行政院國家科學委員會專題研究計畫　期中進度報告

子計畫二：追蹤動態最佳滑差之防鎖死剎車系統之智慧型控制(1/2)

計畫類別： 整合型計畫
計畫編號： NSC94-2213-E-030-011-
執行期間： 94 年 08 月 01 日至 95 年 07 月 31 日
執行單位： 輔仁大學電子工程學系(所)

計畫主持人： 王偉彥

計畫參與人員： 李宜勳，高弘霖，陳銘滄，錢立軒，謝濬鴻

報告類型： 精簡報告
報告附件： 出席國際會議研究心得報告及發表論文
處理方式： 本計畫可公開查詢

中 華 民 國 95 年 6 月 1 日

行政院國家科學委員會補助專題研究計畫 □ 成 果 報 告 ☑期中進度報告

先進車輛控制及安全系統之設計與模擬-子計畫二：追蹤動態最佳滑差之防鎖死剎車系統之智慧型控制(1/2)

計畫類別：□ 個別型計畫 ☑ 整合型計畫

計畫編號： NSC 94-2213-E-030-011

執行期間：94 年 8 月 1 日至 95 年 7 月 31 日

計畫主持人：王偉彥

共同主持人：

計畫參與人員：李宜勳，高弘霖，陳銘滄，錢立軒，謝濬鴻

成果報告類型(依經費核定清單規定繳交)：☑精簡報告 □完整報告

本成果報告包括以下應繳交之附件：

□赴國外出差或研習心得報告一份

□赴大陸地區出差或研習心得報告一份

□出席國際學術會議心得報告

□國際合作研究計畫國外研究報告書一份

處理方式：除產學合作研究計畫、提升產業技術及人才培育研究計畫、列管計畫及下列情形者外，得立即公開查詢

□涉及專利或其他智慧財產權，☑一年□二年後可公開查詢

執行單位：輔仁大學電子工程系

中 華 民 國 95 年 5 月 31 日

行政院國家科學委員會專題研究計畫期中報告

先進車輛控制及安全系統之設計與模擬-子計畫二：追蹤動態最佳滑差之防鎖死剎車系統之智慧型控制(1/2)

計畫編號：NSC 94-2213-E-030-011

執行期限：94 年 8 月 1 日至 95 年 7 月 31 日

主持人：王偉彥　　輔仁大學電子工程系

參與人員：李宜勳, 高弘霖, 陳銘滄, 錢立軒, 謝濬鴻

Abstract

This paper proposes an antilock braking system (ABS), in which unknown road characteristics are resolved by a road estimator defined by LuGre friction model with a road condition parameter. For precisely defining the road condition parameter and further reducing the braking time, two strategies are used: the first is the $\mu-\lambda$ curves are built from the real simulation data and second is the wheel velocity is introduced into the road estimator. The three-dimension mapping function are proposed to transfer the road condition parameter and wheel velocity to a slip ratio of the wheel. The slip ratio controller is used to maintain the slip ratio of the wheel at the reference values for various road surfaces. In the controller design, an observer-based direct adaptive fuzzy-neural controller (DAFC) for an ABS is developed to on-line tune the weighting factors of the controller under the assumption that only the wheel slip ratio is available. Finally, this paper gives simulation results of an ABS with the road estimator and the DAFC, and is shown to provide good effectiveness under varying road conditions.

I. Introduction

Braking under critical conditions, such as those encountered with wet or slippery road surfaces, panicked driver reactions, or mistakes committed by other drivers and pedestrians can lead to wheel lock. This phenomenon is strongly undesirable, since the friction force on the locked wheel is usually considerably less as it slides on the road. Furthermore, while the wheels are locked, steering becomes impossible, leading to loss of control of the vehicle. Hence, preventing locking-up during the braking process is important for driver and passenger safety. For these reasons, anti-lock braking systems (ABS) [15-17] have become one of the most common automotive technologies. The wheel slip ratio, which is the difference between the vehicle speed and the wheel speed, is regarded as one of the most important process parameters affecting the quality of vehicle control. The main goal of most ABS system is to ensure that the wheel slip ratio remains within the range of about 0.1 to 0.3, which is suitable for most road conditions. Most traditional ABS control strategies [1, 2] aim to maintain the wheel slip ratio at 0.2, although this value is a compromise. Hence, one main problem of these methods is determining how to find the optimal slip ratio if the road characteristics are unknown.

