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Research Article

Nonlinear Time-Delay Suspension Adaptive Neural Network Active Control

Yue Zhu and Sihong Zhu

College of Engineering, Nanjing Agricultural University, Nanjing 210031, China

Correspondence should be addressed to Yue Zhu; zhuyue_jin@163.com

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Considering the time-delay in control input channel and the nonlinear spring stiffness characteristics of suspension, a quarter-vehicle magneto rheological active suspension nonlinear model with time-delay is established in this paper. Based on the time-delay nonlinear model, an adaptive neural network structure for magneto rheological active suspension is presented. By recognizing and training the adaptive neural network, the adaptive neural network active suspension controller is obtained. Simulation results show that the presented method can guarantee that the quarter-vehicle magneto rheological active suspension system has satisfying performance on the E_level very poor ground.

1. Introduction

For engineering vehicles, farm tractors, military vehicles, and so on, the road conditions are usually very poor. Therefore, vibration problem is prominent particularly [1]. Seat suspension has been widely used as a simple and effective method to improve ride quality of vehicle which is directly related to driver fatigue, discomfort, and safety [2]. In recent years, the active suspension control research has received the widespread attention of scholars at home and abroad, in the aspect of theoretical analysis and physical test [3–8].

Vehicle suspension system is a complex dynamic system; the road input is a random process and has a strong uncertainty, while the system itself has strong nonlinearity characteristic; therefore, it is difficult to obtain ideal control effect by using conventional control methods [5, 6].

The neural network is a kind of powerful tool to deal with uncertainty and nonlinearity; it can parallel computing and distribute information storage, while it has strong fault tolerance and self-learning ability. Hence, neural network is suitable for the complex system modeling and control [9–11].

In this paper, in order to reduce the vibration of magneto rheological active suspension system, adaptive neural network active suspension controller is designed. At first, a quarter-vehicle active suspension nonlinear model with time-delay is established by considering the time-delay in control input channel of magneto rheological active suspension system and the nonlinear spring stiffness characteristics of suspension. Then, an adaptive neural network structure for magneto rheological active suspension is presented according to the time-delay nonlinear model. Next, the adaptive neural network active suspension controller is obtained by recognizing and training the adaptive neural network. At last, E_level ground which is very poor road condition is considered for a quarter-vehicle magneto rheological active suspension system. Simulation shows that the presented method can guarantee that the system has satisfying performance.

The remainder of this paper is organized as follows. In Section 2, the considered quarter-vehicle magneto rheological active suspension time-delay nonlinear model is presented. Adaptive neural network structure, neural network identification, and neural network training are given in Section 3 and the adaptive neural network active suspension controller is obtained in Section 3 as well. Simulation on a quarter-vehicle magneto rheological active suspension system under E_level very poor ground is illustrated in Section 4. Section 5 draws the conclusions of this paper.

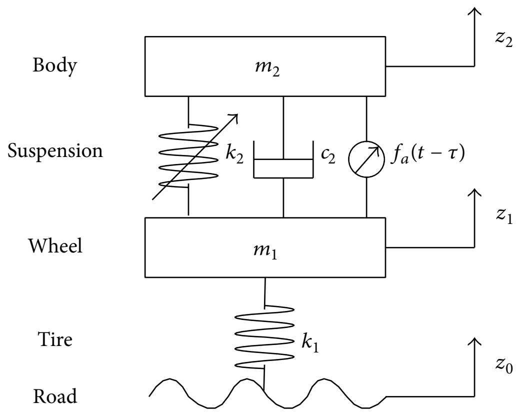

FIGURE 1: Quarter-vehicle model with a magneto rheological active suspension.

2. Quarter-Vehicle Magneto Rheological Active Suspension Time-Delay Nonlinear Model

In this paper, quarter-vehicle model for active control of magneto rheological seat suspension system is studied. At the same time, the nonlinear stiffness characteristics of the suspension spring and control time-delay characteristics are considered. Figure 1 shows a quarter-vehicle model of an active suspension system.

Among them, m_2 is body quality, m_1 is wheel quality, k_2 is suspension stiffness, c_2 is damping coefficient, k_1 is tire equivalent stiffness coefficient, z_2 is the displacement of body, z_1 is displacement of wheels, z_0 is the ground displacement excitation, and $f_a(t-\tau)$ is active control. Here, the variable stiffness spring of restoring force-displacement relationship is expressed as [12] $f_s = k_2\Delta z + \varepsilon k_2 \Delta z^3$, $\Delta z = z_2 - z_1$, ε is nonlinear spring ratio. When $k_2 = 27358$, $\varepsilon = 10$ restoring force f_s and displacement Δz relationship is shown in Figure 2.

