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Real-time Identification Method of Driver Model with Steering Manipulation

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This study proposes a method for real-time identification of a driver model. The proposed method requires only the yaw rate sensor, the steering angle sensor, and velocity sensors that are usually installed in the production car. The identification algorithm involves the division of the recorded data, prefiltering of the divided data, estimation of the driver's desired response, and identification. The prefilter extracts the driver's involuntary response that can be modelled in a simple form. The ideal car response that the driver attempts to track is estimated from the recorded data, and this response is provided to the identification algorithm of the feedback driver model for error tracking. These newly developed methods enable real-time identification under actual driving conditions. The driving simulator experiments and the actual driving tests were performed, and the proposed method was validated. The results show that the time history of the variation in the driver's characteristics can be realized in real time using the proposed method.

Keywords: Real-time identification, Driver model, Driving simulator, Car testing

Nomenclature

r	Yaw rate of a car
s	Laplace variable
t	Time
u	Velocity of a car
δ_s	Steering angle
ψ	Yaw angle of a car
ψ_d	Desired yaw angle of a car
$\ G\ _\infty$	H-infinity norm of the transfer function $G(s)$.
$\ x(t)\ $	Norm of time signal $x(t)$. $\{\int_{-\infty}^{\infty} x^T x dt\}^{1/2}$
$(\bullet)(s)$	The Laplace transform of time function $(\bullet)(t)$.
$\widehat{(\bullet)}$	The smoothed responses of $(\bullet)$ obtained using the smoothing filter. $\widehat{(\bullet)}(s) = F_s(s)(\bullet)(s)$
$\widetilde{(\bullet)}$	The smoothed responses of $(\bullet)$ obtained using the prefilter. $\widetilde{(\bullet)}(s) = F_p(s)(\bullet)(s)$
$\overline{(\bullet)}$	The time average of $(\bullet)$.

Introduction

In the research on intelligence systems of automobiles, it is important to estimate the driver's conditions such as drowsiness. Several methods have been proposed for detecting the driver's conditions. In ref. [1], a method is proposed for detecting the driver's drowsiness from the driver's eye movement and heart rate, while in ref. [2], a method based on video images is proposed for detecting the same. In ref. [3], prediction of the driver's drowsiness from changes in the driver's heart rate has been proposed. Further, a method that detects the driver's drowsiness on the basis of the driver's behavior pattern is proposed in ref. [4]. If the driver's conditions can be estimated in real time, they can be used to create an alert for dangerous driving or to employ the stabilizing controller in order to avoid accidents. However, because of the initial cost and the maintenance cost incurred in deploying additional sensors, their use is preferably avoided. In this regard, a method for estimating the driver's conditions utilizing the sensor that is originally installed in the production car is advantageous. Moreover, a simple algorithm is preferred for estimation methods in order to offset the requirement of a high CPU performance.

The involuntary responses of the driver to the car motion are information that is essential to detect the driver's physiological conditions. If the driver's behavior to the car responses is formulated in a model, this model can be used to estimate the driver's conditions. The formulated driver model reflects some aspects of the driver's physiological conditions, such as the time lag of the response, the amplitude of the response, and the uncertainties in the driving behavior. This information is useful for the intelligence system of the car.

The operator dynamics to the vehicle responses have been investigated using an operator model. Several studies have employed a simple feedback model and analysis to investigate the operator dynamics. Recently, a control theory has been developed, and the computer-aided analysis and design of a vehicle-operator system have been carried out^{[5]~[10]}. Refs. [5], [6], and [7] report the development of a method for estimating the handling qualities of vehicles by using the operator model. In ref. [8], the driver's adaptation behavior, estimated by using the driver model, has been

discussed. Further, in refs. [9] and [10], the controller design method, which improves the performance of closed-loop systems on the basis of vehicle and operator dynamics, has been reported. These studies apply a robust control theory and perform a computer-aided numerical analysis, and these studies have demonstrated the possibility of designing an operator-model-based method. However, these studies are based on an offline analysis that requires extensive information on the driving course and the car motion.

