Vehicle States Observer Using Adaptive Tire-Road Friction Estimator*

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Vehicle stability control system is a new idea which can enhance the vehicle stability and handling in the emergency situation. This system requires the information of the yaw rate, sideslip angle and road friction in order to control the traction and braking forces at the individual wheels. This paper proposes an observer for the vehicle stability control system. This observer consisted of the state observer for vehicle motion estimation and the road condition estimator for the identification of the coefficient of the road friction. The state observer uses 2 degrees-of-freedom bicycle model and estimates the system variables based on the Kalman filter. The road condition estimator uses the same vehicle model and identifies the coefficient of the tire-road friction based on the recursive least square method. Both estimators make use of each other information. We show the effectiveness and feasibility of the proposed scheme under various road conditions through computer simulations of a fifteen degree-of-freedom non-linear vehicle model.

Key Words: Stability Control, Extended Kalman Filter, Tire Road Friction, Recursive Least Square Method

1. Introduction

Because of the increasing demands for improving handling and stability in vehicles, automotive manufactures have concentrated major efforts on the research and development of the vehicle stability control system. ABS (Anti-lock brake system) and TCS (Traction control system) make vehicle stable when drivers brake and drive vehicle on the low friction respectively, but it is impossible for drivers to control the spin, which is dangerous, in the limit-cornering situation. The vehicle stability control system enhances the handling and the vehicle stability

in the emergency situation through controlling the traction and braking forces at the individual wheels. Such systems are the VDC⁽¹⁾ (Vehicle dynamic control system) of BOSCH, the VSC⁽²⁾ (Vehicle stability control system) of Toyota, and the ESP⁽³⁾ (Electronic stability program) of ITT et al.

The vehicle stability control system should control both the longitudinal and the lateral tire forces at the individual wheels by means of both the acceleration and the deceleration in order to maintain the vehicle stability and the handling. To satisfy this condition, the friction forces between tire and road should be optimized. Therefore this system needs additional information about the tire-road friction coefficient, the slip ratio, the side-slip angle, and the lateral velocity in order to control the optimal braking torque. It is expensive and difficult to acquire these signals directly. The vehicle stability control systems use limited number of sensors and estimate the necessary signals based on the vehicle model because measuring all the required signals is not attractive from the practical viewpoint. It is indispensable that the vehicle stability control system uses the state observer for estimating vehicle motions and

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the road condition estimator for identifying the coefficient of the tire-road friction. Recently, many analytical and experimental studies on estimating the coefficient of the tire-road friction and the vehicle states for the intelligent vehicle system have been performed. Ray⁽⁴⁾ estimated the tire force using the extended Kalman filter, and then identified the tire-road friction based on the conditional probability method. Gustafsson⁽⁵⁾ proposed the estimation of the tire-road friction from the initial slip slope and the roughness. Yi, et al.⁽⁶⁾ have presented the tire-road friction estimation for collision warning system using both the reduced order observer and the filtered regressor model. And Pasterkamp⁽⁷⁾ proposed the estimation of the friction between the tire and the road using the brush tire model. Most of these studies have been on estimating the tire-road friction under the longitudinal motion using the driving vehicle model. Their proposed approaches require so much computational load that becomes the limitation for real-time applications such as the vehicle stability control system, which controls the lateral motion of the vehicle.

This study proposes an observer for vehicle stability control system. This observer consists of the state observer for estimating vehicle motions and the road condition estimator for identifying the coefficient of the tire-road friction. The proposed state observer uses 2 degree-of-freedom bicycle model with the Dugoff tire model and estimates the system variables based on the Kalman filter with the tire-road friction coefficient that the tire-road friction estimator identifies. The tire-road friction estimator uses the same vehicle model and identifies the tire-road friction based on the recursive least square method. The proposed observer has a simple structure, which is suitable for the real-time applications such as the vehicle stability control system. We show the effectiveness and usefulness of the proposed scheme compared with the nonlinear observer based on the extended Kalman filter under various road conditions through computer simulations of a nonlinear fifteen degree-of-freedom vehicle model, which has been verified through the experimental vehicle test.