In general, optimal slip ratios are highly dependent on the particular road characteristics, such as whether the road is dry or wet. A tire/road friction estimator using only angular wheel velocity has been proposed to monitor the road characteristics [4]. In [4], a LuGre model [9, 10], which effectively models tire/road friction based on the relative contact velocity, is used to form a tire/road friction estimator. Otherwise, for further reducing the braking time, a wheel velocity is introduced into the road estimator. We build a family of the $\mu-\lambda$ curves for different ω's value, and then define the optimal slip ratio from this family curves. In this paper, the LuGre tire/road estimator is applied to estimate the road characteristics and then supply the reference slip ratio to an ABS controller through a mapping function. A feedforward neural networks [12] using back-propagation learning algorithm proposed to identify the mapping function from road characteristics and the wheel velocity to reference slip ratios. Hence, this ABS, based on the LuGre tire/road friction estimator, called LuGre-based ABS, can recognize the road characteristics and obtain a reference slip ratio.

Regarding controllers, researchers have greatly improved the performance of ABS by utilizing many algorithms, such as sliding mode control (SMC) [5], fuzzy logic control (FLC) [6], adaptive control, genetic neural control [7], etc. All these methods assume that the system states are available for measurement. In traditional anti-lock braking systems, certain states, such as the wheel acceleration and the brake-line pressure, are difficult to obtain, or are prone to noise and other measurement errors. To resolve this problem, a state observer is required. Thus, the observer-based direct adaptive fuzzy-neural controller (DAFC) [14] is applied to ABS control, and its stability can be guaranteed by the universal approximation theorem. The DAFC can overcome system uncertainties and disturbances. In this paper, we propose an antilock-braking system based on a road estimator, using the DAFC to force the wheel slip ratio to follow a reference slip ratio obtained by the road estimator.

II. Problem formulation

The wheel speed can be written as:

$$\dot{\omega}=\frac{T_b-T_t}{I}=\frac{K_bP_i-F_xR}{I} \quad (1)$$

and the differential equation of vehicle longitudinal dynamics is

$$\dot{v}=\frac{F_x}{m_q} \quad (2)$$

where ω is the angular velocity of the wheel, v is the vehicle velocity, F_x is the longitudinal reactive force, T_b is the braking torque, m_q is the mass of the quarter of the vehicle supported by the wheel, R is the tire rolling radius, I is the moment of inertia, and K_b is the gain between the pressure of the ABS, P_i, and the braking torque T_b. The control objective of ABS is to regulate wheel slip to maximize the coefficient of friction between the wheel and the road for any road condition. The coefficient of friction during braking can be described as a function of the slip ratio λ, which is defined as

$$\lambda=\frac{v-R\omega}{v}. \quad (3)$$

A. Friction Model

The tire force includes the normal force, the longitudinal force, and the lateral force. The normal force F_z is a function of the weight of the vehicle, or the component of the weight acting in a vertical plane relative to the road surface. The longitudinal force F_x is effective at road-surface level; it allows the driver to apply throttle and then brakes to accelerate and slow the vehicle. As the vehicle is being steered, the lateral force F_y controls its maneuverability and stability in changing the vehicle's forward direction. The normalized friction force is defined as $\mu = F_x/F_z$. In previous research [4], a road condition θ introduced into the LuGre friction model and the normalized friction force is shown as follows:

$$\dot{z}=v_r-\theta\frac{\delta_0\,|v_r|}{g(v_r)}z-\kappa R|\omega|z \quad (4)$$

$$F_x=(\delta_0 z+\delta_1\dot{z}+\delta_2 v_r)F_z \quad (5)$$

where

$$g(v_r)=F_c+(F_s-F_c)e^{-|\frac{v_r}{v_s}|}, \quad (6)$$

δ_0 is the normalized rubber longitudinal lumped stiffness, δ_1 is the normalized rubber longitudinal lumped damping, δ_2 is the normalized viscous relative damping, F_c is the normalized Coulomb friction, F_s is the normalized static friction, v_s is the Stribeck relative velocity, z is the internal friction state, and v_r is a relative velocity defined as $r\omega - v$, which is equal to $-\lambda v$. The parameter θ is introduced to capture the changes in the road conditions. The constant $\kappa \approx L/2 > 0$ captures the effect in the lumped model of the force distribution. The L is patch length.