In the present study, a real-time identification method of the driver model is proposed. This proposed method can be easily implemented on the production car because it requires a few types of sensors that are originally installed in the production car and because the procedures used in this method can be carried out in real time. Initially, the recorded data are divided into several data sets. Then, prefiltering is applied to the divided data to extract the specific driver's response that can be modelled in a simple form. Subsequently, the desired responses of the driver are estimated and provided for identification. Finally, the proposed method is applied to the driving simulator as well as the actual driving experiments.

Identification method

Structure of the driver model

The driver determines the driving input by detecting information on the car motion and the environment surrounding the car. However, for estimating the involuntary driving response, the driver behavior can be expressed as a simple dynamics to the car responses^{[5], [6]}. Therefore, a linear differential feedback model is used. As discussed in a later section, the modelling error is analyzed from the experimental results. As a first step of the study, we discuss the feedback response of the steering angle to the yaw motion of the car (Eq. (1) and Fig. 1).

$$\delta_s(s) = H(s)(\psi_d(s) - \psi(s)) \quad (1)$$

where δ_s denotes the steering angle; H , the driver model; ψ_d , the desired yaw angle; and ψ , the yaw angle. This model assumes that the driver senses the yaw angle error and generates the steering angle input. The longitudinal control is separated from the lateral-directional control.

[Fig. 1 here]

Prefiltering

In the present study, the input to the driver model is the tracking error of the yaw angle and the output is the steering angle. This simple modelling requires a few types of sensors installed in the car for identification. However, in addition to the yaw dynamics, other dynamics such as the lateral displacement and forward motion of a car affect the driver's steering input. Then, the driver's behavior at the specific bandwidth where the response to the yaw angle is dominant is modelled. The frequency of the yaw dynamics of the car is higher than that of lateral displacement and forward motion. Therefore, a prefilter with an appropriate bandwidth is applied to the recorded data in order to extract the responses of the bandwidth at which the yaw dynamics is dominant. The filtered data are provided for identification to the yaw angle input model of Eq. (1). The bandwidth of the prefilter should be determined in order to minimize the identification error.

Division of the data

The driver's behavior depends on driving conditions such as the car velocity and road profiles. In the post-analysis stage, the models identified with common conditions are compared. Then, the response data with the common conditions are prepared for identification. In real-time identification, the recorded continuous data are divided into data sets such that the yaw rate and the velocity in these data sets are approximately equal.

The recorded velocity responses $u(t)$ and yaw rate responses $r(t)$ are smoothed using the smoothing filter F_s .

$$\hat{u}(s) = F_s(s)u(s) \quad (2)$$

$$\hat{r}(s) = F_s(s)r(s) \quad (3)$$

The smoothed responses are used for data division as follows.

- (i) $t_{f_0} = 0, i = 0$.
- (ii) $t_0 = t_{f_i}, i = i + 1$.
- (iii) Find minimum t_{s_i}, t_{f_i} s.t. $u_{min} \leq \hat{u}(t) \leq u_{max}, r_{min} \leq |\hat{r}(t)| \leq r_{max}$,

$$t_0 \leq t_{s_i} \leq \forall t \leq t_{f_i}, T_{min} \leq t_{f_i} - t_{s_i} \leq T_{max}.$$
- (iv) Define the i th data set as $\Omega_i = \{u(t), r(t), \delta_s(t) | t_{s_i} \leq t \leq t_{f_i}\}$.
- (v) Go to step (ii).

Here, t_{s_i} and t_{f_i} denote the initial and final time of each data set, respectively. They are determined in step (iii). The above procedure indicates that the smoothed velocity and yaw rate of the divided data lie in the given regions. This procedure can be carried out in real time, and the data can be recorded simultaneously.