2. System Formulation and Observer Design

As the vehicle behavior is generally nonlinear, the conventional observers for estimating the vehicle states make use of the nonlinear observer method, which requires the computation of the gradient of the system's dynamic equation. In this paper, we design the observer based on the linear model in order to apply it to the vehicle stability control systems by reducing the complexity of the observer.

Fig. 1 The schematic diagram of the observer for vehicle stability control system

In this section, the vehicle models for designing the observer and the modified Dugoff tire model are introduced. The state observer is derived based on Kalman filter. The tire-road friction estimator designed based on the recursive least square method is proposed. Finally, we propose the configuration of the observer for vehicle stability control system. The schematic of the proposed observer with parallel structure is shown in Fig. 1.

2.1 Vehicle modeling

The observer for the vehicle stability control system estimates the lateral motion of the vehicle and the tire-road friction. In order to analyze the vehicle motion, this study makes use of a two-degrees of freedom vehicle model which is the simplest model to present the lateral motion of vehicle. The model considers the lateral dynamics of the vehicle and the weight transfer of left-right wheels, which is shown in Fig. 2.

The lateral and longitudinal equation of motion can be described by the following equations of motion:

$$M(\dot{v}_y + v_x r) = \sum_i Y_i, \quad (1)$$

$$I_z \dot{r} = 0.5 t_f (X_{fl} - X_{fr}) + 0.5 t_r (X_{rl} - X_{rr}) + a(Y_{fl} + Y_{fr}) - b(Y_{rl} + Y_{rr}), \quad (2)$$

where the subscription expresses the location of wheels ($i = fr$: front right, fl : front left, rr : rear right, rl : rear left), v_x , v_y , r , M , I_z , t_f , t_r , a , b are the longitudinal velocity, the lateral velocity, the yaw velocity, the vehicle mass, the yaw moment of inertia, the front wheel tread, the rear wheel tread, the distance of the front wheel center of c.g. and the distance of the rear wheel center of c.g., respectively.

The component tire forces (X_i , Y_i) of x and y

Fig. 2 The two degrees of freedom vehicle model (bicycle model)

Fig. 3 Lateral force versus slip angle : comparisons of dry and wet roads

directions in each wheel are computed by the longitudinal and lateral tire forces (F_i^x, F_i^y) as follows :

$$\begin{aligned} X_{fr,fl} &= F_{fr,fl}^x \cos \delta - F_{fr,fl}^y \sin \delta \\ &\cong F_{fr,fl}^x - F_{fr,fl}^y \delta, \end{aligned} \quad (3)$$

$$\begin{aligned} Y_{fr,fl} &= F_{fr,fl}^x \sin \delta + F_{fr,fl}^y \cos \delta \\ &\cong F_{fr,fl}^x \delta + F_{fr,fl}^y, \end{aligned} \quad (4)$$

$$X_{rr,rl} = F_{rr,rl}^x, \quad Y_{rr,rl} = F_{rr,rl}^y, \quad (5)$$

where the superscription expresses the direction of the SAE coordination, which is shown in Fig. 2.

The tire force in each wheel can be computed by the modified Dugoff tire model⁽⁸⁾, which considers the effect of tire-road friction. Previous studies have shown that the longitudinal force is proportional to the coefficient of the tire-road friction at small slip ratio⁽⁵⁾. We obtained the experimental results shown in Fig. 3 through the test performed at JARI (Japan Automobile Research Institute). This figure shows that the lateral force is proportional to the coefficient of the tire-road. Because the original Dugoff tire model has a constant stiffness with respect to both weight transfer and the tire-road friction at the small

slip range, it cannot explain the relation of the tire-road. This study proposes the modified Dugoff tire model, and then makes use of it to design a nonlinear observer.

