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Adaptive Global Sliding Mode Control Strategy for the Vehicle Antilock Braking Systems

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***Abstract*—In this paper, the state equation for the dynamics of quarter-car is established, and a stable robust sliding mode control law based on RBF neural network is presented for the vehicle slip ratio control. In addition, a moving sliding surface based on global sliding mode control is presented. Unlike the conventional sliding mode control, the moving sliding surface moves to the desired sliding surface from the initial condition and thus fast tracking can be obtained. The strategy can eliminate the reaching phase from conventional sliding mode control, and guarantee the system robustness during the whole control process. The drawback of control chattering occurred in the classical sliding mode control can be alleviated with the proposed control scheme. Simulations are performed to demonstrate the effectiveness of the proposed controller.**

I. Introduction

THE primary objective of anti-lock braking system (ABS), which was first implemented in vehicles in the late 1970s, is to prevent the wheels from locking while braking. Most ABS controllers on the market are based on tables and relay feedbacks, and make use of hydraulic actuators to deliver the braking force. One approach that is used with hydraulic brakes is to measure wheel rotational velocity and use this to compute wheel deceleration. Then, given prescribed thresholds for wheel deceleration, the braking pressure is increased, held, or decreased while trying to maintain a wheel slip ratio value that is close to the point that gives the maximum amount of friction [1, 2].

Antilock braking systems are highly nonlinear, highly time varying. Moreover, there always exists uncertainty in the system model such as external disturbances, parameter uncertainty, and sensor errors. All kinds of control schemes have been proposed in the field of the ABS control during the past decades [3]. Generally the control of such system has based on classical or PID feedback approaches [4], the intent was to enhance the control by use of state space design and adaptive control [5, 6], standard or linearization control design method based on have some drawbacks for such system, this is due to the lack of knowledge of the model and parameters. Antilock brake systems based on Sliding Mode Control [7], Neural Network [8], and Fuzzy Logic Controller [9-11] are a few examples of the ABS design. In most cases, the system to be controlled may operate at diverse operating regimes and include significant nonlinear couplings which make the abundant tools of the linear control system literature not well-suited for a wide range robust operation.

Sliding mode controllers have been designed previously for the purpose of controlling wheel slip ratio [12,13], However the nonlinearity of the sliding mode control (SMC) causes the high frequency chattering and all the actuator bandwidth is often limited therefore an infinite switching frequency cannot be attained. Furthermore, the high frequency input signal chattering leads to the damage of system elements, therefore chattering is one of the main reasons to hinder the application of the sliding mode control.

This paper also presents a sliding mode controller for tracking a reference wheel slip ratio. Here a moving sliding surface based on global sliding mode control (GSMC) strategy is presented for the vehicle slip ratio control. The strategy can eliminate the reaching phase from conventional sliding mode control. In addition, the sliding mode controller base on RBF neural network is developed for direct control.

RBF neural network have been widely used to represent the nonlinear mappings between inputs and outputs of non-linear control systems. A RBF neural network with a two-layer data processing structure had been adopted to approximate an unknown mapping function. The adaptive rule is employed for online adjustment of the weighting of radial basis functions by using the reaching condition of a specified sliding surface. Since this approach has learning ability for establishing and regulating the weightings of radial basis functions continuously, its control implementation can be started with zero initial weighting for RBF neural network. This approach can reduce the chattering in the sliding mode control systems, it can also reduce significantly the database and computing time burden, thereby increasing the sampling frequency and the availability of industrial implementation.

The rest of the paper is arranged as follows. In Section II, we will introduce a time-varying uncertain model for the dynamics of quarter-car. In this section, state space equations are established. Section III derives a moving sliding mode surface and a robust sliding mode controller based on RBF neural network. Simulation results are presented in Section IV and some conclusions are drawn in Section V.

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II. Problem Setup

It is being assumed that the following sensor information is available [14]: wheel speed, ω, at each corner, longitudinal accelerometer, a_x. Also, tire force sensors or observers are assumed to be present. Figure 1 shows the wheel dynamics. In formulating the wheel slip ratio, λ, control problem, the wheel acceleration, $\dot{\omega}$, is needed.