Estimation of the desired car responses

The driver's behavior is modelled as a feedback model of the yaw angle tracking error (Eq. (1)). The input and output response data are required for identification. The steering input and yaw angle can be measured from the installed sensors. However, the desired yaw angle, which is generated by the driver, cannot be measured directly. In real-time modelling, the desired yaw angle is estimated from the recorded data. Here, the following assumptions are made.

- (i) In the absence of any disturbance, the feedback driver model attains the precise desired responses.
- (ii) The disturbances in the car responses are bounded, and their average is zero.
- (iii) The car dynamics is stable.
- (iv) The desired yaw rate is constant.

Figure 2 shows the closed-loop system, which consists of the driver model and the car dynamics. The transfer function from the desired yaw rate and the disturbance to the yaw rate is formulated, as follows.

$$r = (I + P_1 H/s)^{-1} P_2 d + (I + P_1 H/s)^{-1} P_1 H/s r_d \quad (4)$$

From assumption (i), $(I + P_1 H/s)^{-1} P_1 H/s r_d = r_d$ is satisfied. Thus, the equation

$$r = (I + P_1 H/s)^{-1} P_2 d + r_d \quad (5)$$

is obtained. The state-space realization of Eq. (5) is defined as follows.

$$\dot{x}(t) = Ax(t) + Bd(t) \quad (6)$$

$$r(t) = Cx(t) + Dd(t) + r_d(t) \quad (7)$$

Equation (6) is integrated from 0 to T.

$$x(T) - x(0) = A \int_0^T x(t)dt + B \int_0^T d(t)dt \quad (8)$$

From assumptions (ii) and (iii), $x(T)$ is found to be bounded. From Eq. (8) and assumption (ii), the following equation

$$\bar{x} = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T x(t)dt = \lim_{T \rightarrow \infty} \frac{1}{T} A^{-1} \left[x(T) - x(0) - B \int_0^T d(t)dt \right] = 0 \quad (9)$$

is obtained. From equations (7) and (9),

$$\bar{r} = C\bar{x} + D\bar{d} + \bar{r}_d = \bar{r}_d \quad (10)$$

is satisfied. Equation (10) implies that the desired responses of the driver can be estimated from the time average of the measured car responses as follows.

$$r_d(t) \simeq \frac{1}{T_d} \int_{t-T_d/2}^{t+T_d/2} r(t)dt \quad (11)$$

At a constant desired yaw rate, the estimated desired car response is precise. The yaw angle, ψ , and desired yaw angle ψ_d can be calculated from the integration of yaw rate r and desired yaw rate r_d .

[Fig. 2 here]

Identification procedure

In the previous sections, the structure of the driver mode, data division, and the estimation of the desired car responses are discussed. As a result, the real-time identification procedure of the driver model is designed as follows.

- (i) The smoothing filter, F_s ; data division parameters $u_{min}, u_{max}, r_{min}, r_{max}, T_{min}$, and T_{max} ; average time T_d ; and prefilter F_p are defined.
- (ii) The recorded data are filtered using F_s . Then, the data are divided into data sets Ω_i ($i = 1, 2, \dots$).
- (iii) The divided data are filtered using F_p . $\tilde{r} = F_p r$, $\tilde{\delta}_s = F_p \delta_s$.
- (iv) The desired yaw rate response and the steering input are calculated using the moving average method.

$$\tilde{r}_d(t) = \frac{1}{T_d} \int_{t-T_d/2}^{t+T_d/2} \tilde{r}(t) dt. \quad (12)$$

$$\tilde{\delta}_{s_d}(t) = \frac{1}{T_d} \int_{t-T_d/2}^{t+T_d/2} \tilde{\delta}_s(t) dt. \quad (13)$$

- (v) Transfer function H is identified using the least-squares method.

$$\Delta \tilde{\delta}_s = H \tilde{e}_\psi \quad (14)$$

The input is the filtered tracking error of the yaw angle, $\tilde{e}_\psi \triangleq \tilde{\psi}_d(t) - \tilde{\psi}(t)$, and the output is the deviation of the filtered steering angle from the trimmed input, $\Delta \tilde{\delta}_s \triangleq \tilde{\delta}_{s_d}(t) - \tilde{\delta}_s(t)$, where $\tilde{\psi}(t) = \int_{t_{s_i}}^t \tilde{r}(t) dt$ and $\tilde{\psi}_d(t) = \int_{t_{s_i}}^t \tilde{r}_d(t) dt$.

