag{11}$$

This relation accomplish when input is piecewise-constant in time interval $kT \le t \le (k+1)T$. Where e^{FT} is state transition matrix. If the system has no noise, we approximate $v(t) \approx 0$, $K \approx 0$ and we rewrite the equ. (6), (7), (8) as equ. (1), (2).

A least squares problem to obtain the state space matrices solve equ. (12).

$$\begin{pmatrix} \hat{A} & \hat{B} \\ \hat{C} & \hat{D} \end{pmatrix} = \min_{A,B,C,D} \left\| \begin{pmatrix} \hat{x}_{i+1} & \hat{x}_{i+1} & \cdots & \hat{x}_{i+j} \\ y_i & y_{i+1} & \cdots & y_{i+j-1} \end{pmatrix} - \begin{pmatrix} A & B \\ C & D \end{pmatrix} \begin{pmatrix} \hat{x}_i & \hat{x}_{i+1} & \cdots & \hat{x}_{i+j-1} \\ u_i & u_{i+1} & \cdots & u_{i+j-1} \end{pmatrix} \right\|_F^2 \tag{12}$$

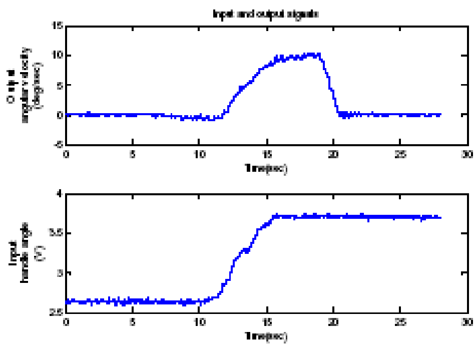

Fig. 1. Input and Output data(angular velocity)

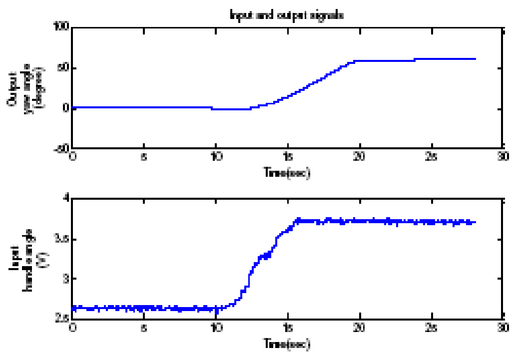

Fig. 2. Input and output data(degree)

Where $\|\cdot\|_F$ denotes the Frobenius-norm of a matrix.

The system input is steering wheel angle and output is vehicle's yaw. Fig. 1 represents the input and output data. Because the output data is angular velocity, integrate the output signal to obtain the displacement data. Fig. 2 represents the integrated output signal.

We use the LabVIEW for data acquisition and use MATLAB toolbox for data processing. Fig. 3 represents the estimation of system model using MATLAB toolbox.

2. Two bicycle model

Fig. 4 represent the two bicycle model. Because of the objective is control of yaw, we ignore the motion of roll and pitch. equ. (13) represents the state equation (Tan, H. S. *et al.* [7]).

$$\dot{X} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & \frac{A_1}{V} & -A_1 & \frac{A_2}{V} & B_1 \cdot n \\ 0 & 0 & 0 & 1 & 0 \\ 0 & \frac{A_3}{V} & -A_3 & \frac{A_4}{V} & B_2 \cdot n \\ 0 & 0 & 0 & 0 & -\frac{1}{T_m} \end{bmatrix} X + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \frac{1}{T_m} \end{bmatrix} u_f \tag{13}$$

Where

m : mass of vehicle,
T_m : time constant of steering wheel actuator,
V : longitudinal velocity of vehicle

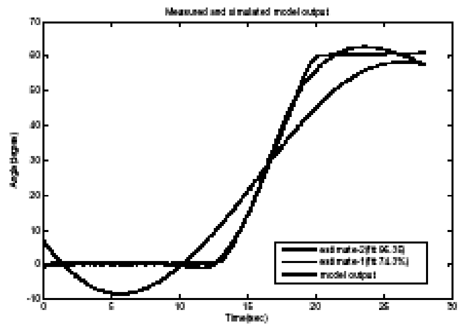

Fig. 3. Comparison of real model and estimation model

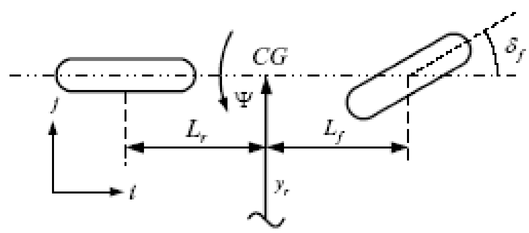

Fig. 4. Bicycle model

Ψ : yaw of vehicle

$$A_1 = -\frac{C_f + C_r}{m} \qquad A_2 = -\frac{(C_f L_f - C_r L_r)}{m}$$

$$A_3 = \frac{(-C_f L_f + C_r L_r)}{J} \qquad A_4 = -\frac{(C_f L_f^2 + C_r L_r^2)}{J}$$

