Robust T–S Fuzzy-Neural Control of Uncertain Active Suspension Systems

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Abstract

This paper proposes a novel method for identification of a class of the uncertain active suspension systems by using on-line adaptive T-S fuzzy-neural controller. In reality, vehicles may encounter unpredictable road conditions, e.g., rocks and potholes influencing the dynamic behavior of active suspension systems. These road conditions are not only cause parts of the active suspension system to fail, but also turn them into uncertain systems. To solve this problem, this paper uses the mean value theorem to transform the active suspension system, which is nonlinear, into a virtual linear system. Furthermore, the proposed robust controller design is used to compensator the modeling errors and the external disturbances. Then the T-S fuzzy-neural network can identify the dynamic model of the uncertain active suspension systems. Finally, the results of simulation are illustrated that the proposed controller design presents good performances and effectiveness.

Keywords: uncertain active suspension systems, T-S fuzzy-neural model, and robust control.

1. Introduction

For active suspension systems, many control techniques [1-5] have been employed to improve the vehicle comfort and safety. These control techniques were assumed that the road was a smooth and consistent, and the dynamic behavior of an active suspension system never changed. However, vehicles are not always running on a smooth road . there may encounter unpredictable road conditions, e.g., rocks and potholes or the road may be otherwise uneven. In the real world, the active suspension system does not maintain static all the time, and some parts of the active suspension system may even fail from time to time. Note that if some parts of the active suspension system fail, the system would become an uncertain system. For solve this problem, a novel control technology is proposed for approximate an uncertain system.

The above problems for the uncertain systems have been addressed in [6-18]. Moreover, theoretical justification development presented in [9, 19-20] was valid only for SISO nonlinear systems, so it is hard to be implemented in real applications such as a tracking control problem of the active suspension system. Although Hwang and Hu [21] have proposed a robust neural learning controller design for MIMO systems, the state feedback control scheme did not always hold in practical applications, because models of these systems were seldom known. The objective of this paper is to propose a novel method using an on-line adaptive T-S fuzzy-neural modeling to approach the uncertain active suspension system.

First, we use the mean value theorem to transform the nonlinear active suspension system into a virtual linear system, following which an on-line identification algorithm and a robust tracking controller design are developed for the uncertain active suspension system. The results of simulation are reduces the tracking error of the closed-loop system to an arbitrarily small value, no matter what the states are made arbitrarily small value under various situations.

The remainder of the paper is organized as follows. In Section 2, we introduce the model of an active suspension system and the concept of the T-S fuzzy-neural modeling. Section 3 gives the details of the active suspension system and simulation results. Finally, Section 4 states the conclusions.

2. Active suspension system using on-line adaptive T-S fuzzy neural modeling

Consider the active suspension system with single input and multiple outputs are shown in Fig. 1. The dynamics behavior of the active suspension system can be written as follows:

$$m_s\ddot{z}_s = -K_a(z_s - z_u) - C_a(\dot{z}_s - \dot{z}_u) + u^s$$
$$m_{us}\ddot{z}_u = K_a(z_s - z_u) + C_a(\dot{z}_s - \dot{z}_u) - u^s - K_t(z_u - z_r) - C_t(\dot{z}_u - \dot{z}_r) \quad (1)$$

and the normal force F_z can be described as,

$$F_z = m_q g - K_t(z_u - z_r) - C_t(\dot{z}_u - \dot{z}_r) \quad (2)$$

$$m_q = m_{us} - m_s \quad (3)$$

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where z_s and z_u are the displacements of the car body and wheel, respectively. z_r is the road disturbance. K_a is the active suspension spring coefficient, C_a is the active suspension damping coefficient, C_t is the tire damping coefficient, and K_t is the tire spring coefficient. m_s and m_{us} are the masses of car body and wheel, respectively. g is the acceleration of gravity, and u^s is the control force from the hydraulic actuator.

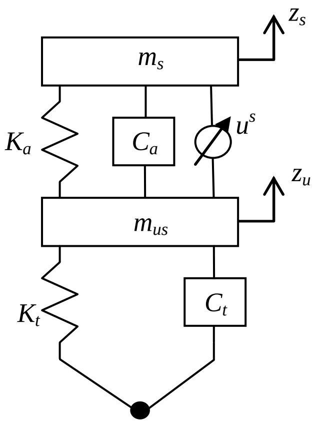

Fig. 1. Quarter-vehicle active suspension system.

From (1), we define the state variables $x_1^s = z_s$, $x_2^s = \dot{z}_s$, $x_3^s = z_u$, and $x_4^s = \dot{z}_u$. u^s is the control input. The active suspension system can be modeled as:

$$
\begin{aligned}
\dot{x}_1^s &= x_2^s \\
\dot{x}_2^s &= \frac{-K_a(x_1^s - x_3^s) - C_a(x_2^s - x_4^s)}{m_s} + \frac{u^s}{m_s} \\
\dot{x}_3^s &= x_4^s \\
\dot{x}_4^s &= \frac{K_a(x_1^s - x_3^s) + C_a(x_2^s - x_4^s) - K_t(x_3^s - z_r^s) - C_t(x_4^s - \dot{z}_r^s)}{m_{us}} - \frac{u^s}{m_{us}}
\end{aligned}
\tag{4}
$$

Now, we consider two cases:

In case1, we define F_{11}^s and F_{12}^s in a normal condition

$$F_{11}^s = \frac{-K_a(x_1^s - x_3^s) - C_a(x_2^s - x_4^s)}{m_s} + \frac{u^s}{m_s}$$

and

$$F_{12}^s = \frac{K_a(x_1^s - x_3^s) + C_a(x_2^s - x_4^s) - K_t(x_3^s - z_r^s) - C_t(x_4^s - \dot{z}_r^s)}{m_{us}} - \frac{u^s}{m_{us}}.$$

In case 2, we define a worst condition, the parameters F_{21}^s and F_{22}^s are defined as

$$F_{21}^s = \frac{-\overline{K}_a(x_1^s - x_3^s) - \overline{C}_a(x_2^s - x_4^s)}{m_s} + \frac{u^s}{m_s}$$

and

$$F_{22}^s = \frac{\overline{K}_a(x_1^s - x_3^s) + \overline{C}_a(x_2^s - x_4^s) - \overline{K}_t(x_3^s - z_r^s) - \overline{C}_t(x_4^s - \dot{z}_r^s)}{m_{us}} - \frac{u^s}{m_{us}}$$

where the coefficients $\overline{C}_t$, $\overline{C}_a$, $\overline{K}_a$, and $\overline{K}_t$ have extreme values (those coefficients are multiplied by an arbitrary constant).