It is worth mentioning that the above procedure can be performed simultaneously with driving. The recorded data can be input to the identification procedure in real time. In steps (ii),

(iii), and (iv), it is necessary to store the data. Therefore, strictly speaking, this procedure is not a real-time process. However, the time lag of identification is at most equal to the time span of the divided data, T_{max} . This time lag does not pose a major problem in practical applications.

Analysis of the driving test data

Setup of driving test

The proposed identification method was applied to the driving simulator experiments and to the driving test using an actual car. A stationary driving simulator was used (Fig. 3). It consisted of a projector (NEC, LT280J), screen, steering wheel, accelerator pedal, brake pedal (Logicool, LPRC-14000), and driver sheet. The driver's control was input to a PC, and the car dynamics were simulated. The car responses were projected on the screen. The driver sensed the car motion from the visual images. The car dynamics is controlled by the steering wheel, accelerator pedal and brake pedal.

In the actual driving test, a sedan was used. The driving tests were performed on a closed-circuit course. In both the simulator experiments and the actual driving test, the driver is expected to maintain a constant velocity along the given course. All subjects were recruited through open call. Before we tested, we provided verbal and written instructions, and all subjects filled out a form of informed consent.

[Fig. 3 here]

Test courses

The simulator experiments were performed on straight courses. The drivers tried to maintain velocities of 40 km/h, 60 km/h, and 100 km/h (Simulator experiments 1~3 in Table 1). Additionally, an experiment that simulates the actual highway environment was performed (Simulator experiment 4 in Table 1). The simulated highway course consisted of many curves, and

the minimum radius of the curves was 500 m. The course length was 135 km (Fig. 4). The drivers tried to maintain a velocity of 100 km/h along the course. In the simulator experiments, the continuous random yaw moment disturbance was input to induce the involuntary responses of the driver. The standard deviation of yaw rate was approximately 0.01 rad/s. The simulated dynamics is the linearized dynamics of the actual driving test car.

The actual driving test was performed on a closed-circuit course. The driven course was a banked oval track. The radius of the curve was 290 m, and the track length was 4 km. The driver tried to maintain a velocity of 80 km/h along the closed-circuit course (Actual driving data in Table 1). The experimental conditions are shown in Table 1.

[Table 1 and Fig. 4 here]

Bandwidth of the prefilter

A prefilter is applied to the recorded data, and the driver responses to the yaw dynamics of the car are extracted. The equation of the used prefilter, W_p , is given below.

$$W_p = \frac{W_{p0}}{\|W_{p0}\|_\infty} \quad (15)$$

$$W_{p0} = \frac{s}{(T_1s + 1)(T_2s + 1)}, \quad T_1 < T_2 \quad (16)$$

This prefilter is a band-pass filter with a bandwidth ranging from $1/T_2$ to $1/T_1$ and an H_∞ norm of 1. If the frequency of the driver's response to the yaw dynamics lies within the bandwidth of the prefilter, the identification error is reduced.