A feedback control law is proposed to force the normalized friction force equation shown in (5) into steady-state characteristic, so that we can get the fixing the velocity v or wheel velocity ω. Then a family of curves $\lambda \mapsto F_x$ for different value of ω's is shown in Fig. 1. Using the same way, Fig. 2 shows that there are various μ vs λ curves under different values for θ, where μ is the normalized friction force and λ is the slip ratio. From Fig. 2 and 3, we can find the maximum normalized friction force in different θ's and ω's. The three-dimensional mapping surface can be defined and is shown in Fig. 4. The reference slip ratio is approximating to an optimal slip ratio when the parameter θ effectively captures the real road characteristics.

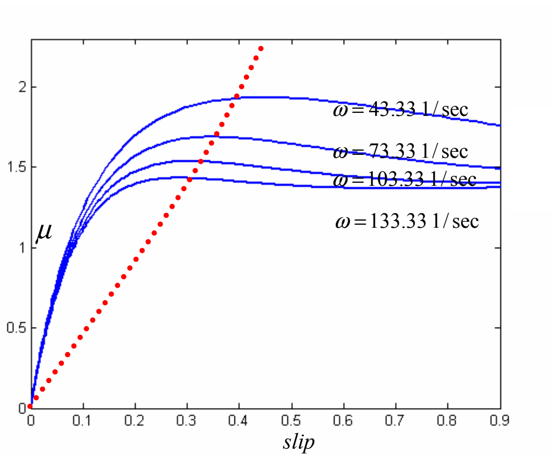

Fig. 1.Steady-state profiles computed for the uniform force distribution.

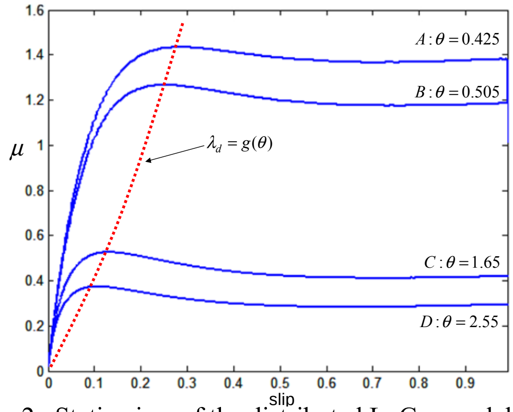

Fig. 2. Static view of the distributed LuGre model under different values for θ.

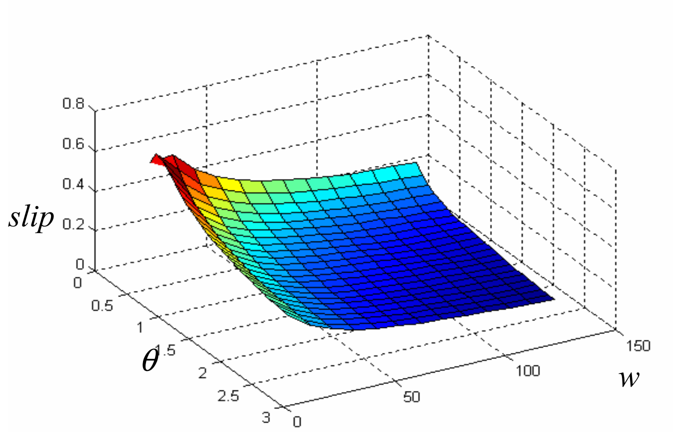

Fig. 4. Three-dimensional mapping surface which is a smooth mapping function from known θ and ω to a reference slip ratio

B. Second order dynamic system

In traditional anti-lock braking systems, certain states, such as the wheel acceleration, and the brake-line pressure, are difficult to obtain, or are prone to noise and other measurement errors. To resolve this problem, we will use an observer-based direct adaptive fuzzy-neural controller to control the ABS following the reference slip ratio. First differentiating equation (3) along with equation (1), we find the differential of λ to be

$$\dot{\lambda} = \frac{1}{v}\left[\frac{R}{I}(F_x R - K_b P_i) + (1-\lambda)\dot{v}\right] \quad (7)$$

Defining $\boldsymbol{\lambda} = [\lambda\ \dot{\lambda}]$ and $\mathbf{z} = [z\ \dot{z}\ \ddot{z}]$, then the time derivative function of (7) can be expressed as

$$\ddot{\lambda} = [\frac{R^2\dot{F}_X}{Iv} + (\frac{(1-\lambda)\dot{a}_v - \dot{\lambda}a_v}{v})] - \frac{RK_b\dot{P}_i}{Iv} + d(\lambda, v, \dot{v}, P_i, \mathbf{z})$$
$$\equiv \widetilde{f}(\lambda, \dot{\lambda}, v, \mathbf{z}) + b(v)u + d(\lambda, v, \dot{v}, P_i, \mathbf{z}) \quad (8)$$

where

$\widetilde{f} = (\lambda, \dot{\lambda}, v, \mathbf{z}) = \frac{R^2\dot{F}_X}{Iv} + (\frac{(1-\lambda)\dot{a}_v - \dot{\lambda}a_v}{v})$,

