Automatica 48 (2012) 1698–1706

Contents lists available at SciVerse ScienceDirect

Automatica

journal homepage: www.elsevier.com/locate/automatica

Brief paper

# Hierarchical $T$–$S$ fuzzy-neural control of anti-lock braking system and active suspension in a vehicle[☆]

Wei-Yen Wang [a,1], Ming-Chang Chen [b], Shun-Feng Su [b]

[a] Department of Applied Electronics Technology, National Taiwan Normal University, 162, He-ping East Road, Section 1, Taipei 106, Taiwan, ROC

[b] Department of Electrical Engineering, National Taiwan University of Science and Technology, 43, Sec.4, Keelung Rd., Taipei 106, Taiwan, ROC

ARTICLE INFO

*Article history:*
Received 1 March 2011
Received in revised form
22 September 2011
Accepted 2 January 2012
Available online 15 June 2012

*Keywords:*
Takagi–Sugeno
Hierarchical FNNs
Active suspension system
Robust adaptive control
And anti-lock braking

ABSTRACT

This paper proposes a novel method for identification and robust adaptive control of an anti-lock braking system with an active suspension system by using the hierarchical Takagi–Sugeno ($T$–$S$) fuzzy-neural model. The goal of a conventional ABS control system is to rapidly eliminate tracking error between the actual slip ratio and a set reference value in order to bring the vehicle to a stop in the shortest time possible. However, braking time and stopping distance can be reduced even further if the same control system also simultaneously considers the state of the active suspension system. The structure learning capability of the proposed hierarchical $T$–$S$ fuzzy-neural network is exploited to reduce computational time, and the number of fuzzy rules. Thus, this proposed controller is applied to achieve integrated control over the anti-lock braking system (ABS) with the active suspension system. Our simulation results, presented at the end of this paper, show that the proposed controller is extremely effective in integrated control over the ABS and the active suspension system.



## 1. Introduction

Various control techniques for anti-lock braking systems (ABS) and active suspension systems are widely applied to improve vehicle comfort and safety. However, integrated control algorithms that coordinate the above two subsystems are rare. The working of the ABS (Canudas-De-Wit, Tsiotras, Velenis, Basset, & Gissinger, 2002; Khatun, Bingham, & Mellor, 2003; Lee & Zak, 2001; Lin & Hsu, 2003; Wang, Li, Chen, Su, & Hsu, 2008) and active suspension system (Allotta, Pugi, & Bartolini, 2008; Cao, Liu, Li, & Brown, 2008; Chen, Wang, Su, & Chien, 2010; Gysen, Sande, Paulides, & Lomonova, 2011) is dictated by changes in the resultant normal force due to changes in road conditions, e.g., when the terrain changes from smooth to rough. However, because a typical ABS controller is not coordinated with the suspension system, vehicle stability may be compromised due to such changes in road conditions. Despite this fact, few studies have explored integrated control (Lin & Ting, 2007; Lou, Fu, Zhang, & Xu, 2010; Shao, Zheng, Li, Wei, & Luo, 2007) for the ABS and active suspension system. Regarding controllers, researchers have greatly improved the performance of integrated framework by utilizing various algorithms, such as backstepping control design (Lin & Ting, 2007), sliding mode control (SMC) (Shao et al., 2007), and fuzzy logic control (FLC) (Lou et al., 2010), etc. All these methods assume that the dynamic system is available. But if the dynamic system is unavailable, these methods cannot be employed to control this integrated system. As an attempt to solve this problem, our proposed method, as a possible solution applied to quarter-vehicle models, integrates the control over the anti-lock braking system (ABS) and the active suspension system.

In this paper, we used structure learning by fuzzy-neural networks (FNNs) to identify an unknown integrated system. The FNNs (Chung & Duan, 2000; Er, Liu, & Li, 2009; Leu, Wang, & Lee, 2005; Lin, Sun, & Chiu, 2010) are used in many applications, but are especially useful in the identification of unknown systems. FNNs can effectively fit a nonlinear system by calculating the optimum coefficients for the learning mechanism. However, conventional multiple-input–multiple-output FNNs (MIMOFNNs) (Gao & Er, 2003; Wang, Chien, & Li, 2008) cannot directly handle systems with a very large number of input variables. In this paper, we address this problem by using a hierarchical fuzzy-neural network with a structure learning to reduce computational time and the number of fuzzy rules. In a hierarchical FNN (Lee, Wang, & Kou, 2008; Li, Wang, Su, & Lee, 2007; Wang, Li, Chen, Su, & Leu, 2010; Zeng & Keane, 2006), a set of low-dimensional subsystems are combined in a modular fashion to achieve high dimensionality and complexity.

☆ This work was supported by the National Science Council, Taiwan, under Grant NSC 99-2221-E-003-022-. The material in this paper was not presented at any conference. This paper was recommended for publication in revised form by Associate Editor Kazuo Tanaka under the direction of Editor Toshiharu Sugie.

*E-mail addresses:* wywang@ntnu.edu.tw (W.-Y. Wang), D9607201@mail.ntust.edu.tw (M.-C. Chen), sfsu@mail.ntust.edu.tw (S.-F. Su).

[1] Tel.: +886 2 77343536; fax: +886 2 2351 5092.