Dynamic differential equation for the suspension system is

$$\begin{aligned} &m_2\ddot{z}_2 + c_2(\dot{z}_2 - \dot{z}_1) + k_2(z_2 - z_1) + \varepsilon k_2 (z_2 - z_1)^3 \\ &\quad = f_a(t-\tau), \\ &m_1\ddot{z}_1 + c_2(\dot{z}_1 - \dot{z}_2) + k_1(z_1 - z_0) - k_2(z_2 - z_1) \\ &\quad - \varepsilon k_2 (z_2 - z_1)^3 = -f_a(t-\tau) \end{aligned} \tag{1}$$

as $x = [x_1, x_2, x_3, x_4]^T = [z_2, z_1, \dot{z}_2, \dot{z}_1]^T = [q^T, p^T]^T$.

$u = f_a$; assume acceleration $\ddot{z}_2$, velocity $\dot{z}_2$, $\dot{z}_1$, and displacement z_2, z_1 are measurable; the introduction of auxiliary control variable is written as

$$\bar{u}(t-\tau) = u(t-\tau) - \varepsilon k_2 (z_2 - z_1)^3 \tag{2}$$

and (1) can be rewritten into

$$\dot{x} = Ax + B\bar{u}(t-\tau) + B_w z_0,$$

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ \dfrac{-k_2}{m_2} & \dfrac{k_2}{m_2} & \dfrac{-c_2}{m_2} & \dfrac{c_2}{m_2} \\ \dfrac{k_2}{m_1} & \dfrac{-k_2 - k_1}{m_1} & \dfrac{c_2}{m_1} & \dfrac{-c_2}{m_1} \end{bmatrix}, \tag{3}$$

$$B = \begin{bmatrix} 0 & 0 & \dfrac{1}{m_2} & \dfrac{-1}{m_1} \end{bmatrix}^T, \qquad B_w = \begin{bmatrix} 0 & 0 & 0 & \dfrac{k_1}{m_1} \end{bmatrix}.$$

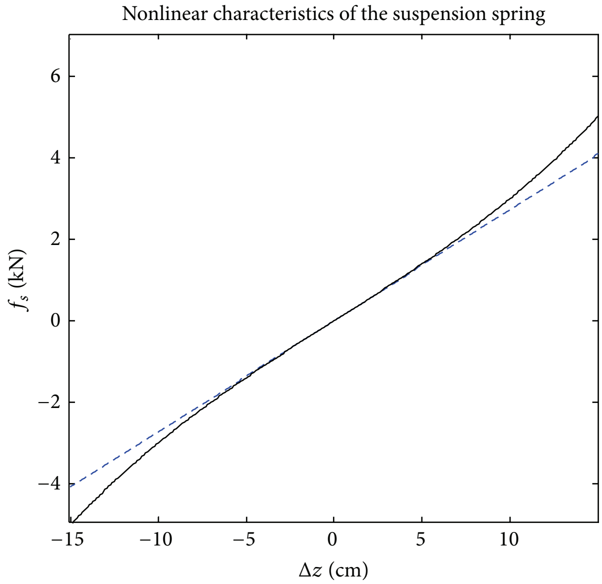

FIGURE 2: Force-displacement curve of nonlinear spring.

The corresponding nominal system model of (3) is

$$\dot{x} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} q \\ p \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} \bar{u}(t-\tau), \tag{4}$$

where

$$\begin{aligned} &A_{11} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \qquad A_{12} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \qquad B_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \\ &A_{21} = \begin{bmatrix} \dfrac{-k_2}{m_2} & \dfrac{k_2}{m_2} \\ \dfrac{k_2}{m_1} & \dfrac{-k_2 - k_1}{m_1} \end{bmatrix}, \qquad B_2 = \begin{bmatrix} \dfrac{1}{m_2} \\ \dfrac{-1}{m_1} \end{bmatrix}, \\ &A_{22} = \begin{bmatrix} \dfrac{-c_2}{m_2} & \dfrac{c_2}{m_2} \\ \dfrac{c_2}{m_1} & \dfrac{-c_2}{m_1} \end{bmatrix}. \end{aligned} \tag{5}$$

3. The Design of Adaptive Neural Network Active Suspension Controller

3.1. Adaptive Neural Network Structure. Adaptive neural network system structure is shown in Figure 3. The system consists of three parts: the controlled active suspension, the neural network identifier AN1, and the neural network

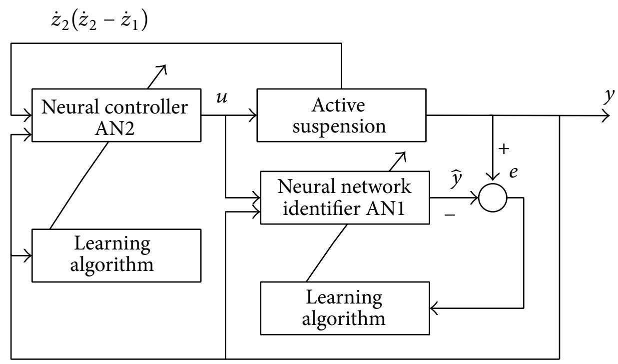

Figure 3: Adaptive neural network structure.