$b(v) = -\frac{RK_b}{Iv}$, and $u = \dot{P}_i$. $d(\lambda, v, \dot{v}, P_i, \mathbf{z})$ represents the nonlinearities obtained by differentiating $\dot{\lambda}$ with respect to v on the premise that other parameters are treated as constants.

III. Estimator for Tire/Road Contact Friction

By substituting equation (5) into (1) and (2) and adding viscous rotational friction δ_w, we can derive a one-wheel vehicle model with the LuGre friction model used in previous studies [8-12], called the LuGre-based ABS,

$$m_q\dot{v} = F_z(\delta_0 z + \delta_1\dot{z}) + F_z\delta_2 v_r \quad (9)$$

$$I\dot{\omega} = -RF_z(\delta_0 z + \delta_1\dot{z} + \delta_2 v_r) - \delta_\omega\omega + u_r \quad (10)$$

$$\dot{z} = v_r - \theta\frac{\delta_0 \mid v_r \mid}{g(v_r)}z - \kappa R|\omega|z \quad (11)$$

$$\dot{\theta} = 0 \quad (12)$$

where u_r is an input variable for the road estimator, and we have neglected the term δ_2 in equation (10). In equations (9)-(12), we assume that only ω is measurable. To set our systems in the same framework as the classical dynamic system, the following change of coordinates is introduced:

$$\eta = Rm_q v + I\omega$$
$$\chi = I\omega + RF_z\delta_1 z \quad (13)$$

Substituting equation (13) into (9)-(10), we obtain the following equations:

$$\dot{\mathbf{x}} = \begin{bmatrix} -\frac{F_z\delta_2}{m_q} & 0 & 0 \\ 0 & -\frac{\delta_0}{\delta_1} & 0 \\ -\frac{1}{Rm_q} & 0 & 0 \end{bmatrix}\mathbf{x} + \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}[\theta\phi(u_r, \mathbf{x}) + \psi(y_r, \mathbf{x})]$$
$$+ \begin{bmatrix} R^2F_z\delta_2 + I\frac{F_z\delta_2}{m_q} - \delta_\omega \\ I\frac{\delta_1}{\delta_0} - \delta_\omega \\ R + \frac{I}{Rm_q} \end{bmatrix} y_r + \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} u_r \quad (14)$$
$$y_r = [0 \quad \frac{1}{I} \quad \frac{-RF_z\delta_1}{I}]\mathbf{x}$$

where the state vector $\mathbf{x} = [\eta\ \chi\ z]^T$, output variable $y_r = \omega$, $\phi(u_r, \mathbf{x}) = \frac{\delta_0|Ry_r - v|}{g(Ry_r - v)}z$ and $\psi(y_r, \mathbf{x}) = \kappa R|\omega|z$.

Under the hypotheses from previous methods [4], an estimator structure is proposed for the LuGre-based ABS shown in equation (14) and it can be expressed as:

$$\dot{\hat{\mathbf{x}}} = \begin{bmatrix} -\frac{F_z\delta_2}{m_q} & 0 & 0 \\ 0 & -\frac{\delta_0}{\delta_1} & 0 \\ -\frac{1}{Rm_q} & 0 & 0 \end{bmatrix}\hat{\mathbf{x}} + \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}[\hat{\theta}\phi(u_r, \mathbf{x}) + \psi(y_r, \mathbf{x}) + \alpha(y_r)\{1 + \hat{\theta}\}\{y_r - \hat{y}_r\}]$$
$$+ \begin{bmatrix} R^2F_z\delta_2 + I\frac{F_z\delta_2}{m_q} - \delta_\omega \\ I\frac{\delta_1}{\delta_0} - \delta_\omega \\ R + \frac{I}{Rm_q} \end{bmatrix} y_r + \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} u_r + \begin{bmatrix} k_1 \\ k_2 \\ k_2 \end{bmatrix}(y_r - \hat{y}_r)$$
$$\dot{\hat{\theta}} = \gamma[\frac{\delta_0 \mid \hat{v}_r \mid}{g(\hat{v}_r)} + \alpha(\omega - \hat{y}_r)]\hat{z}(\omega - \hat{y}_r)$$
$$\hat{y}_r = [0 \quad \frac{1}{I} \quad \frac{-RF_z\delta_1}{I}]\hat{\mathbf{x}} \quad (15)$$

with $\alpha(y_r) = \frac{\theta_{\max}\rho_\phi^2(\hat{y}_r + \rho_\psi^2(\hat{y}_r))}{2(\lambda_{\min}(\mathbf{Q}) - \varepsilon)}$ and $\varepsilon \in (0; \lambda_{\min}(\mathbf{Q}_r))$.