The modified Dugoff tire model is computed by normal force, tire-road friction (μ_i), slip ratio (λ_i), side-slip angle (α_i), longitudinal stiffness coefficient (C_λ), and cornering stiffness coefficient (C_α) as follows :

$$F_i^x = \mu_i F_i^z C_\lambda \frac{\lambda_i}{1 - \lambda_i} f(L), \quad (6)$$

$$F_i^y = \mu_i F_i^z C_\alpha \frac{\tan \alpha_i}{1 - \lambda_i} f(L), \quad (7)$$

where $f(L) = \begin{cases} L(2-L) & \forall L < 1 \Rightarrow (\text{Sliding region}) \\ 1 & \forall L > 1 \Rightarrow (\text{Adhesive region}) \end{cases}$,

$$L = \frac{1}{2\sqrt{C_\lambda^2 \lambda^2 + C_\alpha^2 \tan^2 \alpha}} (1 - \lambda)(1 - \epsilon v_x \sqrt{C_\lambda^2 \lambda^2 + C_\alpha^2 \tan^2 \alpha})$$

and ϵ is the design parameter to describe the effect of the vehicle velocity.

An L indicates the ratio of the adhesive area to the sliding area between the tire and the road. If L is more than 1, the adhesive phenomenon is dominant.

2.2 Vehicle state observer design

The vehicle state observer uses the information from the sensor and the outputs of the controller to decide the reference motion for the vehicle stability control system. The outputs of the controller are the vehicle speed and the longitudinal tire force. A yaw rate, a steering angle, and a lateral acceleration are measured. The observer estimates a lateral velocity, a slip angle, a yaw rate etc.

In order to reduce the computing load for real-time applications, the observer uses two degrees of freedom vehicle model shown in Fig. 2. The relation between the longitudinal tire force and the lateral tire force can be driven as the following linearized tire model :

$$F_i^y = C_{\alpha,i}^* \alpha_i, \quad (8)$$

where $C_{\alpha,i}^* = \begin{cases} \frac{C_\alpha F_i^x}{C_\lambda \lambda} & \text{if } |\lambda| > \epsilon \\ \mu_i F_i^z C_\alpha & \text{if } |\lambda| \leq \epsilon \end{cases}$, and an ϵ is the design parameter of the small slip range.

The linearized tire model and the two degrees of freedom vehicle model can be derived into the state space form. This equation is presented by the time varying function of the longitudinal tire forces and the vehicle speed as follows :

$$\dot{x}(t) = A(t)x(t) + B(t)u(t) + v^*(t), \quad (9)$$

where $x(t) = \{v_y, r\}^T$, $u(t) = \delta(t)$, system matrix ($A(t)$), input matrix ($B(t)$), and $v^*(t)$ is the system noise, respectively.

This equation can be expressed by the discrete time state space equation in order to be applied to the sampled data systems as follows :

$$x(k+1) = G(k)x(k) + H(k)u(k) + v_1(k), \quad (10)$$

where the system noise ($v_1(k)$) satisfies the following condition:

$E[v_1(k)] = 0$, $E[v_1(s)v_1^T(k)] = Q(k)\delta(s-k)$, $Q(k)$ is positive definite, system matrix ($G(k)$), input matrix ($H(k)$) are derived from Eq.(9) based on the sampling theory.

The output equation of the lateral acceleration and yaw rate is derived by the following equation:

$$y(k) = C(k)x(k) + D(k)u(k) + v_2(k), \quad (11)$$

where the measurement noise ($v_2(k)$) satisfies the following condition:

$E[v_2(k)] = 0$, $E[v_2(s)v_2^T(k)] = R(k)\delta(s-k)$, $R(k)$ is positive definite.

The observer for estimating the vehicle states is derived by the Kalman filter. The vehicle state observer is derived as follows:

$$\begin{aligned} \hat{x}(k+1) &= \hat{G}(k)\hat{x}(k) + \hat{H}(k)u(k) \\ &+ K_e(k)[y(k) - \hat{y}(k)], \end{aligned} \quad (12)$$

where the system matrix ($\hat{G}(k)$), input matrix ($\hat{H}(k)$) of observer is equal to the nominal model in Eq.(10).