Let the state vector be $\mathbf{x}^s = [x_1^s, x_2^s, x_3^s, x_4^s]^T$ so that the output vector of generalized coordinates becomes $\mathbf{y}^s = [y_1^s, y_2^s, y_3^s, y_4^s]^T = [x_1^s, x_2^s, x_3^s, x_4^s]^T$. Then (4) can be rewritten as

Case g:

$$
\begin{aligned}
\dot{x}_1^s &= x_2^s \\
\dot{x}_2^s &= F_{g1}^s(\mathbf{x}^s) + G_1(u^s) \\
\dot{x}_3^s &= x_4^s \\
\dot{x}_4^s &= F_{g2}^s(\mathbf{x}^s) + G_2(u^s)
\end{aligned}
\tag{5}
$$

and the outputs are

$$
\begin{aligned}
y_1^s &= x_1^s \\
y_2^s &= x_2^s \\
y_3^s &= x_3^s \\
y_4^s &= x_4^s
\end{aligned}
$$

where $g = 1$ and $g = 2$ are for case 1 and case 2, respectively.

Definition 1: The mean value theorem [22] that is the most important theoretical tools in Calculus shows the illustration in Figure 2. Suppose a function f^s is continuous on the closed interval $[\overline{x}^s, x^s]$ and differentiable over the interval's interior $(\overline{x}^s, x^s)$, where $\overline{x}^s = t_1 x^s$, for $0 < t_1 < 1$. Then for some x^{s*} between $(\overline{x}^s, x^s)$, we have $f^s{}'(x^{s*}) = (f^s(x) - f^s(\overline{x}))/(x^s - \overline{x}^s)$. Here $\overline{x}^s$ is defined as a critical point, and x^{s*} is the differential mean point of f^s on $(\overline{x}^s, x^s)$.

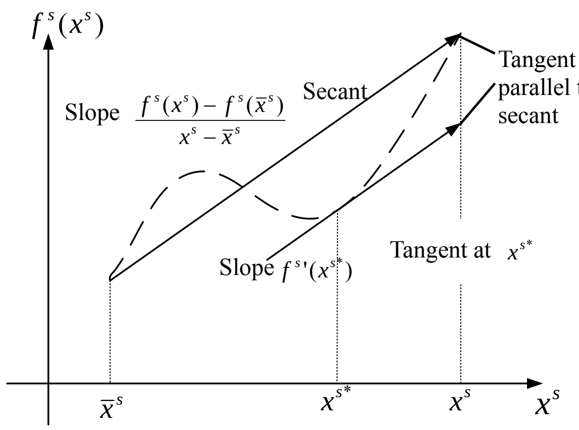

Fig.2. Illustration of the mean value theorem.

A. T-S Fuzzy Neural Model

By definition 1, there are points x_i^{s*} $(i = 1,2,3,4)$ on the linear segments joining x_i^s to $\overline{x}_i^s$ $(i = 1,2,3,4)$. Thus, system (5) can be derived as follows:

$$\dot{\mathbf{x}}^s = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \mathbf{x}_\xi^s + \begin{bmatrix} 0 \\ \dfrac{1}{m_s} \\ 0 \\ \dfrac{1}{m_{us}} \end{bmatrix} u^s + \begin{bmatrix} F_1^s(\bar{\mathbf{x}}^s) \\ F_2^s(\bar{\mathbf{x}}^s) \\ F_3^s(\bar{\mathbf{x}}^s) \\ F_4^s(\bar{\mathbf{x}}^s) \end{bmatrix}$$

$$= \mathbf{A}^s \mathbf{x}_\xi^s + \mathbf{B}^s u^s + \mathbf{d}_d^s \tag{6}$$

where $\bar{\mathbf{x}}^s = [\bar{x}_1^s, \bar{x}_2^s, \bar{x}_3^s, \bar{x}_4^s]^T = t_1 \mathbf{x}^s$ $(0 < t_1 < 1)$ is a vector of critical points, $\mathbf{x}_\xi^s = [x_{\xi 1}^s, x_{\xi 2}^s, x_{\xi 3}^s, x_{\xi 4}^s]^T = \mathbf{x}^s - \bar{\mathbf{x}}^s$, $F_i^s(\bar{\mathbf{x}}^s)$ (i=1,2,3,4) is an unknown function, $\alpha_{ij} = \partial F_{gk}^s / \partial x_j^s |_{(\mathbf{x}^{s*})}$ (i=1,2,3,4, j=1,2,3,4, k=1,2, g=1,2) and $\mathbf{d}_d^s = [F_1^s(\bar{\mathbf{x}}^s),\ F_2^s(\bar{\mathbf{x}}^s),\ F_3^s(\bar{\mathbf{x}}^s),\ F_4^s(\bar{\mathbf{x}}^s)]^T = [d_{d1}^s, d_{d2}^s, d_{d3}^s, d_{d4}^s]^T$.