$$B_1 = \frac{C_f}{m} \qquad B_2 = \frac{C_f L_f}{J}$$

III. Controller Design

Design conditions of lateral controller of the test vehicle are steady state error 2%, overshoot 1%, and settling time 1 second. The controller is designed by using system parameters.

The transfer function of PID controller is given by equ. (14).

$$K(s) = K_P + \frac{K_I}{s} + K_D s \qquad (14)$$

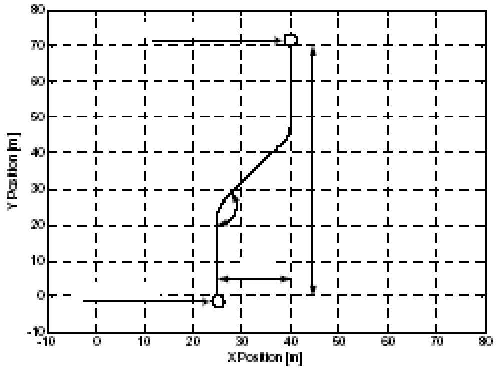

Fig. 5. Reference road for simulation

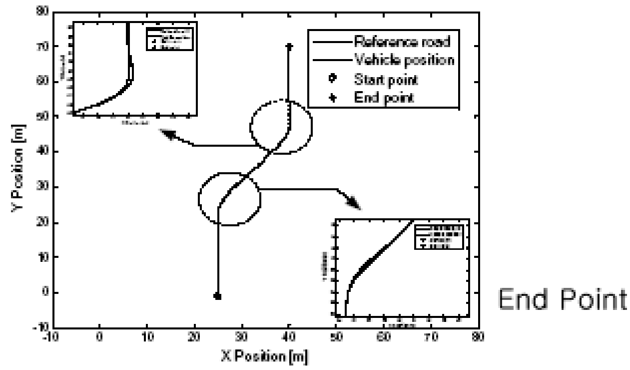

Fig. 6. Simulation (System Identification)

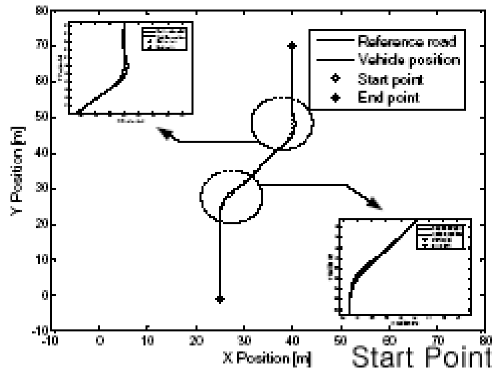

Fig. 7. Simulation (bicycle model)

IV. Simulation

The road data for simulation is shown Fig. 5. We evaluate two types of model data using simulation results. The Simulation result for system identification model is shown in Fig. 6.

Simulation result of bicycle model is shown in Fig. 7. We can see comparison with two system's simulation error. The simulation error of bicycle model is bigger than it of the system identification.

V. Experiment

We perform the experiment of real system, in order to validate the simulation results. Test vehicle is shown Fig. 8. The outline of experiment equipment is represented Fig. 9. The experimental vehicle is located near the starting point with its head facing starting point. The angle range of steering wheel is from left 22° to right 22° with the maximum unit deflection 15°. In the condition of this experiment, the car receives at least 5