The gain of the Kalman filter ($K_e(k)$) is computed based on the covariance matrix of the system noise ($Q(k)$) and measurement noise ($R(k)$).

$$\begin{aligned} K_e(k) &= \hat{G}(k)P(k)\hat{C}^T(k) \\ &\times [R(k) + \hat{C}(k)P(k)\hat{C}^T(k)]^{-1}, \\ P(k+1) &= Q(k) + \hat{G}(k)P(k)\hat{G}^T(k) \\ &- K_e(k)\hat{C}(k)P(k)\hat{G}^T(k) \end{aligned} \quad (13)$$

The slip angle is computed by the following equation:

$$\hat{\beta} = \frac{\hat{v}_y}{\hat{v}_x}. \quad (14)$$

If the covariance matrix of the measurement noise were sufficiently larger than that of the system noise, the gain of the observer would converge into zero and the output would only depend on the vehicle model. This observer computes the covariance matrix of the estimation error ($P(k) = E[(x(k) - \hat{x}(k))(x(k) - \hat{x}(k))^T]$) and $K_e(k)$ at each computing time.

The estimation based on the linear observer has the limitation that there are large modeling error caused by the highly nonlinear behavior of the vehicle on low friction road. In order to overcome the limitation and compare with the performance of the linear observer, in this study we design a nonlinear observer based on the extended Kalman filter. This observer estimates the vehicle states by means of the nonlinear vehicle model instead of the linearized vehicle model.

The nonlinear equation of motion can be expressed as follows:

$$\begin{aligned} z(k+1) &= f(z(k), u(k), v_1(k)), \\ y(k) &= h(z(k), u(k), v_2(k)). \end{aligned} \quad (15)$$

System noise and measurement noise is defined by the following equation:

$$E\left\{\begin{bmatrix} v_1(t) \\ v_2(t) \end{bmatrix} \begin{bmatrix} v_1^T(s) & v_2^T(s) \end{bmatrix}\right\} = \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \delta(t-s). \quad (16)$$

The nonlinear equation can be expanded into Taylor series at current state. If the higher order terms than 2 are ignored, the nonlinear equation could be expressed by the Eq.(16);

$$\begin{aligned} z(k+1) &\cong f(\hat{z}(k), u(k), 0) \\ &+ F(k)[z(k) - \hat{z}(k)] + G(k)v_1(k), \\ y(k) &\cong h(\hat{z}(k), u(k), 0) \\ &+ H(k)[z(k) - \hat{z}(k)] + J(k)v_2(k), \end{aligned} \quad (17)$$

where the gradient of system equation is computed by the following equations;

$$\begin{aligned} F(k) &= \frac{\partial f(z(k), u(k), v_1(k))}{\partial z(k)} \bigg|_{\substack{z(k) = \hat{z}(k), \\ v_1(k) = 0}}, \\ G(k) &= \frac{\partial f(z(k), u(k), v_1(k))}{\partial v_1(k)} \bigg|_{\substack{z(k) = \hat{z}(k), \\ v_1(k) = 0}}, \\ H(k) &= \frac{\partial h(z(k), u(k), v_2(k))}{\partial z(k)} \bigg|_{\substack{z(k) = \hat{z}(k), \\ v_2(k) = 0}}, \\ J(k) &= \frac{\partial h(z(k), u(k), v_2(k))}{\partial v_2(k)} \bigg|_{\substack{z(k) = \hat{z}(k), \\ v_2(k) = 0}}. \end{aligned}$$

The nonlinear observer based on the extended Kalman filter is derived as;

$$\begin{aligned} \hat{z}(k+1) &= f(\hat{z}(k), u(k), 0) \\ &+ L(k)[z(k) - h(\hat{z}(k), u(k), 0)]. \end{aligned} \quad (18)$$

The gain of the extended Kalman filter ($L(k)$) is computed as follows;

$$\begin{aligned} L(k) &= [F(k)\Sigma(k)H^T(k) + G(k)SJ^T(k)] \\ &\times [H(k)\Sigma(k)H^T(k) + J(k)RJ^T(k)]^{-1}, \\ \Sigma(k+1) &= F(k)\Sigma(k)F^T(k) + G(k)QG^T(k) \\ &- L(k)[H(k)\Sigma(k)H^T(k) + J(k)RJ^T(k)]L^T(k), \end{aligned} \quad (19)$$

$$(20)$$

where $\Sigma(k)$ is the covariance matrix of the estimation error.