The T-S fuzzy-neural model defined in [23] is

$$R^{(i)}: \text{If } z_1^s \text{ is } F_1^{si} \text{ and} \ldots z_5^s \text{ is } F_5^{si} \quad \text{Then } \bar{y}_l^s = p_{l1}^{si} z_1^s + p_{l2}^{si} z_2^s + \ldots + p_{l5}^{si} z_5^s \tag{7}$$

where $\mathbf{z}^s = [z_1^s, z_2^s, \cdots z_5^s]^T \in \mathrm{R}^5$ is an input vector of the fuzzy-neural model, $\bar{y}_l^s$ is the output of the model, $F_j^{si}\ (j = 1,2,\cdots,5)$ are fuzzy sets, p_{lk}^{si} (i=1,2, ⋯ ,h, l=1,2,3,4, k=1,2,3,4) are adjustable parameters, and $[p_{15}^{si}, p_{25}^{si}, p_{35}^{si}, p_{45}^{si}]^T = [0, 1/m_s, 0, 1/m_{us}]^T$ is a given vector. According to center of gravity defuzifier, the output p_{lk}^s of the fuzzy-neural network is

$$p_{lk}^s = \frac{\sum_{i=1}^{h} p_{lk}^{si} (\prod_{j=1}^{5} \mu_{F_j^{si}}(z_j^s))}{\sum_{i=1}^{h} (\prod_{j=1}^{5} \mu_{F_j^{si}}(z_j^s))} \tag{8}$$

where $\mu_{F_j^{si}}(z_j^s)$ is the value of the membership function. For the tuning of the weighting factors p_{lk}^s, we define

$$w^{si} = \frac{\prod_{j=1}^{5} \mu_{F_j^{si}}(z_j^s)}{\sum_{i=1}^{h} (\prod_{j=1}^{5} \mu_{F_j^{si}}(z_j^s))},\ i = 1,2,\ldots,h. \tag{9}$$

Assumption 1: The antecedent part of the fuzzy implication describes the conditions of the state deviations and input deviations $[\mathbf{x}_\xi^{sT}, u^s]^T$. The consequent part of the fuzzy implication represents the virtual linear system (VLS) model in (6).

For the purpose of approximating the system in (6), the ith fuzzy implication can be described as,

$$R^{(i)}: \quad \text{If } x_{\xi 1}^s \text{ is } F_1^{si} \text{ and} \ldots x_{\xi 4}^s \text{ is } F_4^{si} \text{ and } u^s \text{ is } F_5^{si} \quad \text{Then } [\dot{x}_1^s, \dot{x}_2^s, \dot{x}_3^s, \dot{x}_4^s]^T = \hat{\mathbf{A}}^{si} \mathbf{x}_\xi^s + \mathbf{B}^{si} u^s \tag{10}$$

where

$$\hat{\mathbf{A}}^{si} = \begin{bmatrix} p_{11}^{si} & p_{12}^{si} & p_{13}^{si} & p_{14}^{si} \\ p_{21}^{si} & p_{22}^{si} & p_{23}^{si} & p_{24}^{si} \\ p_{31}^{si} & p_{32}^{si} & p_{33}^{si} & p_{34}^{si} \\ p_{41}^{si} & p_{42}^{si} & p_{43}^{si} & p_{44}^{si} \end{bmatrix} \tag{11}$$

After applying (8), (9), and some commonly used defuzzification strategies, (6) can be derived as,

$$[\dot{x}_1^s, \dot{x}_2^s, \dot{x}_3^s, \dot{x}_4^s]^T + \mathbf{d}_d^s + \mathbf{d}_f^s = \sum_{i=1}^{h} w^{si} \hat{\mathbf{A}}^{si} \mathbf{x}_\xi^s + \mathbf{B}^{si} u^s + \mathbf{d}_d^s + \mathbf{d}_f^s$$

$$= \begin{bmatrix} p_{11}^s & p_{12}^s & p_{13}^s & p_{14}^s \\ p_{21}^s & p_{22}^s & p_{23}^s & p_{24}^s \\ p_{31}^s & p_{32}^s & p_{33}^s & p_{34}^s \\ p_{41}^s & p_{42}^s & p_{43}^s & p_{44}^s \end{bmatrix} \mathbf{x}_\xi^s + \begin{bmatrix} 0 \\ \dfrac{1}{m_s} \\ 0 \\ \dfrac{1}{m_{us}} \end{bmatrix} u^s + \mathbf{d}_d^s + \mathbf{d}_f^s \tag{12}$$

where $\mathbf{d}_f^s = (\mathbf{A}^s - \sum_{i=1}^{h} w^{si} \hat{\mathbf{A}}^{si}) x_\xi^s$, and p_{ij}^s (i=1,2,3,4, j=1,2,3,4) is used to approximate α_{ij} (i=1,2,3,4, j=1,2,3,4) of the system in (6).

B. Controller Design for On-line Modeling and Robust Tracking

To design a robust controller for (5) or (12), the following assumptions are required.

Assumption 2: Let $\mathbf{x}_\xi^s$ belongs to the compact sets $\mathbf{U}_\mathbf{x}$ and $\mathbf{U}_u$, respectively, where

$$\mathbf{U}_\mathbf{x} = \{\mathbf{x}_\xi^s \in R^4 : \| \mathbf{x}^s \| \le m_\mathbf{x}^s < \infty\}$$

$$\mathbf{U}_\mathbf{u} = \{u^s \in R^1 : | u^s | \le m_u^s < \infty\},$$

where $m_\mathbf{x}^s$ and m_u^s are designed parameters. We define $\phi_{lj}^s = [p_{lj}^{s1}\ p_{lj}^{s2} \cdots p_{lj}^{sh}]$, $l = 1,2,3,4$ and $j = 1,2,3,4$. It is known that the optimal adjustable parameters ϕ_{lj}^{s*} lie in some convex regions

$$\mathbf{M}_{\phi_{lj}^s} = \{\phi_{lj}^s \in R^h : \| \phi_{lj}^s \| \le m_{\phi_{lj}^s}, l = 1,2,3,4,\ j = 1,2,3,4\}$$

where the radii $m_{\phi_{lj}^s}$ are constants and

$$\varphi_{lj}^{s*} = \arg \min_{\varphi_{lj}^s \in \mathrm{M}_{\varphi_{lj}^s}} [\sup_{\mathbf{x}_\xi^s \in \mathbf{U}_\mathbf{x}, u_\xi^s \in \mathbf{U}_u} | p_{lj}^{si}(\mathbf{x}_\xi^s) - \hat{p}_{lj}^{si}(\mathbf{x}_\xi^s | \varphi_{lj}^s)],$$

$$l = 1,2,3,4,\ j = 1,2,3,4.$$

According to assumption 2, we define the optimal adjustable matrices for case g (g=1 or g=2) as

$$\hat{\mathbf{A}}_g^{s*i} = \begin{bmatrix} p_{g11}^{s*i} & p_{g12}^{s*i} & p_{g13}^{s*i} & p_{g14}^{s*i} \\ p_{g21}^{s*i} & p_{g22}^{s*i} & p_{g23}^{s*i} & p_{g24}^{s*i} \\ p_{g31}^{s*i} & p_{g32}^{s*i} & p_{g33}^{s*i} & p_{g34}^{s*i} \\ p_{g41}^{s*i} & p_{g42}^{s*i} & p_{g43}^{s*i} & p_{g44}^{s*i} \end{bmatrix}. \tag{13}$$