0005-1098/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
doi:10.1016/j.automatica.2012.05.033

The proposed controller design relies on an online hierarchical $T$–$S$ fuzzy-neural model to identify a class of uncertain system. The hierarchical $T$–$S$ fuzzy-neural model can reduce the tracking error of a closed-loop system to an arbitrarily small value. This paper uses the mean value theorem (Grossman & Derrick, 1998; Wang, Chien, Leu, & Lee, 2008, 2010; Wang, Li, Li, Tsai, & Su, 2009) to transform the nonlinear system dynamic into a virtual linear system because most systems are nonlinear. Then the hierarchical $T$–$S$ fuzzy-neural model can identify the dynamic model of the virtual linearized system. Furthermore, the proposed robust controller design is used to compensator the modeling errors and the external disturbances.

The aim of paper is to achieve an integrated control over two unknown nonlinear systems – the ABS and active suspension system – of a road vehicle. Compared with conventional FNNs, the hierarchical $T$–$S$ fuzzy-neural network has a lower number of fuzzy rules, lower complexity, and significantly reduced computational time. In addition, our simulation results for the integrated system, as presented at the end of this paper, indicate that the proposed method is effective.

## 2. System model and dynamics

For the general quarter-vehicle-braking-system model shown in Fig. 1, the wheel dynamics can be determined by summing the rotational torques as,

$$I\dot{\omega}_s = T_b - T_t = K_b P_i - F_x R, \tag{1}$$

and the differential equation describing the vehicle longitudinal dynamics is,

$$\dot{v} m_q = F_x, \tag{2}$$

where $\omega_s$ is the angular velocity of the wheel, $v$ is the linear vehicle velocity, $F_x$ is the longitudinal reactive force, $T_b$ is the braking torque, $T_t$ is the torque generated due to slip between the wheel and the road surface, $m_q$ 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, $K_b$ is the gain between the pressure of the ABS, and $P_i$ is the braking torque. When brakes are applied, friction is generated between the tire and road surface. The mathematical formula for the wheel slip is,

$$\lambda = \frac{v - R\omega_s}{v}. \tag{3}$$

### 2.1. Friction model

The frictional force arising due to braking has the following components: the normal force, the longitudinal force, and the lateral force. The normal force $F_z = m_q/g$ is a function of the weight of the vehicle, or the component of the weight acting in a plane perpendicular to the road surface. $g$ is gravitational constant. The longitudinal force $F_x$ is effective at the road-surface level; it allows the driver to apply the throttle and then brakes for acceleration and deceleration, respectively, as the vehicle is being steered. The friction coefficient is defined as $\mu = F_x/F_z$. In previous research (Canudas-De-Wit et al., 2002), a road condition parameter $\theta$ was introduced into the LuGre friction model, where the friction force is shown as follows:

$$\dot{z} = v_r - \theta\frac{\delta_0|v_r|}{g(v_r)}z \tag{4}$$

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

$$g(v_r) = F_c + (F_s - F_c)e^{-|\frac{v_r}{v_s}|^{1/2}} \tag{6}$$

where $\delta_0$ is the rubber longitudinal lumped stiffness, $\delta_1$ is the rubber longitudinal lumped damping, $\delta_2$ is the 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 $R\omega_s - v$. By substituting equations (4) and (5) into (1) and (2) and adding the viscous rotational friction $\delta_\omega$, a quarter-vehicle model equipped with an ABS, which is called the LuGre-based ABS (Canudas-De-Wit et al., 2002), can be obtained as follows:

$$m_q\dot{v} = F_z(\delta_0 z + \delta_1\dot{z}) + F_z\delta_2 v_r \tag{7}$$

$$I\dot{\omega}_s = -RF_z(\delta_0 z + \delta_1\dot{z}) - \delta_\omega\omega_s + u_r \tag{8}$$

$$\dot{z} = v_r - \theta\frac{\delta_0|v_r|}{g(v_r)}z \tag{9}$$

$$\dot{\theta} = 0, \tag{10}$$

where $u_r$ is an input variable, and we have neglected the term $\delta_2$ in Eq. (8). In Eqs. (7)–(10), we assume that only $\omega_s$ is measurable. The following coordinate transformation of the classical dynamic model is introduced:

$$\begin{aligned} \eta &= Rm_q v + I\omega_s \\ \chi &= I\omega + RF_z\delta_1 z. \end{aligned} \tag{11}$$

Substituting equation (11) in Eqs. (7)–(10), the following equations are obtained:

$$\begin{aligned} \dot{\eta} &= -\frac{F_z\delta_2}{m_q}\eta + \left(\frac{IF_z\delta_2}{m_q} + R^2F_z\delta_2 - \delta_\omega\right)\omega_s + u_r \\ \dot{\chi} &= -\frac{\delta_0}{\delta_1}\chi + \left(I\frac{\delta_0}{\delta_1} - \delta_\omega\right)\omega_s + u_r \\ \dot{z} &= v_r - \theta\frac{\delta_0|v_r|}{g(v_r)}z \\ \dot{\theta} &= 0. \end{aligned} \tag{12}$$

Defining the state vector $\mathbf{x}_s$ and output variable $y_r$ as,

$$\mathbf{x}_s = \begin{bmatrix}\eta \\ \chi \\ z\end{bmatrix}, \qquad y_r = \omega_s. \tag{13}$$

Afterward equations (12) can be rewritten as follows:

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

where

$$\phi(y_r, u_r, \mathbf{x}_s) = \frac{\delta_0|Ry_r - v|}{g(Ry_r - v)}z, \tag{15}$$

and

$$v = \frac{\eta - I\cdot y_r}{Rm_q}. \tag{16}$$