2.3 The tire-road friction estimator design

The vehicle stability control system requires the information on the road condition so that the system adjusts the vehicle states accordingly. In this study, we design a tire-road friction estimator based on the assumption that the tractive force is proportional to the friction coefficient at a given slip ratio, which previous studies have assumed⁽⁶⁾. The tire-road friction estimator identifies the tire-road friction coefficients based on both the vehicle model and the newly proposed modified Dugoff tire model.

The conventional bicycle model has 2 degrees of freedom; the motion of the lateral direction and that of the yaw direction. In this study, we use 3 degrees of freedom bicycle model that has the additional longitudinal directional motion to identify the tire-road friction coefficient in the case of the combined lateral and longitudinal directional motions.

Both the tractive force and the lateral force can be expressed by the function of friction coefficient, slip ratio, slip angle and normal force by means of the

modified Dugoff tire model as follows:

$$F_i^x = \mu_i F_i^{x0}(F_i^z, \lambda_i, \alpha_i) + \Delta_i^x, \quad (21)$$

$$F_i^y = \mu_i F_i^{y0}(F_i^z, \lambda_i, \alpha_i) + \Delta_i^y, \quad (22)$$

where Δ_i^x, Δ_i^y are the offset force due to unmodeled systems such as the camber angle, the conicity, etc.

The equation of motions of the longitudinal direction, the yaw direction, and the lateral direction based on above equations are expressed as follows:

$$Ma_x = \mu_{fr}(F_{fr}^{x0} - F_{fr}^{y0}\delta) + \mu_{fl}(F_{fl}^{x0} - F_{fl}^{y0}\delta) + \mu_{rr}F_{rr}^{x0} + \mu_{rl}F_{rl}^{x0} + \Delta_1, \quad (23)$$

$$Ma_y = \mu_{fr}(F_{fr}^{x0}\delta + F_{fr}^{y0}) + \mu_{fl}(F_{fl}^{x0}\delta + F_{fl}^{y0}) + \mu_{rr}F_{rr}^{y0} + \mu_{rl}F_{rl}^{y0} + \Delta_2, \quad (24)$$

$$I_z \dot{r} = \mu_{fr} \left(a(F_{fr}^{x0}\delta + F_{fr}^{y0}) - \frac{t_f}{2}(F_{fr}^{x0} - F_{fr}^{y0}\delta) \right) + \mu_{fl} \left(a(F_{fl}^{x0}\delta + F_{fl}^{y0}) + \frac{t_f}{2}(F_{fl}^{x0} - F_{fl}^{y0}\delta) \right) - \mu_{rr} \left(bF_{rr}^{y0} + \frac{t_r}{2}F_{rr}^{x0} \right) - \mu_{rl} \left(bF_{rl}^{y0} - \frac{t_r}{2}F_{rl}^{x0} \right) + \Delta_3. \quad (25)$$

The least square method (LSM) are generally used for the estimation method of unknown values from input signals and output signals. Because the LSM makes use of the pseudo inverse matrix, which needs much computing power, it is not proper for the online estimation of unknown values. In this study, we proposed the identification method of the tire-road friction based on the Recursive Least Square method (RLSM)⁽⁹⁾. To estimate the tire-road friction using RLSM, the equations of vehicle motion is expressed as follows:

$$y(k) = \phi(k-1)^T \theta(k), \quad (26)$$

where $\theta(k)$ are unknown values that are tire-road friction in four wheels and offsets, $\phi(k)$ are input values, and $y(k)$ are output values,

$$\phi(k) = \begin{bmatrix} F_{fr}^{x0} - F_{fr}^{y0}\delta & F_{fr}^{x0}\delta + F_{fr}^{y0} \\ F_{fl}^{x0} - F_{fl}^{y0}\delta & F_{fl}^{x0}\delta + F_{fl}^{y0} \\ F_{rr}^{x0} & F_{rr}^{y0} \\ F_{rl}^{x0} & F_{rl}^{y0} \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ a(F_{fr}^{x0}\delta + F_{fr}^{y0}) - \frac{t_f}{2}(F_{fr}^{x0} - F_{fr}^{y0}\delta) \\ a(F_{fl}^{x0}\delta + F_{fl}^{y0}) + \frac{t_f}{2}(F_{fl}^{x0} - F_{fl}^{y0}\delta) \\ -\left(bF_{rr}^{y0} + \frac{t_r}{2}F_{rr}^{x0}\right) \\ -\left(bF_{rl}^{y0} - \frac{t_r}{2}F_{rl}^{x0}\right) \\ 0 \\ 0 \\ 1 \end{bmatrix},$$

