Neuro-Fuzzy Controller Design of the Anti-Lock Braking System*

Ming-Chin WU**, Lian-Chian LEE**
and Ming-Chang SHIH**

The main purpose of the ABS (Anti-lock Braking System) of a personal car is to keep the greatest adhesion between the tires and the road surface to shorten the braking distance and secure the controlling and stability of the vehicle. This research is to design an ABS controller, which has the following functions: slip prediction, detection of road surface state, scanning of the optimal slip and neuro-fuzzy controller, and to discuss the braking performance of the ABS under the influences of different road surface states.

Key Words: Slip Prediction, Detection of Road State, Scanning of the Optimal Slip, Neuro-Fuzzy Controller

1. Introduction

In order to prevent the braking deadlock, nowadays, most cars are equipped with the ABS to make driving safer. The purpose of the ABS is to shorten the braking distance and secure the controlling and stability of the vehicle by controlling the braking pressure of the slave cylinder to get the greatest tractive force between the tire and the road surface.

When the braking action is started, there is slipping between the tire and the contacted road surface, which makes the speed of the vehicle different from that of the tire. Thus the slip is defined as

$$S = \frac{V_v - R_w \cdot \omega}{V_v} \quad (1)$$

Where V_v is the speed of the vehicle, R_w is the radius of the tire, ω is the angular velocity of the tire.

Figure 1 indicates the relation of the tire slip and the surface adhesion coefficient of the road⁽¹⁾. As the slip increases from zero, the longitudinal coefficient ascends firstly then proceeds to descend. When the slip becomes to be one, i.e., the tire is completely locked. At this time, the controllability and stability

of the vehicle disappear. From the diagram, one can control the slip around the peak, then the braking force can be large and so that the stopping distance can be shortened and one can also get a good steering controllability of the car.

The former method of controlling ABS is to compare the estimated slip with a preset value, and then decide the time instant increase pressure quickly,

Fig. 1 Relationship between the slip and adhesion coefficient

* Received 11th May, 1998

** Department of Mechanical Engineering, National Cheng Kung University, Tainan, Taiwan, R.O.C.

F_t : the tractive force between tire and road

C_s : the longitudinal tire stiffness

μ : the friction coefficient

N : the normal force of the tire.

When the road surface is dry, then

$$\mu = \mu_0(1 - A_s \cdot V_v \cdot S), \quad (3)$$

where μ_0 is the friction coefficient under pure rotation and A_s is the adhesion reduction coefficient.

If the road surface is wet, then

$$\mu = \mu_0 \cdot \exp\left(-\frac{V_v \cdot S}{V_c}\right) \quad (4)$$

where V_c represents the characteristic speed, which is constant related to the root mean square texture height.

3.2 Quarter vehicle model

In the study, the quarter-car model is applied to simplify the motion of a whole-car. Figure 3 is a free body diagram of one tire. The tire is considered to be a uniform rigid body. Then, the governing equations are as followed:

$$T_b = K_b \cdot p_s \quad (5)$$

$$T_t = F_t \cdot R_w \quad (6)$$

$$\dot{\omega} = \frac{1}{I_w} (T_t - T_b) \quad (7)$$

$$a_v = -\frac{F_t}{M_v/4}, \quad (8)$$

where

T_t : tractive torque

T_b : brake torque

$\dot{\omega}$: angular acceleration of tire

p_s : brake pressure

I_w : moment of inertia of the tire

M_v : vehicle mass

a_v : acceleration of vehicle

K_b : transfer coefficient from brake pressure to brake torque.

4. Neuro-Fuzzy Control Theory

The main processes of the fuzzy theorem include normalization, fuzzification, decision-making logic

Fig. 3 Free body diagram of the tire

(Mamdani method) and defuzzification. Therefore, one can construct a feed-forward neural network, as shown in Fig. 4, to serve as a fuzzy controller. The back-propagation method enable the traditional fuzzy controller not only to simulate the man's thinking but also to have the learning ability.

In the paper, the back-propagation training algorithm is used to tune some related parameters. The objective function is defined as

$$E = \frac{1}{2}(y_d - y)^2, \quad (9)$$

where y_d is the reference input and y is the output of the plant.

In this network, there is no parameter regulated in the first, third and fourth layers. Only the centers and widths of the neurons in the second and fourth layers need to be adjusted.