Lemma 1 [24]: Suppose that a matrix $\mathbf{\Lambda} \in R^{4\times 4}$ is given. For every symmetric positive definite matrix $\mathbf{Q}^s \in R^{4\times 4}$, the Lyapunov matrix equation $\mathbf{\Lambda}^T \mathbf{\Gamma} + \mathbf{\Gamma} \mathbf{\Lambda} = -\mathbf{Q}^s$ has a unique solution for $\mathbf{\Gamma} = \mathbf{\Gamma}^T > 0$ if and only if

$\mathbf{\Lambda} \in R^{4\times 4}$ is a Hurwitz matrix.

Lemma 2 [25]: When $\mathbf{e}^s(t) \in L_p^2$, for a real number $p \in [1,\infty)$ and both $\mathbf{e}^s(t)$ and $\dot{\mathbf{e}}^s(t) \in L_\infty^2$, then $\lim_{t\to\infty} \| \mathbf{e}^s(t) \| = 0$.

Define the reference signal vector as $\mathbf{r}^s = [r_1^s, r_2^s, r_3^s, r_4^s]^T$. Thus the error vector is $\mathbf{e}^s = \mathbf{y}^s - \mathbf{r}^s = [e_1^s, e_2^s, e_3^s, e_4^s]^T$. Let $\omega_j^s = \dot{r}_j^s - \lambda_j^s e_j^s$ (*j*=1,2,3, 4).

Define a coefficient matrix

$$\mathbf{\Lambda} = \begin{bmatrix} -\lambda_1 & 0 & 0 & 0 \\ 0 & -\lambda_2 & 0 & 0 \\ 0 & 0 & -\lambda_3 & 0 \\ 0 & 0 & 0 & -\lambda_4 \end{bmatrix} \tag{14}$$

where the coefficients, $\lambda_1, \lambda_2, \lambda_3, \lambda_4$, are selected such that the matrix $\mathbf{\Lambda}$ is a Hurwitz matrix. From the error dynamic equation $\dot{\mathbf{e}}^s = \mathbf{\Lambda}\mathbf{e}^s$, we could define $\boldsymbol{\omega}^s = [\omega_1^s\, \omega_2^s\, \omega_3^s\, \omega_4^s]^T = \dot{\mathbf{r}}^s + \mathbf{\Lambda}\mathbf{e}^s = \dot{\mathbf{x}}^s$. Since there are external disturbances $\mathbf{d}_d^s$ in the system (6) and considering the design of the controller, we redefine $\boldsymbol{\omega}^s = \dot{\mathbf{r}}^s + \mathbf{\Lambda}\mathbf{e}^s = \dot{\mathbf{x}}^s + \mathbf{u}_s^s - \mathbf{d}_d^s$, where $\mathbf{u}_s^s$ is an error compensator designed to compensate for $\mathbf{d}_d^s$. From equation (6), based on the certainty equivalence approach, a control input can be chosen as,

$$u^s = [\mathbf{B}^{s^T}\mathbf{B}^s]^{-1}\mathbf{B}^{s^T}(\dot{\mathbf{x}}^s - \mathbf{A}^s\mathbf{x}_\xi^s - \mathbf{d}_d^s)\,. \tag{15}$$

Since $\mathbf{d}_d^s$ is unknown, we redesign u^s as follows:

$$u^s = [\mathbf{B}^{s^T}\mathbf{B}^s]^{-1}\mathbf{B}^{s^T}(-\mathbf{A}^s\mathbf{x}_\xi^s + \boldsymbol{\omega} - \mathbf{u}_s^s)\,. \tag{16}$$

Then, the error dynamic equation can be derived as

$$\dot{\mathbf{e}}^s = \dot{\mathbf{x}}^s - \dot{\mathbf{r}}^s = \mathbf{\Lambda}\mathbf{e}^s - \mathbf{u}_s^s + \mathbf{d}_d^s$$

Because the right side of (6) is unknown, we replace $\mathbf{A}^s$ by $\sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}$ in (12). From (16) a fuzzy-neural control input can be derived as,

$$u^s = [\mathbf{B}^{s^T}\mathbf{B}^s]^{-1}\mathbf{B}^{s^T}(-\sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \dot{\mathbf{r}}^s + \mathbf{\Lambda}\mathbf{e}^s - \mathbf{u}_s^s)\,. \tag{17}$$

Using assumption 2 and substituting (17) for (12), the error dynamic equation of the VLS model becomes,

$$\begin{aligned}
\dot{\mathbf{e}}^s &= \dot{\mathbf{x}}^s - \dot{\mathbf{r}}^s. \\
&= \dot{\hat{\mathbf{x}}}^s + \mathbf{d}_d^s + \mathbf{d}_f^s - \dot{\mathbf{r}}^s \\
&= \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \mathbf{B}^s u^s + \mathbf{d}_d^s + (\mathbf{A}^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i})\mathbf{x}_\xi^s \\
&\quad + \sum_{i=1}^h w^{si}(\hat{\mathbf{A}}^{s*i} - \hat{\mathbf{A}}^{si})\mathbf{x}_\xi^s - \dot{\mathbf{r}}^s \\
&= \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \mathbf{B}^s u^s + \mathbf{d}_d^s + \mathbf{A}^s\mathbf{x}_\xi^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i}\mathbf{x}_\xi^s + \\
&\quad + \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i}\mathbf{x}_\xi^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s - \dot{\mathbf{r}}^s \\
&= \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s + (-\sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \dot{\mathbf{r}}^s + \mathbf{\Lambda}\mathbf{e}^s - \mathbf{u}_s^s) + \mathbf{d}_d^s \\
&\quad + \mathbf{A}^s\mathbf{x}_\xi^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i}\mathbf{x}_\xi^s + \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i}\mathbf{x}_\xi^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s - \dot{\mathbf{r}}^s \\
&= \mathbf{\Lambda}\mathbf{e}^s - \mathbf{u}_s^s + \mathbf{d}_d^s + \mathbf{A}^s\mathbf{x}_\xi^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i}\mathbf{x}_\xi^s + \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i}\mathbf{x}_\xi^s \\
&\quad - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{si}\mathbf{x}_\xi^s \\
&= \mathbf{\Lambda}\mathbf{e}^s + \sum_{i=1}^h w^{si}\tilde{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \tilde{\mathbf{d}}^s - \mathbf{u}_s^s
\end{aligned} \tag{18}$$