$$\theta(k) = [\mu_{fr} \quad \mu_{fl} \quad \mu_{rr} \quad \mu_{rl} \quad \Delta_1 \quad \Delta_2 \quad \Delta_3]^T,$$

$$y(k) = [Ma_x(k) \quad Ma_y(k) \quad I_z \dot{r}(k)]^T.$$

To estimate the unknown values of the time varying system, RLSM can use either the forgetting factor ($\lambda(k)$) or the constant values instead of the variance matrix ($F(k)$). The estimating values of RLSM with the forgetting factor are given as the following equation;

$$\hat{\theta}(k+1) = \hat{\theta}(k) + F(k)\phi(k)R(k)\varepsilon^0(k+1), \quad (27)$$

where

$$F(k+1) = \frac{1}{\lambda(k)}(F(k) - F(k)\phi(k)R(k)\phi(k)^T F(k)),$$

$$R(k) = [\lambda(k)I + \phi(k)^T F(k)\phi(k)]^{-1},$$

$$\varepsilon^0(k+1) = y(k+1) - \hat{\theta}(k)^T \phi(k).$$

The performance of the forgetting factor and that of the constant values are compared. To prevent misdecision caused by the weight transfer in left-right steering, the tire-road friction estimator utilizes the average values of both front wheels. And the yaw acceleration of the Eq. (25) is computed by the numerical method. Because the method is sensitive to the noise, the observer for the vehicle stability control system uses the lowpass filtered differentiator.

2.4 Observer for VSC

The observer for VSC should estimate not only the coefficient of the tire-road friction but also the side slip angles of each wheel, the slip angle, and the yaw rate by means of both the state observer and the tire-road friction estimator. The observer that is described by Fig. 4 has the parallel structure.

The tire-road friction estimator uses a lateral acceleration, a yaw acceleration computed by pre-filters from a lateral acceleration sensor, a yaw rate sensor equipped with vehicle, and slip angles computed from the output of the vehicle state observer. The state observer uses the tire-road friction coefficient computed by the tire-road friction estimator. The lowpass filter is utilized to remove the sensitivity caused by the measurement noise. Because the vehicle is generally operated on the high friction road, the initial values of the friction coefficients of the tire-road friction estimator are set to be 1.0 assuming the high friction coefficient. The initial values of the friction coefficient of the state observer are set to be

Fig. 4 The functional diagram of the vehicle stability control system

0.3 assuming the low friction coefficients in order to prevent the over shoot caused by the over-estimation of slip angle in case of the state observer with high friction coefficient.

The lowpass filter removes the noise of the lateral acceleration signal and the noise of the estimated friction coefficient. Because the filter has the delay characteristic, the performance of the estimation is reduced. The differentiator with the lowpass filter computes an yaw acceleration from an yaw rate sensor, also the filter hampers the performance of the identification.

3. Results and Discussion

The computer simulation was carried out, to evaluate the proposed estimator based on the 15 degrees of freedom nonlinear vehicle model shown in Fig. 5. The used vehicle model is verified by comparing with the results of middle size passenger-car test. Figure 6 shows the experimental results and the outputs of the non-linear vehicle model in the step steering test. This test is the general steering test with 80-kph constant vehicle speed and 45° steering input on high friction road. The outputs of the observer were obtained based on the noisy output of the non-linear vehicle model at the same simulation condition. The noise level is set to be the 20-dB SN ratio that is generally accepted. The outputs of the experimental test with small noise components show the general behavior of the conventional vehicle on high friction road. The outputs of vehicle model have small error at the transient, but perfectly follow the output of experiment test. The results show the reliability of nonlinear vehicle model that enables us to use the nonlinear vehicle model for the evaluation of the proposed observer on various road conditions. The

simulations are executed on both the high and low friction roads.