For example, if we want to tune $m_{ij}^{(4)}$, the center of the neuron in the fourth layer, by chain rule. The following equations can be derived:

$$\frac{\partial E}{\partial m_{ij}^{(4)}} = \frac{\partial E}{\partial y} \frac{\partial y}{\partial u} \frac{\partial u}{\partial m_{ij}^{(4)}} = -(y_d - y) \frac{\partial y}{\partial u} \frac{\sigma_{ij}^{(4)} x_i^{(4)}}{\sum \sigma_{ij}^{(4)} x_i^{(4)}}, \quad (10)$$

$$\Delta m_{ij}^{(4)} = \eta (y_d - y) \frac{\partial y}{\partial u} \frac{\sigma_{ij}^{(4)} x_i^{(4)}}{\sum \sigma_{ij}^{(4)} x_i^{(4)}}, \quad (11)$$

where η is the learning rate of the network, u is the output of the controller, $\sigma_{ij}^{(4)}$ is the width of the membership function, $x_i^{(4)}$ is the input of that neuron and $\Delta m_{ij}^{(4)}$ is the variation of the center.

Because the precise mathematical model of the system isn't needed by using fuzzy method, the outcome of $\frac{\partial y}{\partial u}$ can not be obtained directly. A decou-

Fig. 4 Structure of neuro-fuzzy controller

pling approach is introduced, Eq.(12) is regarded as similar to the Eq.(11).

$$\frac{\partial y}{\partial u} \approx \frac{\Delta y}{\Delta u} = \frac{y(t) - y(t-1)}{u(t) - u(t-1)}. \quad (12)$$

5. Design of the Controller

The ABS controller designed for this research includes: prediction of slip, detection of road state, the scanning of the optimal slip and neuro-fuzzy controller. The slip predictor can estimate the slip, the road surface state can be judged through the deceleration of the vehicle, the angular deceleration and their variations; according to the Dugoff's tire model, the optimal slip can be found out, in which there is greatest tractive force between the tire and the road surface. This optimal slip is used as the reference input of the neuro-fuzzy controller. The neuro-fuzzy controller controls the slip to trace the reference input and try to keep the greatest tractive force under different braking conditions. Figure 5 illustrates the block diagram of this controller.

5.1 Rules of slip prediction

The braking system by using the slip as the feedback signal to control the antilock braking system is proved to shorten the braking distance effectively and improve the controlling and stability of the vehicle while the braking are applied. Therefore, one can design a slip predictor to predict the slip and use it as the feedback signal to overcome the delay time of the mechanical system. Equation (1) can be rewritten as

$$S(t) V_v(t) = V_v(t) - R_w \omega(t). \quad (13)$$

The derivative of the Eq.(13) is shown in the follow-

ing

$$\dot{S}(t) = \frac{1}{V_v(t)} [(1 - S(t)) \cdot a_v(t) - R_w \alpha(t)]. \quad (14)$$

5.2 The scanning of the optimal slip

The greatest tractive force will be happened in the best slip S^* , therefore one can find

$$\left. \frac{\partial F_x}{\partial S} \right|_{s=S^*} = 0, \quad (15)$$

and the following equation can be obtained

$$2\mu_0 A_s V_v S^3 - \left(\frac{4C_s}{N} + 2\mu_0 + \mu_0 A_s V_v \right) \cdot S^2 + \frac{\mu_0}{A_s V_v} = 0. \quad (16)$$

Because the S^* is very slight when the vehicle is at high speed, and $A_s V_v \ll 1$ when at low speed, therefore the Eqs.(17), (18) can be derived.

$$2\mu_0 A_s V_v S^{*3} \ll \frac{\mu_0}{A_s V_v}, \quad 2\mu_0 A_s V_v S^{*3} \ll \frac{4C_s}{N}, \quad (17)$$

$$-\left(\frac{4C_s}{N} + 2\mu_0 + \mu_0 A_s V_v \right) \cdot S^{*2} + \frac{\mu_0}{A_s V_v} = 0. \quad (18)$$

And,

$$S^* \cong \sqrt{\frac{\mu_0}{A_s V_v \left(\frac{4C_s}{N} + 2\mu_0 + \mu_0 A_s V_v \right)}}, \quad (19)$$

On the wet road surface, one choose first two items of the Taylor's series of the Eq.(4) and obtain

$$\mu \approx \mu \left(1 - \frac{V_v}{V_c} S \right) \quad (20)$$

Comparing the Eqs.(3) and (20), one can get

$$A_s \cong \frac{1}{V_c}, \quad (21)$$

and (20) is rewritten to

$$\mu \cong \mu_0 (1 - A_s V_v S). \quad (22)$$

Therefore, the Eq.(19) can be used both in the dry

Fig. 5 Block diagram of the ABS controller

road and the wet road states.