where $\tilde{\mathbf{A}}^{si} = \hat{\mathbf{A}}^{s*i} - \hat{\mathbf{A}}^{si}$ and

$$\tilde{\mathbf{d}}^s = \mathbf{d}_d^s + (\mathbf{A}^s - \sum_{i=1}^h w^{si}\hat{\mathbf{A}}^{s*i})\mathbf{x}_\xi^s = [\tilde{d}_1^s\ \tilde{d}_2^s\ \tilde{d}_3^s\ \tilde{d}_4^s]^T\,.$$

We define $\mathbf{u}_s^s$ (the error compensator) and $\mathbf{e}_\Delta^s$ as

$$\begin{aligned}
\mathbf{u}_s^s &= \begin{bmatrix} sign(e_{\Delta 1}^s) & 0 & 0 & 0 \\ 0 & sign(e_{\Delta 2}^s) & 0 & 0 \\ 0 & 0 & sign(e_{\Delta 3}^s) & 0 \\ 0 & 0 & 0 & sign(e_{\Delta 4}^s) \end{bmatrix}\mathbf{k} \\
&= [u_{s1}^s, u_{s2}^s, u_{s3}^s, u_{s4}^s]
\end{aligned} \tag{19}$$

and

$$\mathbf{e}_\Delta^s = \mathbf{e}^{sT}\mathbf{\Gamma} = [e_{\Delta 1}^s\ e_{\Delta 2}^s\ e_{\Delta 3}^s\ e_{\Delta 4}^s] \tag{20}$$

where $\mathbf{\Gamma} > 0$ is a Lyapunov matrix and $\mathbf{k} = [k_1, k_2, k_3, k_4]^T$. Let $\mathbf{e}^{sT}\mathbf{\Gamma}\tilde{\mathbf{d}}^s \le \bar{k}$, where $\bar{k}$ is a positive constant. There exist positive values of k_j ($j = 1,2,3,4$) such that $\sum_{j=1}^4 k_j |e_{\Delta j}^s| > \bar{k}$.

On the basis of the above discussion, the following theorem can be obtained.

Theorem 1: Consider an active suspension system (5), which is approximated as (12) and satisfies assumptions 1-2. If the controller is designed as (17) with update law

$$\dot{\hat{\mathbf{A}}}^{si} = \eta_1 w^{si}\mathbf{e}^s\mathbf{x}_\xi^{sT},\ i = 1, 2, \cdots, h \tag{21}$$

where η_1 is the positive constant, then the closed-loop system is robust stable and $\lim_{t\to\infty} \| \mathbf{e}^s(t) \| = 0$.

Proof: Consider the Lyapunov-like function candidate

$$v = \frac{1}{2}\mathbf{e}^{sT}\mathbf{\Gamma}\mathbf{e}^s + \frac{1}{2\eta_1}\sum_{i=1}^h tr(\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\tilde{\mathbf{A}}^{si})\,. \tag{22}$$

Differentiating (22) with respect to time, we get

$$\begin{aligned}
\dot{v} &= \frac{1}{2}\dot{\mathbf{e}}^{sT}\mathbf{\Gamma}\mathbf{e}^s + \frac{1}{2}\mathbf{e}^{sT}\mathbf{\Gamma}\dot{\mathbf{e}}^s + \frac{1}{2\eta_1}\sum_{i=1}^h tr(\dot{\tilde{\mathbf{A}}}^{siT}\mathbf{\Gamma}\tilde{\mathbf{A}}^{si}) \\
&\quad + \frac{1}{2\eta_1}\sum_{i=1}^h tr(\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\dot{\tilde{\mathbf{A}}}^{si})
\end{aligned} \tag{23}$$

Inserting (18) and (19) in the above equation yields

$$\begin{aligned}
\dot{v} &= \frac{1}{2}\mathbf{e}^{sT}(\Lambda^T\mathbf{\Gamma} + \mathbf{\Gamma}\Lambda)\mathbf{e}^s + \mathbf{e}^{sT}\mathbf{\Gamma}\sum_{i=1}^h w^{si}\tilde{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \frac{1}{\eta_1}\sum_{i=1}^h tr(\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\dot{\tilde{\mathbf{A}}}^{si}) \\
&\quad + \mathbf{e}^{sT}\mathbf{\Gamma}\tilde{\mathbf{d}}^s - \mathbf{e}^{sT}\mathbf{\Gamma}\mathbf{u}_s^s
\end{aligned} \tag{24}$$