The wheel acceleration is calculated by

$$I\dot{\omega} = F_x R - M_b \tag{1}$$

where I is the mass moment inertia of the wheel about the axis of rotation, F_x is the longitudinal tire force, R is the wheel radius, and M_b is the brake torque applied to the wheel. Here air friction and rolling resistance of wheel are neglected.

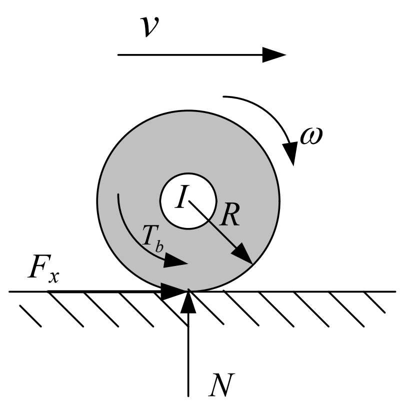

Fig. 1 Wheel dynamics layout (during braking)

The longitudinal tire force is calculated by

$$m\dot{v} = -F_x = -\mu mg \tag{2}$$

where μ is the road friction coefficient which is a function of the wheel slip, λ.

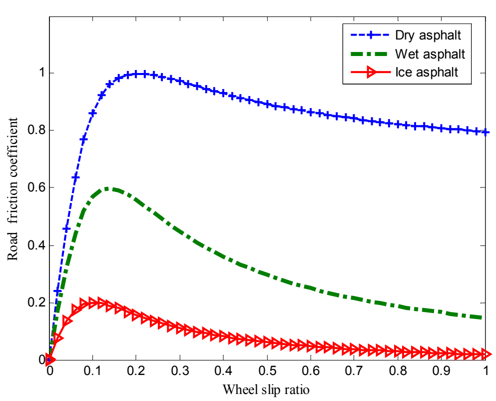

Fig. 2 Typical relation between the road friction coefficient, μ and the wheel slip, λ

The wheel slip ratio, λ, is defined as

$$\lambda = \frac{v - \omega R}{v} \times 100\ \% \tag{3}$$

where v is the vehicle velocity. Typical relationships between slip ratio λ, and the friction coefficient, μ, is shown in figure 2.

Differentiating equation (3) gives the derivative form

$$\ddot{\lambda} = \frac{1}{v}\left[-\ddot{\omega}R - 2\dot{v}\dot{\lambda} + (1-\lambda)\ddot{v}\right] \tag{4}$$

Substituting (1) and (2) into (4) give the follow form

$$\ddot{\lambda} = \frac{1}{v}\left[\frac{R}{I}(\dot{M}_b - \dot{\mu}NR) - (1-\lambda)\dot{\mu}g + 2\mu g\dot{\lambda}\right] \tag{5}$$

Carrying on the integral simplification to (2),

$$v = v_0 - g\int_{t_0}^{t} \mu d\tau \tag{6}$$

where v_0 is the initial speed.

Substituting (6) into (5) and defining

$$a = \frac{2\mu g}{v_0 - g\int_{t_0}^{t}\mu dt};\ b = \frac{\dot{\mu}g}{v_0 - g\int_{t_0}^{t}\mu dt};\ c = \frac{R}{I(v_0 - g\int_{t_0}^{t}\mu dt)}$$

Thus (5) can be rewritten as follow form

$$\ddot{\lambda} = a\dot{\lambda} + b\lambda - b\left(1 + \frac{mR^2}{I}\right) + c\dot{M}_b \tag{7}$$

Defining

$$\begin{aligned} e_1 &= \lambda - \lambda_d \\ e_2 &= \dot{\lambda} - \dot{\lambda}_d \end{aligned} \tag{8}$$

where constant λ_d is the reference wheel slip ratio.

The (7) can be rewritten in the state variable form as

$$\begin{aligned} \dot{x}_1(t) &= x_2(t) \\ \dot{x}_2(t) &= ax_2(t) + bx_1(t) + cu(t) + d(t) \end{aligned} \tag{9}$$

where x is the vector state and $x = [x_1\ \ x_2]^T = [e_1\ \ e_2]^T$, u is the control input and $u = \dot{M}_b$, $d(t) = -b\left(1 + \frac{mR^2}{I} + \lambda_d\right)$.