Error analysis is performed to estimate the preciseness of identification. Let us suppose that the linearized feedback model of a driver is as follows.

$$\begin{bmatrix} \Delta\delta_s \\ \Delta\delta_o \end{bmatrix} = \begin{bmatrix} H_{\psi\psi} & H_{\psi o} \\ H_{o\psi} & H_{oo} \end{bmatrix} \begin{bmatrix} e_\psi \\ e_o \end{bmatrix} \quad (17)$$

where $\Delta\delta_s$ denotes the variation of the steering angle from the trimmed angle; $\Delta\delta_o$, the variation of the other driver's input from the trimmed value; e_ψ , the tracking error of the yaw angle; and e_o , the other tracking error sensed by the driver. This model is stricter than the model represented by Eq. (14) because it contains the driver's response to other dynamics. The prefilter is applied to Eq. (17). The steering input response is given by the following equation.

$$\Delta\tilde{\delta}_s = H_{\psi\psi}\tilde{e}_\psi + W_p H_{\psi o} e_o \quad (18)$$

$$\Delta\tilde{\delta}_s = W_p \delta_s, \quad \tilde{e}_\psi = W_p e_\psi \quad (19)$$

Let us denote the identified driver model as $H_{\psi\psi_I}$. This identified model assumes that the input to the model is only the filtered tracking error of the yaw angle, $\tilde{e}_\psi$, and the output is the filtered steering input variation, $\Delta\tilde{\delta}_s$. Driver model $H_{\psi\psi_I}$ is obtained so that the norm of the output error, $\Delta\tilde{\delta}_s - H_{\psi\psi_I}\tilde{e}_\psi$, is minimized. Let the outputs of the identified driver model $H_{\psi\psi_I}$ be $\Delta\tilde{\delta}_{s_I}$.

$$\Delta\tilde{\delta}_{s_I} = H_{\psi\psi_I}\tilde{e}_\psi \quad (20)$$

The error of the steering angle, $\tilde{w} \triangleq \Delta\tilde{\delta}_s - \Delta\tilde{\delta}_{s_I}$, is the residual of identification. The identification error is given by the following equation.

$$\Delta H_{\psi\psi} = H_{\psi\psi} - H_{\psi\psi_I} \quad (21)$$

From Eqs. (18) ~ (21),

$$\tilde{w} = \Delta H_{\psi\psi}\tilde{e}_\psi + W_p H_{\psi o} e_o \quad (22)$$

is obtained. When the norm of $\tilde{e}_\psi$ is small, the norm of the residual becomes small as well.

Therefore, identification error J_e is defined as follows.

$$J_e = \frac{\|\tilde{w}\|}{\|\tilde{e}_\psi\|} = \frac{\|\Delta H_{\psi\psi}\tilde{e}_\psi + W_p H_{\psi o} e_o\|}{\|\tilde{e}_\psi\|} \quad (23)$$

The minimum value of J_e indicates that the norms of $\Delta H_{\psi\psi}$ and $W_p H_{\psi o} e_o$ are small. In this optimum case, the bandwidth of prefilter W_p is approximately the same as that of $H_{\psi\psi}$ and differs considerably from that of $H_{\psi o}$. As a result, the driver's feedback control behavior, which is the

response to the yaw dynamics, is successfully identified. Using prefilters with various bandwidths, we identified the driver models as first-order models; next, we calculated the average of identification error J_e of each driver and course as follows.

$$J_{e_i} = \frac{\left\{ \int_{t_{s_i}}^{t_{f_i}} \tilde{w}^T \tilde{w} dt \right\}^{1/2} / (t_{f_i} - t_{s_i})}{\left\{ \int_{t_{s_i}}^{t_{f_i}} \tilde{e}_\psi^T \tilde{e}_\psi dt \right\}^{1/2} / (t_{f_i} - t_{s_i})} \quad (24)$$

$$J_e = \frac{\sum_{i=1}^N J_{e_i}}{N} \quad (25)$$

where t_{s_i} and t_{f_i} denote the initial and final times, respectively, of data set Ω_i , and N denotes the number of data sets. It is worth noting that the residual contains not only the linear response to the other dynamics but also the nonlinearity and uncertainty aspects of the driver's behavior.