Lipschitz Properties of ϕ and ψ: It is immediately domination function and constant

$$\rho_\psi(y_r) = \kappa R|y_r| \quad , \quad L_\psi = \kappa R|y_r|_{\max} \quad (16)$$

A tedious but straight forward derivation show that the ϕ function is also Lipschitz, with the constant given by

$$L_\phi = \frac{\delta_0}{\mu_c}[|v_r|_{\max}\frac{|z|_{\max}}{Rm}\{1 + \frac{|\mu_s - \mu_c||v_r|_{\max}}{\mu_c v_s}\}] \quad (17)$$

$\hat{\eta}, \hat{\chi}, \hat{z}, \hat{y}_r$, and $\hat{v}_r$ are the estimated values of η, χ, z, y_r , and v_r . The estimator gain vector of the road estimator is $K = [k_1\ k_2\ k_3]$.

IV. Observer-Based Direct Adaptive Fuzzy-Neural Control

In this paper, the control objective is to design a DAFC such that the slip ratio, $y = \lambda$, follows a reference slip ratio, $y_m = \lambda_d$. First, we convert the tracking problem to a regulation problem, so equation (8) is rewritten as

$$\dot{\boldsymbol{\lambda}} = \mathbf{A}\boldsymbol{\lambda} + \mathbf{B}(f(\boldsymbol{\lambda}) + bu + d) \qquad (18)$$
$$y = \mathbf{C}^T\boldsymbol{\lambda}$$

where $\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$, $\mathbf{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, $\mathbf{C} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$, and $\boldsymbol{\lambda} = [\lambda \quad \dot{\lambda}]^T = [\lambda_1 \quad \lambda_2]^T \in R^2$ is a vector of state. Define the output tracking error $e = y_m - y = \lambda_d - \lambda$, the reference vector $\mathbf{y}_m = [y_m \quad \dot{y}_m]^T = [\lambda_d \quad \dot{\lambda}_d]^T$ and the tracking error vector $\mathbf{e} = [e \quad \dot{e}]^T = [e_1 \quad e_2]^T$.

Based on the certainty equivalence approach, an optimal control law is

$$u^* = \frac{1}{b}[-f(\lambda) + \ddot{y}_m + K_c^T\hat{\mathbf{e}}] \quad (19)$$

where $\hat{\mathbf{e}}$ denotes the estimate of **e**, and $\mathbf{K}_c = [k_2^c \quad k_1^c]^T$ is the feedback gain vector, chosen such that the characteristic polynomial of $\mathbf{A} - \mathbf{B}\mathbf{K}_c^T$ is Hurwitz because (**A, B**) is controllable. Since only the system output (the slip ratio), $y = \lambda$, is assumed to be measurable, and $f(\lambda)$ is assumed to be unknown, the optimal control law (19) cannot be implemented.

Thus, we suppose a control input u is

$$u = u_f + u_{sv} \quad (20)$$

where an observer-based direct adaptive fuzzy-neural controller (DAFC) u_f is designed to approximate the optimal control law (19), and the control term u_{sv} is employed to compensate for the external disturbances and modeling error. The adaptive control laws u_f and u_{sv} can be expressed as:

$$u_f(\hat{\mathbf{e}} \mid \boldsymbol{\theta}_c^T) = \frac{\sum_{i=1}^{h} p^i [\prod_{j=1}^{2} \mu_{A_j^i}(\hat{e}_j)]}{\sum_{i=1}^{h} \prod_{j=1}^{2} \mu_{A_j^i}(\hat{e}_j)} = \boldsymbol{\theta}_c^T \varphi(\hat{\mathbf{e}}) \qquad (21)$$

and

$$u_{sv} = \begin{cases} \rho \ \ if \ \ \tilde{e}_1 \geq 0 \ \text{ and } |\tilde{e}_1| > \alpha \\ -\rho \ \ if \ \ \tilde{e}_1 < 0 \ \text{ and } |\tilde{e}_1| > \alpha, \ \text{where } \alpha \text{ is a positive constant} \\ \rho\tilde{e}_1 / \alpha \ \ if \ |\tilde{e}_1| > \alpha \end{cases}$$