5.3 Detection of road state

In the study, one try to make use the deceleration of the vehicle, the angular deceleration and their variations to infer the road state under braking process. Because the braking deceleration on a dry road is bigger than that on a wet road, if the deceleration is bigger than a predetermined value, it is inferred that the road is dry. Otherwise, it is inferred that the road is wet. When the braking happens on one road state, if the variations of the angular deceleration and the vehicle deceleration are greater (or smaller) than the

Fig. 6 Flowchart of the road condition detector

preset values, it is inferred that the road is changing to be the other road state. The block diagram is shown in Fig. 6⁽¹⁵⁾.

5.4 Controller design

(1) Choice of states variables: The error of the slip and the derivative of slip error are chosen as the input signals and the control signal of the solenoid valve is the output signal, which are defined as follows:

$$\begin{cases} e(t) = y_d(t) - y(t) \\ de(t) \approx \frac{e(t) - e(t-1)}{T_s} \end{cases} \quad (23)$$

where

T_s : the sampling time

$e(t)$: the error of slip

$de(t)$: the derivative of the slip error

(2) Choice of the membership function and the fuzzy sets: For the convenience of differentiation. The bell-shaped membership function is chosen and three fuzzy sets are determined (NB: negative big, ZO: zero, PB: positive big) for each state variable.

(3) Design of Fuzzy rules: Fuzzy rules adopted

Table 1 Fuzzy rules

$e \backslash de$	NB	ZO	PB
NB	NB	NB	ZO
ZO	NB	ZO	PB
PB	ZO	PB	PB

Fig. 7 Braking history on dry road

in this research is shown in Table 1.

6. Results and Discussion of the Experiment

The braking distance and the deceleration are two important factors to evaluate a braking system. The braking performances on different road states (dry, wet, from dry to wet) are discussed in the paper. The sampling time of this system is chosen to be 10 ms. The normalization factors and the learning rate are determined through the tests by using Taguchi method. (normalizing factor of $e(t)$: $G_e=25.0$, normalizing factor of $de(t)$: $G_{de}=1.0$, normalizing factor of output signal $u(t)$: $G_u=2.0$, learning rate: $\eta=0.005$)

(1) Braking on dry road

Figure 7(a) shows the vehicle velocity, the tire speed and the braking distance, while the braking is on dry road. Under the function of ABS, the experimental results show that the stopping distance is 50.88 m, the average deceleration is -8.31 m/sec^2 and the braking period is 3.34 seconds. Figure 7(d) is the control signal for the solenoid valve where +1, 0, -1 represent increasing pressure, holding pressure and releasing pressure separately.

Table 2 is the parameter table of pre-learning and post-learning membership functions of the ABS neuro-fuzzy controller when the vehicle brakes on a dry road. Table 3 shows the comparison of neuro-fuzzy controller with learning and without learning when braking. Because the control signal for the solenoid valve is discrete (+1, 0, -1), the improvement of the neuro network is not great. However, it

is a new trial and really has some improvement.

(2) Wet road braking

Figure 8 shows the braking history of the simulated experimental results on the wet road surface. The experiment shows that the braking period is 5.71 seconds, the stopping distance is 84.43 m and the average deceleration is -4.86 m/sec^2 .