Simulator experiments 1, 2, 3, and 4 and the actual driving test were examined. The recorded data of Simulator experiments 1, 2, and 3 were divided by a time span of 30 s. These experiments were performed on straight courses. The straight course data of Simulator experiment 4 were divided under the condition $|\hat{r}(t)| \leq 1$ deg/s. The straight course data and curved course data of the actual driving test were divided under the conditions $|\hat{r}(t)| \leq 1$ and $|\hat{r}(t)| \geq 3$ deg/s, respectively. A moving average of 5 s is used as the desired response ($T_d = 5$ s in Eqs. (12) and (13)). The identification errors J_e were calculated for each divided data set, and these values were then averaged (Table 2).

In the simulator experiments performed on straight courses (Simulator experiments 1~3), the identification error of the data that is not prefiltered is small. These results indicate that the driver was responsive to the yaw dynamics of the car having a wide bandwidth. On the other hand, in the divided straight course of Simulator experiment 4 and in the actual driving test, the identification error is small for prefiltered data. It can be inferred that the driver responds to the yaw dynamics of a specific bandwidth in the experiment performed on a curved course. In the actual driving test, the driver responds to the yaw dynamics of a frequency ranging from

approximately 0.1 to 10 rad/s on a straight course, and from approximately 10 to 100 rad/s on a curved course. In the actual driving test, the driver's response frequency varies depending on the curvature of the course. In the implementation of the real-time identification method, the bandwidth of the prefilter is adjusted according to the course characteristics.

[Table 2 here]

Effect of data division parameters

The data division parameters were examined using actual driving data. In this experiment, the drivers were instructed to maintain a velocity of 80 km/h along the course. Therefore, the recorded data are divided under different yaw rate conditions, and the identification errors are compared. The straight course data were divided under the conditions, $|\dot{r}| < 0.5, 1, 1.5, 2,$ and 2.5 deg/s, using prefilters of various bandwidths. The averaged identification errors are listed in Fig. 5. The identification error for prefilters of lower bandwidths (0.1~1 rad/s) is small for the data divided at a low yaw rate ($|\dot{r}| < 0.5, 1,$ and 1.5 deg/s). However, at high yaw rates ($|\dot{r}| < 2$ and 2.5 deg/s), the identification error for prefilters of higher bandwidths (1~10 rad/s) is small. The above observation implies that when the yaw rate of the car is high, the driver responses to the yaw dynamics are of a higher frequency.

[Fig. 5 here]

Application of the identified model

A real-time driver model can be developed using the proposed method. The identified linear model contains several parameters that reflect the driver's inner conditions. In the above analysis, the driver models were formulated as first-order linear differential models.

$$H(s) = \frac{K}{Ts + 1} \quad (26)$$

The first-order model has two parameters: the steady state gain K and time constant T . As an example, the time constant variation in the actual driving test was analyzed. The time constant of the first-order model indicates the time delay in the input. The driver model with a large time constant responds to the input more slowly than that with a small time constant. In this paper, the driver models were identified as first-order models. If a driver model can be identified as a higher-order model, the driver characteristics can be analyzed in detail. However, when modeling as a higher-order model, considerable time is required for identification and validation.

Straight course data corresponding to the condition $|\dot{\theta}| < 0.5^\circ/\text{s}$ are identified, and a prefilter with a bandwidth of 0.1–1 rad/s is applied to these data. The time constant variations obtained for different driving times are shown in Fig. 6. The curved course data corresponding to the condition $|\dot{\theta}| > 4^\circ/\text{s}$ are identified, and a prefilter with a bandwidth of 1–10 rad/s is applied to these data. The time constant variations obtained for different driving times are shown in Fig. 7. Because the amount of data of driver D_{10} is very small, the data are omitted in the analysis. The time constants of all the drivers for the straight course data are distributed around 0.8 s. In contrast, the time constants of all the drivers for the curved course data are distributed around 0.15 s. These results indicate that the drivers' fast responses with a small delay in the curved course can be identified by using a prefilter with an appropriate bandwidth. The variation in the time constant with the driving time of the identified model indicates the variation in the time delays in the steering manipulation when the car is in motion. For example, an increase in the time constant is observed at 930 s in the curved course data of driver D_3 . This indicates that the driver's response became slower at this time. Such a variation in the driver's characteristics can be obtained in real time using the proposed method. As the next step of our research program, we plan to examine the relations between the identified driver model and the driver's conditions, and we intend to apply these findings to develop an alert system in order to avoid accidents caused by inappropriate driving behavior.