(22)

with the adaptive law

$$\dot{\boldsymbol{\theta}}_c = \begin{cases} \kappa\tilde{e}_1\varphi(\hat{\mathbf{e}}), & if \ \|\boldsymbol{\theta}_c\| < m_{\boldsymbol{\theta}_c} \ or (\|\boldsymbol{\theta}_c\| < m_{\boldsymbol{\theta}_c} \text{ and } \tilde{e}_1\boldsymbol{\theta}_c^T\varphi(\hat{\mathbf{e}}) \geq 0) \\ \mathbf{P_r}(\kappa\tilde{e}_1\varphi(\hat{\mathbf{e}})), & if \ \|\boldsymbol{\theta}_c\| < m_{\boldsymbol{\theta}_c} \text{ and } \tilde{e}_1\boldsymbol{\theta}_c^T\varphi(\hat{\mathbf{e}}) < 0 \end{cases}$$

(23)

where

$$\mathbf{P_r}(\kappa\tilde{e}_1\varphi(\hat{\mathbf{e}})) = \kappa\tilde{e}_1\varphi(\hat{\mathbf{e}}) - \kappa\frac{\tilde{e}_1\boldsymbol{\theta}_c^T\varphi(\hat{\mathbf{e}})}{\|\boldsymbol{\theta}_c\|^2}\boldsymbol{\theta}_c$$

, $\boldsymbol{\theta}_c = [p^1 \ \ p^2 \cdots p^h]^T$ is adjusted vector, $\hat{\mathbf{e}}$ denote estimate of the error vector $\mathbf{e} = [e_1 \ e_2]^T$ and $\tilde{\mathbf{e}} = \mathbf{e} - \hat{\mathbf{e}}$. Thus, using control law u, we can prove that $e_1(t)$ converges to zero as $t \to \infty$.

V. Overall Control System and Simulation Results

Slip ratio control is a well-known method in ABS [3]. In general, a given optimal slip ratio with respect to various road conditions is used as a reference signal. One main disadvantage of this method is the difficulty in getting the optimal slip ratio when the road conditions are unknown.

Optimal slip ratios vary according to the individual road surfaces, such as a dry or wet road. The ABS with the LuGre friction model (LuGre-based ABS) proposed in this paper can recognize the road condition and then supply the corresponding reference slip ratio to the vehicle system through a mapping function. To monitor the road situation in the LuGre-based ABS, it is only necessary to have the angular wheel velocity

ω, which is easily measured by actual sensors. The overall control system is shown in Fig. 4.

The mapping function $\lambda_d = g(\theta)$ is shown in Fig. 3. It maps the road condition parameter θ and wheel velocity to the reference slip ratio λ_d. Neural networks are well-known nonlinear approximators [12, 13], especially for function approximation. Thus, to quickly and accurately learn the mapping function $g(\theta)$, we adopt NNs as the learning mechanism.

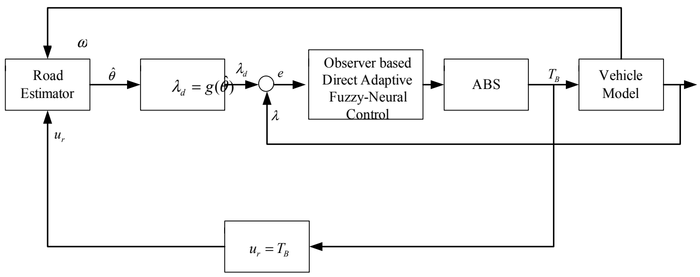

Figure 4. The overall system of LuGre-Based ABS

This section presents the simulation results of the proposed LuGre-based ABS to show that the tracking error of the closed-loop system can approach an arbitrarily small value. The data used for the simulation are shown in Table 1. To identify the mapping function $\lambda_d = M(\theta,\omega)$, the back-propagation learning algorithm is applied to multilayer feedforward neural networks consisting of processing elements with continuous differentiable activation functions. An examples are used to test the proposed LuGre-based ABS. The first assumes the road condition θ is 0.425 (dry road) and the parameters relating to the road estimator are $\theta_{\max} = 0.5$ and $\gamma = 100000$. Figure 5 shows the curve for the dry road condition, $\theta = 0.425$, and the estimate, $\hat{\theta}$. Figure 5 shows that the road estimator is not effective when the relative velocity is too small. Figure 6 shows the curves of the vehicle speed as it is reduced from 33.3 *m/sec* in18.54 seconds and the corresponding velocity of the wheel. In Figure 7, it can be observed that after a very short period of transient response, the wheel slip λ has approached the reference slip ratio. Figure 8 shows the control signal for the dry road.