From Lemma 1, substituting $\mathbf{\Lambda}^\mathbf{T}\mathbf{\Gamma} + \mathbf{\Gamma}\mathbf{\Lambda} = -\mathbf{Q}^s$ in (24), we have

$$\dot{v} = -\frac{1}{2}\mathbf{e}^{sT}\mathbf{Q}^s\mathbf{e}^s + \mathbf{e}^{sT}\mathbf{\Gamma}\sum_{i=1}^{h} w^{si}\tilde{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \frac{1}{\eta_1}\sum_{i=1}^{h} tr(\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\dot{\hat{\mathbf{A}}}^{si})$$

$$+\mathbf{e}^{sT}\mathbf{\Gamma}\tilde{\mathbf{d}}^s - \mathbf{e}^{sT}\mathbf{\Gamma}\mathbf{u}_s^s$$

$$= \Delta + \mathbf{e}^{sT}\mathbf{\Gamma}\tilde{\mathbf{d}}^s - \mathbf{e}^{sT}\mathbf{\Gamma}^s Diag[sign(\mathbf{e}_\Delta^s)]\mathbf{k} \quad (25)$$

where

$$\Delta = -\frac{1}{2}\mathbf{e}^{sT}\mathbf{Q}^s\mathbf{e}^s + \mathbf{e}^{sT}\mathbf{\Gamma}\sum_{i}^{h} w^{si}\tilde{\mathbf{A}}^{si}\mathbf{x}_\xi^s + \frac{1}{\eta_1}\sum_{i=1}^{h} tr(\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\dot{\hat{\mathbf{A}}}^{si})$$

$$= -\frac{1}{2}\mathbf{e}^{sT}\mathbf{Q}^s\mathbf{e}^s + tr\left(\sum_{i=1}^{h} w^{si}\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\mathbf{e}^s\mathbf{x}_\xi^{sT} - \sum_{i=1}^{h}\frac{\tilde{\mathbf{A}}^{siT}\mathbf{\Gamma}\dot{\hat{\mathbf{A}}}^{si}}{\eta_1}\right) \quad (26)$$

If we select $\dot{\hat{\mathbf{A}}}^{si}$ as (21), (25) become

$$\dot{v} \le -\frac{1}{2}\mathbf{e}^{sT}\mathbf{Q}^s\mathbf{e}^s + \bar{k} - \sum_{j=1}^{4} k_j \,|\, e_{\Delta j}^s \,| \quad (27)$$

Choose the value of $k_j (j = 1,2,3,4)$, such that $\sum_{j=1}^{4} k_j \,|\, e_{\Delta j}^s \,| > \bar{k}$, then

$$\dot{v} = -\frac{1}{2}\mathbf{e}^{sT}\mathbf{Q}^s\mathbf{e}^s \le 0 \quad (28)$$

Equations (22) and (28) only guarantee that $\mathbf{e}^s(t) \in L_\infty^l$, but not that it converges. The boundedness of $\mathbf{e}^s(t)$ implies the boundedness of $\mathbf{x}^s(t)$. Since the operating state are finite, $\mathbf{x}_\xi^s$ is bound. Based on Assumption 2 and the boundedness of $\mathbf{x}_\xi^s$, u^s is bounded. Therefore, $\dot{\mathbf{e}}^s(t)$ is bounded, i.e. $\dot{\mathbf{e}}^s(t) \in L_\infty^l$. Integrating both sides of (28) yields

$$v(t) - v(0) \le -\frac{1}{2}\lambda_{\min}(\mathbf{Q}^s)\int_0^t \| \mathbf{e}^s(\tau) \|^2 \, d\tau \quad (29)$$

where $\lambda_{\min}(\mathbf{Q}^s) > 0$ is the minimum eigenvalue of $\mathbf{Q}^s$. When t tends to infinity, (29) becomes

$$\int^t \| \mathbf{e}^s(\tau) \|^2 \, d\tau \le \frac{v(0) - v(\infty)}{\frac{1}{2}\lambda_{\min}(\mathbf{Q}^s)} \quad (30)$$

Since the right side of (30) is bound, $\mathbf{e}^s(t) \in L_2^l$. Therefore, by using Lemma 2, $\| \mathbf{e}^s(\tau) \| \to 0$ as $t \to \infty$. This completes the proof.

The design algorithm and on-line tuning algorithm is summarized as follows

1) Select the coefficients λ_1, λ_2, λ_3, and λ_4 such that the matrix $\mathbf{\Lambda}$ is a Hurwitz matrix.
2) Choose an appropriate vector $\mathbf{k}$ in (19). In order to remedy the chattering of control inputs, (19) can be modified as

$$u_{sj}^s = \begin{cases} k_j & \text{if } e_{\Delta j}^s \ge 0 \text{ and } |\, e_{\Delta j}^s| > \gamma_j \\ -k_j & \text{if } e_{\Delta j}^s < 0 \text{ and } |\, e_{\Delta j}^s| > \gamma_j \text{ , } j = 1,2,3,4 \\ \dfrac{k_j e_{\Delta j}^s}{\gamma_j} & \text{if } |\, e_{\Delta j}^s| < \gamma_j \end{cases}$$

3) Construct fuzzy sets for $\mathbf{x}_\xi^s$ and u_ξ^s.
4) Obtain the control law (17) and the update law (21).

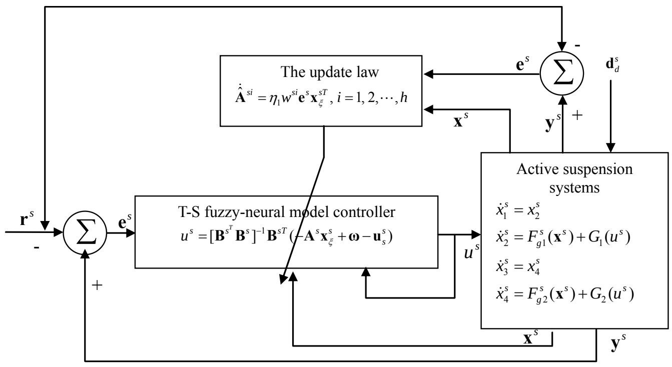

Fig. 3. Overall scheme of the T-S fuzzy-neural controller.

Fig. 3 shows the overall scheme of the T-S fuzzy-neural controller proposed in this paper. It is an on-line identification algorithm using T-S fuzzy–neural modeling and a robust tracking controller for the uncertain active suspension system.

3. Simulation Results

The aim of the active suspension system is to improve the comfortableness and safety of passengers in the vehicle, that is, to maintain both the displacement z_s of the vehicle body and the displacement z_u of the vehicle wheel to track the optimum balance point which is defined to be zero. In this section, the results of simulation using the proposed controller are shown that the tracking errors can be made arbitrarily small values, and on top that, the results of experimental are also confirmed that the tracking errors of displacement can be attenuated efficiently.

Reports of this type of research have apparently not been published which rough roads may not only cause some parts of the active suspension system to fail, but also turn them into uncertain system. Therefore, we compare the previous method [1] with our proposed method, and the simulation results can be explained that the proposed control method is efficiency better than the previous method [1].