Fig. 8. Test vehicle

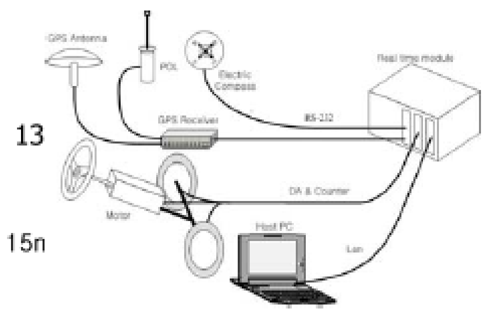

Fig. 9. Measurement and Control system

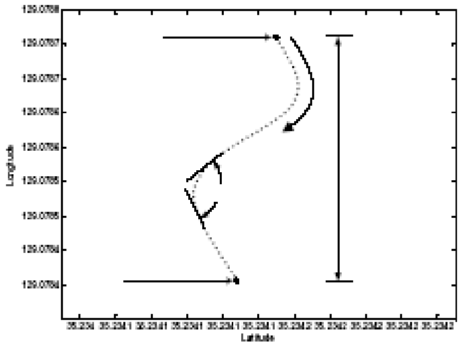

Fig. 10. Path data for test

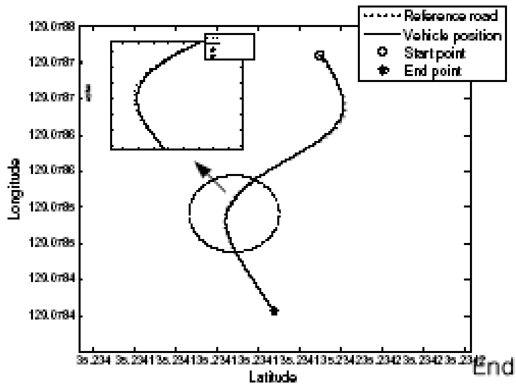

Fig. 11. Experiment result (System identification)

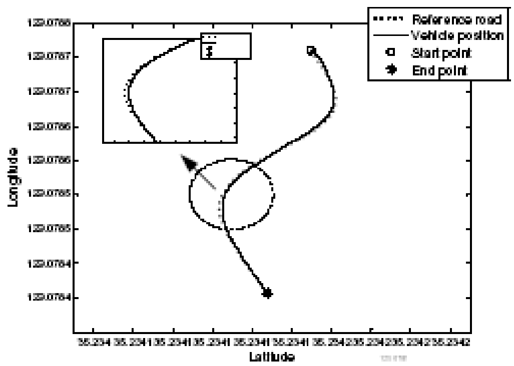

Fig. 12. Experiment result (bicycle model)

signal from GPS and calibration information from station. Fig. 9 represents path for test obtained from GPS. We obtain the reference road data using GPS. They are shown in Fig. 10. Fig. 11 and Fig. 12 are experimental results. System identification model based controller system better tracks the reference road.

VI. Conclusion

In this paper, we determined the system model of an autonomous vehicle for lateral control that is important to design parameter based controller in unmanned vehicle system. Through comparison the model using the subspace system identification method with dynamics model, we confirmed that the experimental model is more accuracy than dynamic model. It is important to design a controller that uses system parameters.

We minimized the modeling error using system identification that using system input-output data. And we design the PID controller. To design controller, we get state matrices that represent the relation of input and output. The performance of the compensated system that based on the system identification model is better than bicycle model. Because modeling error of dynamic model is more than it of system identification model.

We will research the vehicle system identification with other dynamic and system condition. For example, longitudinal control, nonlinear system and MIMO system. And also we design controller that is robust to system disturbance and parameter uncertainty.

REFERENCES

[1] Broggi, A., Bertozzi, M. and Fascioli, A. (1999), ARGO and the Millemiglia in Autoatico Tour, *IEEE intelligent system*, 14(1):55-64.

[2] Shladover, S. (1991), Automated vehicle control developments in the PATH Program, *IEEE transaction on vehicular technology*, 40(1):114-130.

[3] Chen, C., and Han Shue, T. (1998), Steering control of high speed vehicles: dynamic look ahead and yaw rate feedback, *Proc. of the 37th IEEE conference and decision & control*, 1025-1030.

[4] Van Overschee, P. and De Moor, B. A (1995), unifying theorem for three subspace system identification algorithms, *Automatica*, 31:1855-1864.

[5] Chou, C.T. and Verhagegen, M. (1997), Subspace algorithms for the identification of multivariable dynamic errors-in-variables models, *Automatica*, 33:1857-1869.

[6] Ljung, L. and McKelvey, T. (1996), Subspace identification from closed-loop data, *Signal processing*, 1996, 52, 209-215

[7] Chiang, Hsin-Han, Ma, Li-Shan, Perng, Jau-Woei, Wu, Bing-Fei, and Lee, Tsu-Tian (2006), Longitudinal and lateral fuzzy control systems design for intelligent Vehicles, *Proc. of the 2006 IEEE international conference*, 1:544 – 549.