Figures 6 and 7 show the outputs of the proposed observer that consists of the state observer based on the linear Kalman filter and the tire-road friction estimator based on the RLSM with the constant gain. In Fig. 7(a), we compare the measured slip angle with the estimate. The output of the high friction road has some error. That is caused by the modeling error between the 2 degrees of freedom linear model and the 15 degrees of freedom nonlinear vehicle. Though the tuning of the gain of the Kalman filter can decrease this error, that increases the effect of the measurement noise. The output of the low friction road has the large error in the steady states. The error is caused by the error of the large slip range due to the simple tire model in Eq.(8). In Fig. 7(b), the tire-road friction estimator identifies the tire-road friction both on the high and low friction roads. This result shows that the RLSM with the constant gain has the fast estimation performance. While the method shows the small chattering phenomenon, it has the fast convergence and the satisfactory

Fig. 5 The fifteen degrees of freedom vehicle model

(a) Lateral acceleration

(b) Yaw velocity

Fig. 6 Comparison of the experimented and simulated results

(a) Side slip responses

(b) Friction coefficient responses

Fig. 7 Actual states and estimated states for step steering with the linear state observer and the constant gain RLMS

Fig. 8 Histogram of estimated error for step steering with the linear state observer and the constant gain RLMS

classification among the road conditions

Figure 8 analyzes the estimation errors of the proposed observer in the step steering. This shows that the errors of the estimated values are within maximum 5% and 10% on the high and low friction roads, respectively.

Figure 9 analyzes the estimation errors of the

Table 1 Comparison the proposed method with the nonlinear method

	Tire-friction observer	State observer	Computational load*	
Case 1	Constant gain	Linear observer	12.448 msec/cycle	Small computational load
Case 2	Forgetting factor	Nonlinear observer	34.140 msec/cycle	Small estimation error

* MATRIXx computing time on Pentium II 400

Fig. 9 Histogram of estimated error for step steering with EKF and forgetting gain

proposed observer that consists of the state observer based on the extended Kalman filter (EKF) and the tire-road friction observer based on the RLMS with the forgetting factor in the same simulation condition. EKF has the estimation error within 4% on the high and low friction roads. Because EKF precisely explains the nonlinear motion of the vehicle, it has excellent performance on both the high and low friction roads. If the friction coefficient of the driving road is different to that of the observer, it causes very large estimation error. Table 1 compares the computing load and the characteristics of the previous two methods. In Table 1, the state observer based on EKF requires the three times of the computational power of the state observer based on Kalman filter due to computing the gradient of the system states at each step. Because the state observer based on EKF has a large computing load and is sensitive to the system errors, it may not be suitable for the practical applications.

The tire-road friction observer with the forgetting factor shows a small overshoot and fast convergence. We can classify the road conditions based on the convergent value. While the tire-road friction observers with the constant factor and with the forgetting factor have the fast convergence performance and are capable of classifying the road condition, the tire-road friction observer with the constant factor is better suitable for the vehicle stability control system due to the small computing load.

4. Conclusion

This paper proposed the observer for the vehicle

stability control system that has the parallel structure consisted of the vehicle state observer and the tire-road friction estimator. The vehicle state observer uses 2 degree-of-freedom bicycle models with the modified the Dugoff tire model and estimates the vehicle states based on the Kalman filter. The road condition estimator uses the same vehicle model and identifies the tire-road friction based on the recursive least square method.

The state observer based on Kalman filter has the estimation error within 5% range for the step steering on the high friction road and has it within 10% range on the low friction road. Because this method has the small estimation error for various driving conditions and tire-road conditions, and needs the small computing time, it is suitable for the vehicle stability control system. The tire-road friction observer based on RLSM has the fast convergence and is capable of classifying the tire-road conditions. Using the constant gain method is more effective than using the forgetting factor because the former requires smaller computing power.

The observer for the vehicle stability control system with the paralleled structure that make use of both observers, the pre-filters and some sensors equipped with ABS has the validity and the effectiveness. The proposed observer can be applied to 4 WS and the integrated vehicle control systems.

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