(3) From dry road to wet road

Figure 9 shows the braking history when the ABS

Table 2 Parameter values

parameters	Membership functions	pre-learning		post-learning	
		center	width	center	width
e	NB	-1	0.5	-0.999997	0.500003
	ZO	0	0.5	0.000159	0.500354
	PB	1	0.5	1.091886	0.656168
de	NB	-1	0.5	-0.999223	0.501948
	ZO	0	0.5	0.006234	0.506489
	PB	1	0.5	1.109802	0.751271
u	NB	-1	0.5	-1.000106	0.500015
	ZO	0	0.5	-0.000042	0.500081
	PB	1	0.5	0.786237	0.531482

Table 3 Comparisons of braking performance

	braking period(s)	stopping distance(m)	deceleration (m/sec^2)
pre-learning	3.36	51.03	-8.29
post-learning	3.34	50.88	-8.31

Fig. 8 Braking history on wet road

Fig. 9 Braking history from dry road to wet road

is working and the vehicle moves from dry road to wet road in two seconds. The experiment shows that the braking distance is 57.34 m, the braking average deceleration is -6.37 m/sec^2 , and the braking period is 4.36 seconds. Figure 6-3(b) shows the slip trace in the process of braking.

7. Conclusion

Through the above experimental results, a neuro fuzzy ABS controller of a personal car can be designed successfully. Both the variable road surface states can be judged correctly and the optimal slip can be found by the controller, so that the excellent braking performance can be obtained.

Acknowledgments

The support provided by National Science Center of R.O.C. (NSC 86-2212-E006-083) is greatly appreciated.

References

- (1) Oppenheimer, P., Comparing Stopping Capability of Cars with and without Antilock Braking Systems (ABS), SAE Paper No. 880324, (1988).
- (2) Watanabe, M. and Noguchi, N., A New Algorithm for ABS to Compensate for Road-Disturbance, SAE Paper No. 900205.
- (3) McLoughlin, J.H., Limited Slip Braking, Anti-lock Braking Systems for Road Vehicles, IMechE Conference Publications, (1985-8), p. 23-34.
- (4) Fling, R.T., and Fenton, R.E., A Describing-Function Approach to Anti-skid Design, IEEE Trans. on Vehicular Technology, Vol. VT-30, No. 3 (1981), p. 134-143.
- (5) Tan, H. and Tomizuka, M., Discrete-Time Controller Design for Robust Vehicle Traction, IEEE Contr. Syst. Mag., (1990), p. 107-113.
- (6) Chin, Y.K., Lin, W.C., Sidlosky, D.M. and Rule, D. S., Sliding Mode ABS Wheel-Slip Control, 1992 American Control Conference, Chicago IL, (1992), p. 1-5.
- (7) Layne, J.R., Passino, K.M. and Yurkovich, S., Fuzzy Learning Control for Antiskid Braking Systems, IEEE Trans. on Control Systems Technology, Vol. 1 (1993), p. 122-129.
- (8) Yuan, F., Puskorius, G.V., Feldkamp, L.A. and Davis, L.I., Neural Network Control of a Four-Wheel ABS Model, Proc. of the 1995 IEEE Inter. Symp. on Intelligent Control, (1995), p. 1503-1506.
- (9) Kueon, Y.S. and Bedi, J.S., Fuzzy-Neural-Sliding Mode Controller and Its Applications to the Vehicle Anti-Lock Braking Systems, 1995 Inter. IEEE/IAS Conf. on Industrial Automation, (1995), p. 391-397.
- (10) Bakker, E.T., Pacejka, H.B. and Lidner, L., A New Tire Model with an Application in Vehicle Dynamics Studies, SAE Paper No. 890087.
- (11) Stewart, E.E. and Bowler, L.L., Road Testing of Wheel Slip Control Systems in the Laboratory, SAE Paper No. 690215.
- (12) Dugoff, H., Fancher, P.S. and Segel, L., An Analysis of Tire Traction Properties and Their Influence on Vehicle Dynamic Performance, SAE Paper No. 700377, (1970).
- (13) Lin, C.T. and George Lee, C.S., Neural-Network-Based Fuzzy Logic Control and Decision System,

- IEEE Trans. on Computers, Vol. 40, No. 12, Dec. 1991, p. 1320-1336.
- (14) Psaltis, D., Sideris, A. and Yamamura, A.A., A Multilayered Neural Network Controller, IEE Control Systems Magazine, Vol. 8, No. 2 (1988), p. 17-21.
- (15) Mauer, G.F., Gissinger, G.F. and Chamaillard, Y., Fuzzy Logic Continuous and Quantizing Control of an ABS Braking System, SAE Paper No. 940830.
-