Because the test course is an oval track, the driver model and the desired yaw rate in each divided data set are approximately constant. Therefore, the time-invariant driver model is identified

for each divided data set. The preciseness of the identified model depends on the appropriate division of the data and the precise estimation of the desired car responses. On the actual road, the driver changes lanes and maneuvers around obstacles occasionally. The driver model and desired car responses in these transient maneuvers vary from those in the case of steady driving. For these transient maneuvers, the data are divided into small data sets, and the desired car responses are estimated by the proposed method. Subsequently, the transient driver model is identified. This procedure should be validated in the future.

[Figs. 6 and 7 here]

Conclusion

In this study, a method for real-time identification of a driver model is proposed. In the proposed method, the recorded data are divided on the basis of conditions such as filtered yaw rate and velocity. Next, a prefilter is applied to the data sets, and the responses of a particular frequency are extracted. The desired car response is estimated using the moving average method; subsequently, the driver model is identified as a feedback model to calculate the yaw angle tracking error. The driving simulator experiments and actual driving tests were performed, and the proposed method was validated. The results indicate the appropriate bandwidth of the prefilter and the division conditions.

This procedure can be carried out in real time. The proposed method requires a few sensors that are usually installed in a production car. These features are advantageous for the implementation of the proposed system on the production car. Because a driver model is developed for each divided data set, the variations in driver characteristics can be analyzed in real time. Our research group is presently studying the estimation of the driver's conditions using a real-time identification method.

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Captions

Table 1. Driving experiment

Table 2. Identification error

Fig. 1. Feedback driver model

Fig. 2. Desired response of the feedback driver model

Fig. 3. Driving simulator system

Fig. 4. Simulated highway course

Fig. 5. Identification error under various division conditions (Actual driving)

Fig. 6. Time constant variation for the identified model (actual driving on a straight course)

Fig. 7. Time constant variation for the identified model (actual driving on a curved course)

Table 1. Driving experiment

Experiment name	Course	Intended velocity [km/h]	Number of drivers
Simulator experiment 1	Straight	40	10
Simulator experiment 2	Straight	60	10
Simulator experiment 3	Straight	100	10
Simulator experiment 4	Highway	100	10
Actual driving	Closed-circuit	80	8

Table 2. Identification error

Experiment	Je					Average velocity [km/h]
	Without prefilter	Bandwidth of prefilter [rad/s]				
		0.1~1	1~10	10~100	100~1000	
Simulator experiment 1	12.20	731.26	128.70	16.74	24.11	39.46
Simulator experiment 2	8.45	7.77×10 ⁴	9.15	13.98	20.07	59.67
Simulator experiment 3	6.44	90.80	4.46×10 ⁵	11.05	16.08	99.82
Simulator experiment 4 Divided data for straight course	6.73×10 ³	3.65×10 ¹³	1.67×10 ⁴	9.89	14.64	99.33
Actual driving Divided data for straight course	2.42×10 ¹¹	5.07	6.52	12.27	12.84	81.46
Actual driving Divided data for corved course	2.57×10 ¹³	1.43×10 ¹⁵	262.97	3.55	6.78	79.67

Fig. 1. Feedback driver model

Fig. 2. Desired response of the feedback driver model

Fig. 3. Driving simulator system

Fig. 4. Simulated highway course

Fig. 5. Identification error under various division conditions (Actual driving)

Fig. 6. Time constant variation for the identified model (actual driving on a straight course)

Fig. 7. Time constant variation for the identified model (actual driving on a curved course)