III. Adaptive Sliding Mode Controller Design

The sliding mode control theory has been widely employed to control non-linear systems, especially systems having model uncertainties and external disturbance. Robustness is the best advantage of sliding mode control. It employs a non-continuous control effort to drive the system towards a sliding surface, followed by switching on that surface. Theoretically, it will gradually approach the control objective, the origin of a phase plane. Here, a novel sliding mode control strategy based on RBF neural network is proposed to control the antilock braking system.

A. Global Sliding Mode Surface Design

To design the sliding mode controller, what to do firstly is to design the sliding mode surface, then to design the control law.

In conventional sliding mode control, a sliding mode surface is chosen as

$$s(x,t) = Kx(t) = k_1 x_1(t) + k_2 x_2(t) = 0 \quad (10)$$

where $k_1 > 0$, $k_2 > 0$ are the design parameters which define the sliding surface, they should be chosen such that in the case that $s = 0$ all remaining dynamics are stable. Without loss of generality, $k_2 = 1$.

For this conventional design, there are several drawbacks, such as robust performance is not ensured, because the sliding regime may occur only on the phase plane and response during the reaching phase is sensitive to system perturbation.

Here, a moving global sliding mode surface is presented as

$$s(x,t) = k_1 x_1(t) + x_2(t) - \eta(t) = 0 \quad (11)$$

To guarantee sliding mode motion of the system lie on the sliding surface on the beginning, the function $\eta(t)$ drives the system states in any state space directly to the sliding surface without a reaching phase. The response of the conventional sliding mode control is sensitive to system perturbations during the reaching phase. For this, the conditions of the function $\eta(t)$ should be satisfied,

(i) $k_1 x_1(0) + x_2(0) + \eta(0) = 0$

(ii) $\eta(t) \to 0 \ \ as \ \ t \to \infty$

(iii) $\dot{\eta}(t)$ exists and is bounded

Condition (i) represents the initial location of the states on the sliding surface, (ii) represents asymptotic stability, and (iii) represents the existence of the sliding mode.

According to these conditions, we define $\eta(t)$ as

$$\eta(t) = \eta(0)e^{-\lambda t} \quad (12)$$

where $\lambda > 0$, and λ is small enough.

From $\eta(t)$, we can see that the system state is initially located in the sliding regime, the asymptotic stability of the closed-loop system and the existence of a sliding mode are all satisfied.

B. Sliding Mode Controller Design

In the previous section, when the system (11) was in the sliding mode, the sliding mode surface was designed to guarantee the asymptotic stability. Next, we should find feedback control law u to drive system state trajectories to arrive at the sliding surface in limit time and maintain in the sliding surface. This means that the control law is designed to guarantee system satisfy the reaching condition.

Differentiating (11) gives

$$\dot{s}(x,t) = K\dot{x}(t) = 0 \quad (13)$$

Substituting (9) into (13) gives

$$u_{eq} = -\frac{1}{c}[k_1 x_2(t) + a x_2(t) + b x_1(t) + d(t) - \dot{\eta}(t)] \quad (14)$$

Theroem 1 If the output of the controller is

$$u = u_{eq} + \beta \operatorname{sgn}(s)$$

the reaching condition is established.
here, $\beta > 0$.

It is not difficult to proof that the reaching law chosen by the theroem contents the reaching condition, $s\dot{s} < 0$, which can guarantee the system asymptotically stabilized via the sliding mode surface (11).

Proof: consider Lyapunov function $v(t) = \frac{1}{2}s^2(x,t)$, we obtain as follow,

$$\begin{aligned} v(t) &= \frac{1}{2}s^2(t) \\ \dot{v}(t) &= s(t)\dot{s}(t) \\ &= -s(t)(k_1\dot{x}_1(t) + \dot{x}_2(t) - \dot{\eta}(t)) \\ &= -s(t)(k_1 x_2(t) + \dot{x}_2(t) - \dot{\eta}(t)) \\ &= -c\beta|s(t)| \\ &\le 0 \end{aligned}$$

Proof completed.

we can see that a larger β will speed up the reaching phase but induce an amplified chattering in the sliding phase, inversely a smaller β will speed down the reaching phase though induce a reduced chattering. This is in a dilemma.

Here, a novel neural network sliding mode control strategy is proposed to adjust the value of β online, this can reduce the chattering.

C. The Parameter of Sliding Mode Controller Design

Here, an RBF neural network is employed to model the relationship between the sliding function s and the value of β . The block diagram of neural network is shown in figure 3.