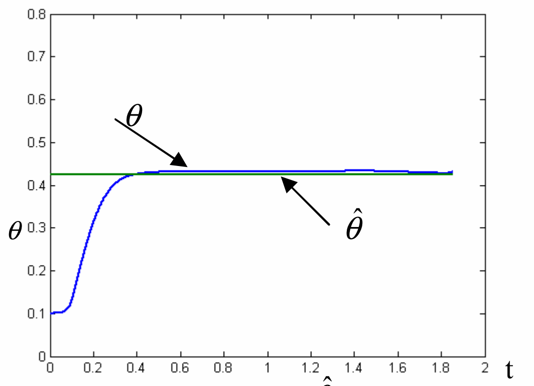

Figure 5 Estimated parameter $\hat{\theta}$ and evolution of θ.

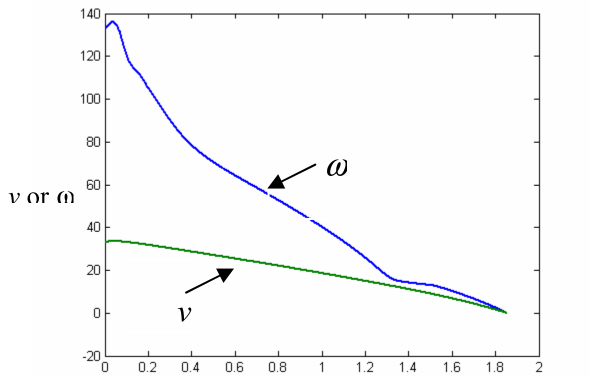

Figure 6. Real vehicle velocity(v) and rotation rate (ω).

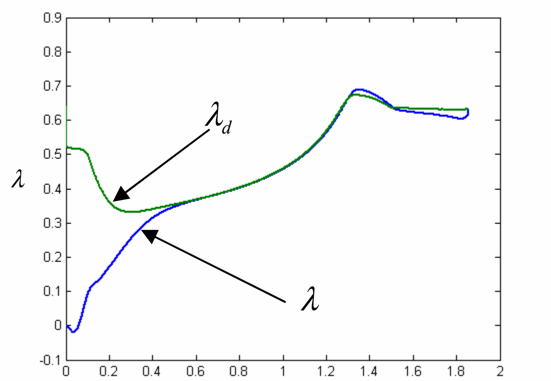

Figure 7. Estimated slip ratio λ_d and tracking slip ratio λ.

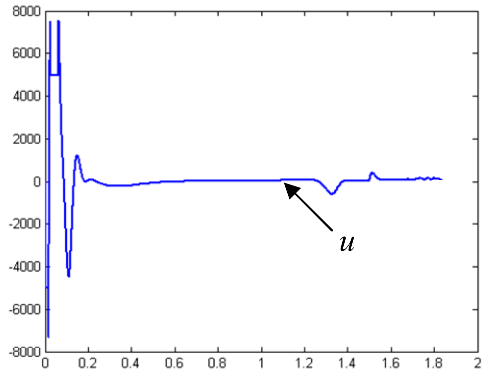

Figure 8. control input u.

VI. Conclusion

In this paper, we introduce a road estimator based on the LuGre friction model into the ABS system, called the LuGre-based ABS. This solves the traditional problem of slip ratio control when the road condition is unknown. Otherwise, for further reducing the braking time, a wheel velocity is introduced into the road estimator. In anti-lock braking systems, certain states are difficult to obtain by real physical sensors, or are prone to noise and other measurement errors. To resolve this problem, the observer-based direct adaptive fuzzy-neural controller (DAFC) is applied to ABS control, and its stability is guaranteed by the universal approximation theorem. The simulation results show that the road estimator effectively and quickly captures the road conditions, and the DAFC can force the output to track the reference slip ratio obtained by the road estimator.

References

[1] Proceedings of the Institution of Mechanical Engineers, "Traction control and anti-wheel-spin systems for road vehicles," *IMechE Conference*, London, Sept. 1988.