The dynamic model of the active suspension system is shown in (5), where $F_{gi}^s(\mathbf{x}^s)$ $(i = 1, 2)$ are uncertain nonlinear functions, u^s is the control input, and d_{di}^s $(i = 1,2,3,4)$ are external disturbances. The interior parameters of vehicles are read from Table 1. The initial states of the active suspension system are assumed to be $\mathbf{x}^s = [0.02, 0.02, 0.02, 0.02]^T$. We use the proposed control law in (20) to control the output

y_j^s ($j=1,\cdots,4$) of the closed–loop system to track the reference signals r_j^s ($j=1,\cdots,4$). The fuzzy sets over the interval [-10000, 10000] are defined for $\mathbf{x}_\xi^s=[x_{\xi 1}^s, x_{\xi 2}^s, x_{\xi 3}^s, x_{\xi 4}^s]^T$ with the term sets (PB, PS, Z, NS, NB). The design parameters are selected as $\eta=0.001$, $\lambda_i=2$ $(i=1,2,3,4)$, and $\mathbf{Q}=[20\ 0\ 0\ 0; 0\ 20\ 0\ 0;\ 0\ 0\ 20\ 0; 0\ 0\ 0\ 20]$.

Table 1. List of symbols and parameters.

Symbols	Descriptions	Parameters
m_g	The total mass of the car	440.0 kg
m_s	The mass of the car body	400.0 kg
m_{us}	The mass of the car wheel	40.0 kg
C_a	The active suspension damping coefficient	1050.0 N/m
C_t	The tire damping coefficient	1500 N/m
K_t	The tire spring coefficient	175500 N/m
K_a	The active suspension spring coefficient	19960.0 N/m

In the following example, a vehicle is driving on smooth road. Figure 4 shows the displacement (z_s) of the vehicle body. We can control the displacement of the vehicle body to track the optimum balance point which is defined to be zero. The active suspension system encounters rough road conditions after 10s. An instant later the tire spring K_t and the active suspension spring K_a are broken by a rough road (the spring coefficients are multiplied by 50, i.e., $\overline{K}_t=50K_t$ and $\overline{K}_a=50K_a$). Furthermore, the dynamic model of the active suspension system is changed from case 1 (g=1) to case 2 (g=2) in (5). Based on the system variation, the T-S fuzzy-neural model must re-learn and re-approximate the new states of the active suspension system. And the simulation results are shown that our proposed control scheme is still effective under the uncertain system, we magnify Fig. 4 around the 10s region; this is clearly that the actual trajectory x_1^s (red line) can quickly track the desired trajectory r_1^s (blue line). Fig. 5 shows the displacement (z_u) of the vehicle wheel. We control the displacement of the vehicle wheel to track the optimum balance point zero. We magnify Fig. 5 around the 10s region. This is clearly that the actual trajectory x_3^s (red line) can quickly track the desired trajectory r_2^s (blue line). The experimental results are confirmed that the tracking performance is good, even when the some parts of the active suspension system fail. Fig. 6 (a) shows the normal force F_z. From (5), we know that the value of the normal force F_z stays fixed when z_s and z_u approach zero. If the values of the normal force would not stay fixed, the vehicle would lose its balance. In order to explicitly shown that the value of the normal force F_z can stay fixed, we magnify Fig. 6 (a) around the 18s region. We noticed that value of the normal force can stay fixed. Fig. 6 (b) shows the value of the normal force F_z for a nonlinear backstepping control method [1] under the same conditions. Before 10s, z_u and z_s are controlled to approach zero and the value of the normal force F_z stays fixed. After 10s, the normal force F_z is shown in Fig. 6(c). The value of the normal force F_z that is very large and the instant maximum or minimum is around $\pm 10^5$. From 18s to 20s, the value of the normal force F_z cannot stay fixed. It is quite obvious that the nonlinear backstepping controller cannot handle the fault well. Fig. 7 (a) shows the control signal of the active suspension system using the proposed controller. Fig. 7(b) shows the control signal of the nonlinear backstepping controller [1]. The maximum force is limited to be 3000 N. The control signal of the nonlinear backstepping controller is larger than ours. Moreover, after 10s, the control signal of the nonlinear backstepping controller method has serious chattering. From Figs. 4–7, we are confirmed that the proposed controller can track the reference signal quickly and control the dynamic behavior of the active suspension system well.

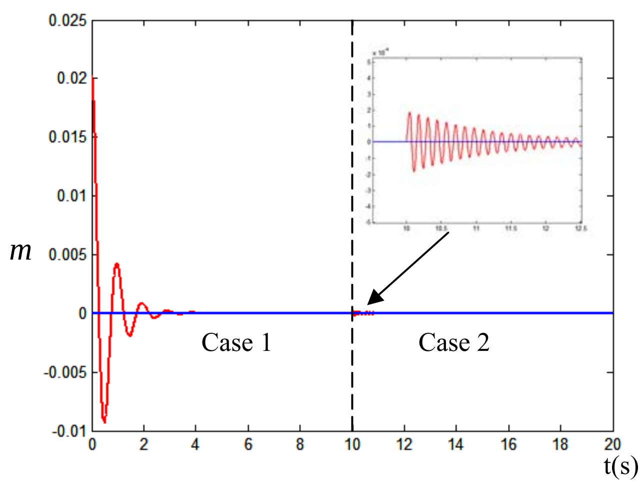

Fig. 4. z_s the displacement of vehicle body.

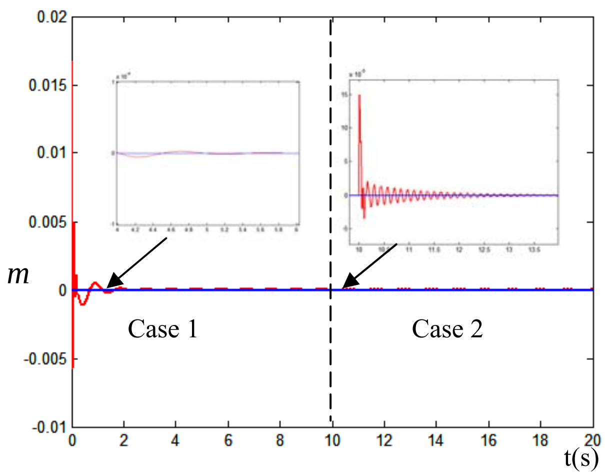

Fig. 5. z_u the displacement of vehicle body.