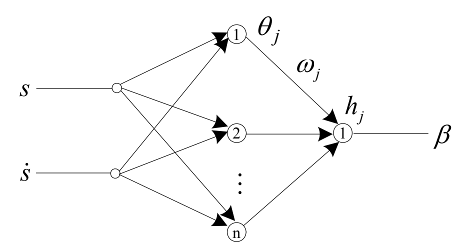

Fig. 3 The block diagram of RBF neural network

The excitation value of these Guassian functions is the distance between the input value of the sliding function s and the central position of a Guassian function

$$\theta_j = (s - c_j)^2 = \left\| s - c_j \right\| \tag{15}$$

where c_j is the central position of neuron j. The weightings, between input-layer neurons and hidden-layer neurons are specified as constant at 1.0. The weightings, ω_j, between hidden-layer neurons and output-layer neurons are adjusted on the basis of an adaptive rule. The output of an RBF neural network is

$$h_j(s) = \sum_{j=1}^{n} \omega_j \phi_j \tag{16}$$

where

$$\phi_j = \exp\left(-\frac{\left\| s - c_j \right\|^2}{b_j^{\,2}}\right) \tag{17}$$

is a Guassian function, j is the jth neuron of the output layer, b_j and c_j are the spread factor and central positon of the Guassian function respectively, n is the number of neurons, and s is the input value of the RBF neural network.

Then, the controller based on RBF neural network is proposed by combining an adaptive rule and the technique of sliding mode control. For a single-input and single-output case, the output of the radial basis function neural network β is

$$\beta = \sum_{j=1}^{n} \omega_j \exp\left(-\frac{\left\| s - c_j \right\|^2}{b_j^{\,2}}\right) \tag{18}$$

The weightings of the RBF neural network should be regulated on the basis of the reaching condition $s\dot{s} < 0$. An adaptive rule is used to adjust the weightings for searching the optimal weighting values and obtaining the stable convergence property. The adaptive rule is derived from the steep descent rule to minimize the value of $s\dot{s}$ with respect to ω_j. Then, the modification equation of the weighting parameters is

$$\begin{aligned} d\omega_j &= -\alpha \frac{\partial E}{\partial \omega_j} = -\alpha \frac{\partial s(t)\dot{s}(t)}{\partial \omega_j} \\ &= -\alpha \frac{\partial s(t)\dot{s}(t)}{\partial \beta(t)} \frac{\partial \beta(t)}{\partial \omega_j} \end{aligned} \tag{19}$$

where α is the adaptive rate parameter.

Since

$$\frac{\partial s(t)\dot{s}(t)}{\partial \beta(t)} = s(t)\frac{\partial \dot{s}(t)}{\partial \beta(t)} =-\rho\, s(t) \tag{20}$$

$$\frac{\partial \beta(t)}{\partial \omega_j(t)} = \exp\left(-\left\| s - c_j \right\|^2 / b_j\right) \tag{21}$$

Based on the chain rule, the above equation can be rewritten as

$$\begin{aligned} d\omega_j &= \gamma s(t) \exp\left(-\frac{\left\| s - c_j \right\|^2}{b_j}\right) \\ &= \gamma s(t) h_j(s) \end{aligned} \tag{22}$$

where the adaptive rate parameter, α is combined as a learning rate parameter, γ. Then, the weightings between hidden-layer and output-layer neurons can be adjusted online to achieve the learning ability of the RBF neural network.

IV. SIMULATION

To demonstrate the effectiveness of the proposed controller, a quarter-car model is introduced and simulated using MATLAB/ SIMULINK software, the example is an antilock system braking from 25m/s to full stop. The simulation parameters are [14]: mass moment inertia of the wheel is $I = 0.8 kg * m^2$, the wheel radius is $R = 0.3m$, a quarter-car mass is $m = 300\ kg$, the initial wheel braking velocity is 25m/s.

Because of the limitation of pages, the partial simulation results are given in Figs.4 (a)-(c) and Figs.5 (a)-(c) and Figs.6 (a)-(c) which show the performances of global sliding mode controller and sliding mode controller with the external disturbance respectively.