[2] J. W. Douglas and T. C. Schafer, "The Chrysler sure brake: The first production four-wheel anti-skid system," *SAE Tech*. Paper 710248, 1971.

[3] W. Y. Wang, G. M. Chen, C.W. Tao, "Stable anti-lock braking system using output-feedback direct fuzzy neural control," *IEEE International Conference Systems, Man and Cybernetics,* pp. 3675-3680, Oct. 2003.

[4] C. Canudas-De-Wit, Morten Lind Petersen and Anton Shiriaev "New Nonlinear Observers for tire/road Distributed friction," *Proceedings of the 38th Decision & control Conference,* Phoenix, Arizona USA, December 2003.

[5] T. Kawabe, M. Nakazawa, I. Nostu and Y. Watanabe, "Sliding mode control for anti-lock brake system: Usage of sluggish actuators," *Proceedings of the 35th Conference on Decision and Control*, Kobe, Japan, December 1995.

[6] G. F. Mauer, "A fuzzy logic controller for an ABS braking system," *IEEE Trans. on Fuzzy Syst.*, vol. 3, No. 4, November 1995.

[7] Y. Lee and S. H. Zak, "Genetic neural fuzzy control of anti-Lock brake systems," *Proceedings of the American Control Conference,* Arlington VA, June 25-27, 2001.

[8] E. Bakker, L. Nyborg, and H. Pacejka, "Tire Modelling for Using in Vehicle Dynamic Studies," *Society of Automotive Engineers Paper* #870421, 1987.

[9] C. Canudas-De-Wit, and P. Tsiotras, "Dynamic tire friction models for vehicle traction," I*n 38th IEE-CDC* 1999.

[10] E. Bakker, L. Nyborg, and H. Pacejka, "Tire Modelling for Using in Vehicle Dynamic Studies," *Society of Automotive Engineers Paper* #870421, 1987.

[11] C. Canudas-De-Wit, P. Tsiotras, E. Velenis, M. Basset, and G. Gissinger, "Dynamic Friction Models for Road/Tire Longitudinal Interaction," *Vehicle System Dynamics*, pp. 1-23, Oct. 14, 2002.

[12] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Networks*, no. 2, pp. 359-366, 1989.

[13] L.X. Wang and J.M. Mendel, "Fuzzy basis functions, universal approximation, and orthogonal least squares learning," *IEEE Trans. on Neural Networks*, vol. 3, no. 5, pp. 807-814, 1992.

[14] Y. G. Leu, W. Y. Wang, and T. T. Lee, "Observer-based direct adaptive fuzzy-neural control for nonaffine nonlinear systems," *IEEE Trans. on Neural Networks*, vol. 16, no. 4, pp. 853-861, July. 2005.

[15] C. Mi, H. Lin, and Y. Zhang, "Iterative learning control of antilock braking of electric and hybrid vehicles," *IEEE Trans. on Vehicular Technology,* vol. 54, no. 2, page 486-494, March 2005.

[16] R. Seaks, C. J. Cox, J. Neidhoefer, P. R. Mays, and J. J. Murray, "Adaptive control of a hybrid electric vehicle," *IEEE Tran. on Intelligent Transportation System,* vol. 3, no. 4, page 213-234, December 2002.

[17] X. He and J. W. Hodgson, " Modeling and simulation for hybrid electric vehicles-part I: Modeling," *IEEE Trans. on Intelligent Transportation System,* vol. 3, no. 4, page 235-243, December 2002.

[18] X. He and J. W. Hodgson, " Modeling and simulation for hybrid electric vehicles-part I: Simulation," *IEEE Trans. on Intelligent Transportation System,* vol. 3, no. 4, page 244-251, December 2002.

Table 1. Data used for simulation

Parameter		Value
m	Vehicle mass	275 *kg*
v_0	Initial vehicle velocity	33.33(*m/sec*)
ω_0	Initial wheel velocity	133.33(*1/sec*)
R	Wheel radius	0.25 m
K_b	Gain between p_i and T_b	25
g	Gravitational constant	9.8 (m/s^2)
I	Moment of inertia of wheel	12.891($kg-m^2$)
F_z	Normal force	2695 *N*
δ_0	Normalized rubber longitudinal lumped stiffness	181.54 (*1/m*)
δ_1	Normalized rubber longitudinal lumped damping	1 (*s/m*)
δ_2	Normalized viscous relative damping	0.0018
F_C	Normalized Coulomb friction	0.6
F_S	Normalized static friction	1.55
v_s	Stribeck relative velocity	12.5 *m/s*