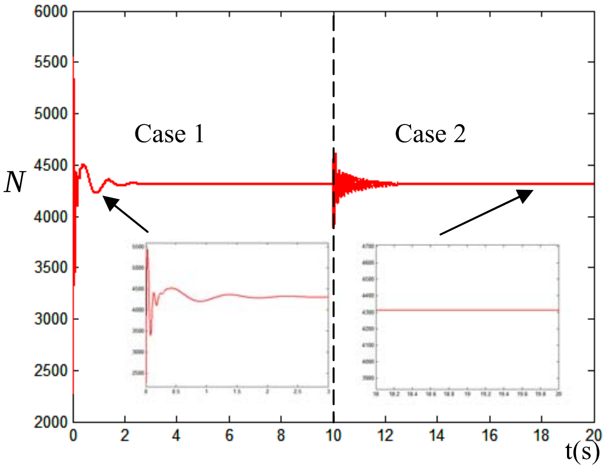

Fig. 6. (a) curves of normal force F_z .

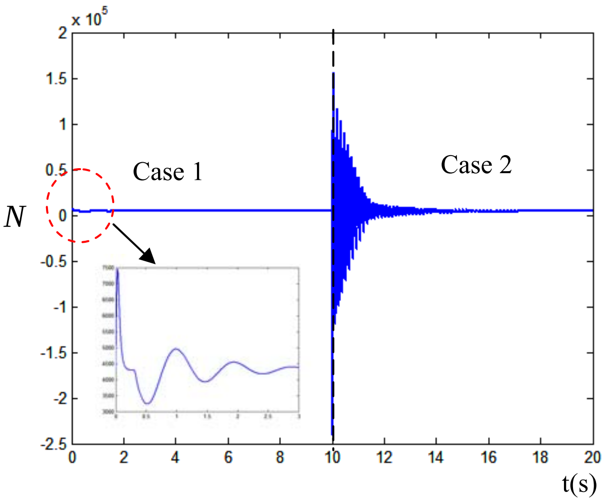

Fig. 6. (b) curves of normal force F_z by using [1].

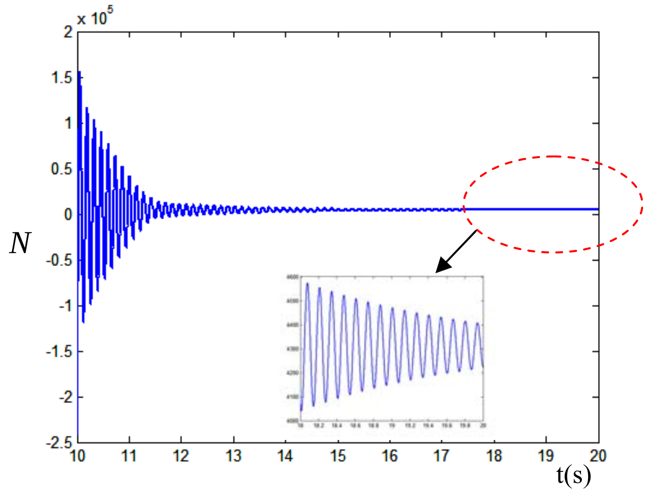

Fig. 6. (c) curves of normal force F_z by using [1].

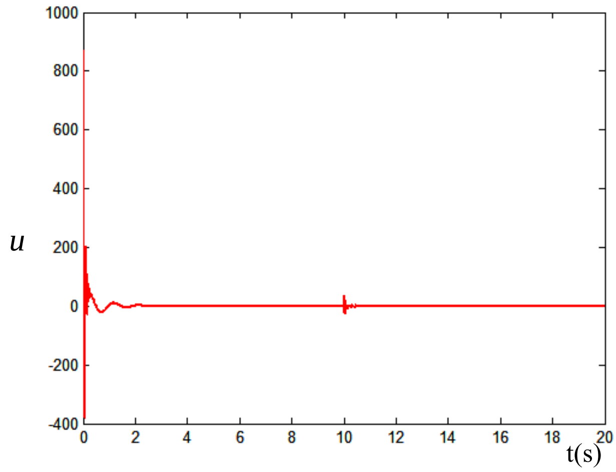

Fig. 7. (a) the control input signal of the active suspension system.

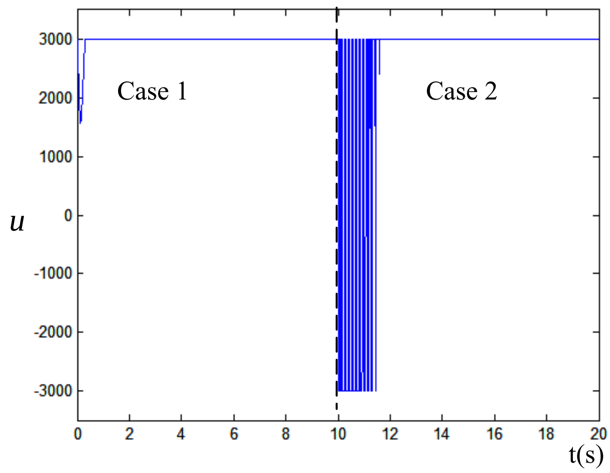

Fig. 7. (b) the control input signal of the active suspension system by using [1].

4. Conclusions

In this paper, a novel on-line adaptive T-S fuzzy-neural modeling has been proposed for uncertain active suspension system that can be transformed into a virtual linearized system model through the mean value theorem. Furthermore, the robust controller was used to compensate the modeling errors and the external disturbances. The results of simulation using proposed controller are shown that the displacement tracking performance is good and effectiveness, even when the springs of active suspension system are broken. Finally, it should been re-emphasized that the on-line adaptive T-S fuzzy-neural controller proposed in this paper can achieve a better control performance than the conventional methods.

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