Fig.4 and Fig.5 exhibit the state response of the system under the GSMC and SMC, it can be clearly seen that the fast tracking can be obtained using GSMC. The proposed strategy can eliminate the reaching phase. It is observed that the global sliding mode controller shows better performance, with exhibiting faster responses and better regulation properties.

Fig. 6 presents the control signal, and on this Figure we can easily find that the drawback of control chattering occurred in the classical sliding mode control can be alleviated with the proposed control scheme.

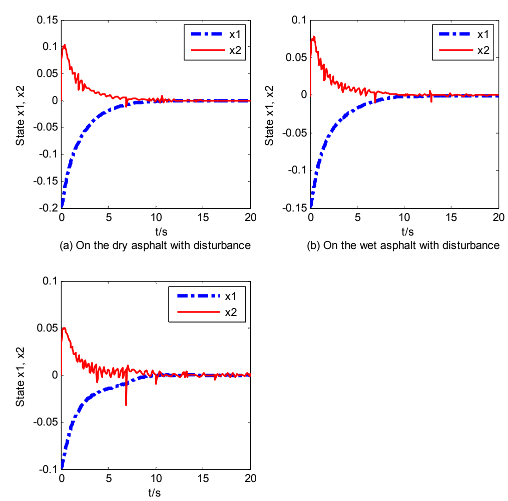

Fig. 4 States response under SMC with disturbance

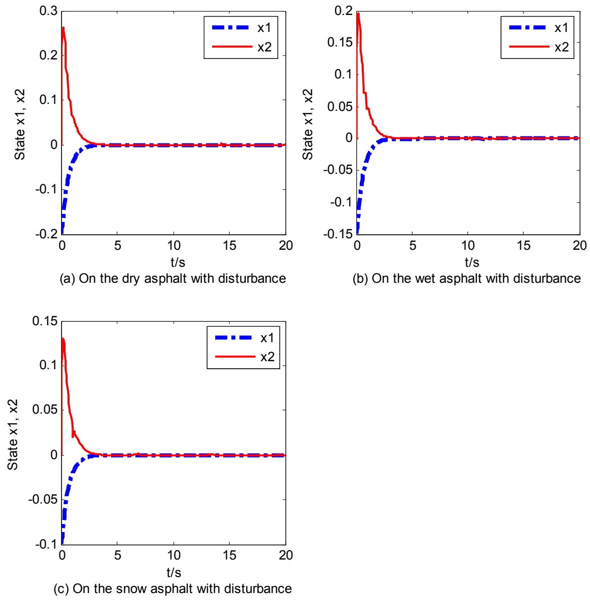

Fig. 5 States response under GSMC with disturbance

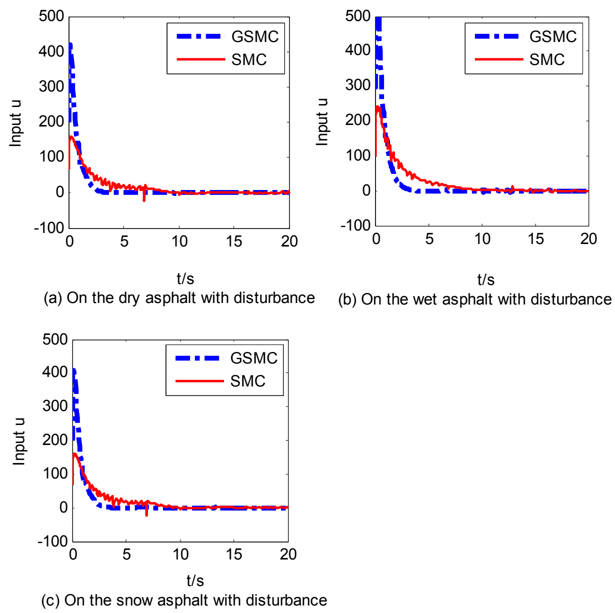

Fig. 6 System input under the GSMC and SMC with disturbance

V. Conclusion

This paper proposes a adaptive global sliding mode control strategy for the controlling of the wheel slip ratio. The design of sliding mode controller based on RBF neural network is presented, by which system can be guaranteed robust stabilization and the chattering around sliding surface is reduced effectively also. The stable sliding surface can eliminate the reaching phase problem so that the closed-loop system always shows the invariance property to parameter uncertainties of antilock braking system. Simulations showed the effectiveness of the proposed sliding mode controller.

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