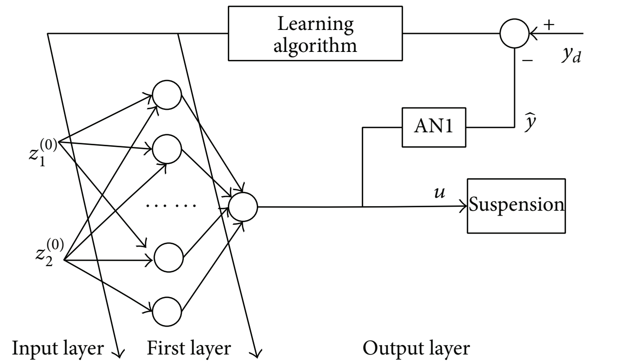

Figure 4: Adaptive neural network controller.

controller AN2. AN1 is used for online identification of active suspension systems; AN2 is used to realize the network parameters adjustment by tuning the network weights and the threshold online and then to get the best effect of vibration reduction.

In Figure 3, output y is the body acceleration, control signal u is damping force, and its normalized range is 0~1. The common way to implement u is to regulate electrohydraulic proportional throttle valve flow area or valve core displacement. $\dot{z}_2(\dot{z}_2-\dot{z}_1)$ is as an input for the neural network controller AN2. The input for neural network identifier AN1 is the body acceleration and control signal u.

3.2. Neural Network Identification. The road excitation can be viewed as a white noise signal and it is suitable to identify active suspension system by using nonlinear autoregressive moving average (NARMA) model; namely,

$$y(k) = f\left[y(k-1),\ldots,y(k-n),\overline{u}(k-1-\tau),\ldots,\overline{u}(k-m-\tau),v(k-1),\ldots,v(k-l)\right], \tag{6}$$

where $y(k)$ is for body acceleration at the kth step; $\overline{u}(k-1-\tau)$ is for the control signal at the $(k-1-\tau)$th step; $v(k-1)$ is for road random input (white noise) at the $(k-1)$th step.

AN1 identifies the system model and multilayer feedforward neural network was used by the network structure. Network is composed of two layers: the first layer is input layer and has $n+m$ inputs. Hyperbolic function is chosen as neurons transformation; each of the neurons has a threshold. The second layer is output layer and is with one neuron which represents the estimate of the system output. Proportion function is selected as neuron function and it also has neuron threshold.

3.3. The Adaptive Neural Network Controller. The structure of the neural network controller AN2 is shown in Figure 4. The network has two inputs and one output. The first input $z_1^{(0)} = \psi_{z_2}$ is the root mean square value of the body acceleration; the second input $z_2^{(0)} = \dot{z}_2(\dot{z}_2-\dot{z}_1)$ is the product of the speed of the suspension. Network output value $\mu = r/r_{\max}$ is the variable damping. In order to facilitate network training, suppose $r_{\max} = 1\times10^5(\mathrm{N\cdot s^2/m^2})$. Network structure applies multilayer feed-forward neural network. The network has two layers (not including the input layer); the first layer is composed of 10 neurons with thresholds; the hyperbolic function is used as neurons transformation function S. The second layer has a neuron with threshold; the sigmoid function is utilized as neurons transformation function S, so that the output of the network can be always in the range of 0~1.

In order to obtain good performance, Marquardt backpropagation algorithm (MBP algorithm) which is of high training efficiency is used in training neural network identifier ANl. During training, the error between desired body acceleration and the output of neural network identifier ANl is as the input for MBP algorithm. And the weights and thresholds of AN1 keep unchanging.

Because the desired control signal is unknown at the very beginning, neural network controller AN2 is cascaded with neural network identifier AN1, as shown in Figure 3. During training, MBP algorithm is employed as well, but the weights and thresholds of AN2 are changed, in order to obtain and optimize adaptive neural network controller.

The input-output relationship of the first layer is

$$S_i^{(1)} = \sum_{j=0}^{2}\omega_{ij}^{(1)}x_j^{(0)}\left(x_0^{(0)}=1,\omega_{r0}^{(1)}=\theta_r^{(1)}\right), \tag{7}$$

$$x_i^{(1)} = f\left(S_i^{(1)}\right) = \frac{1-e^{-2S_i^{(1)}}}{1+e^{-2S_i^{(1)}}}, \quad i=1,2,\ldots,10,\ j=0,1,2. \tag{8}$$

The input-output relationship of the first layer is

$$S_i^{(2)} = \sum_{j=0}^{10}\omega_{ij}^{(2)}x_j^{(1)}\left(x_0^{(0)}=1,\omega_{r0}^{(2)}=\theta_r^{(2)}\right), \tag{9}$$

$$u = f\left(s_i^{(2)}\right) = \frac{1}{1+e^{-2s_j^{(2)}}} \quad (j=0,1,2,\ldots,10). \tag{10}$$

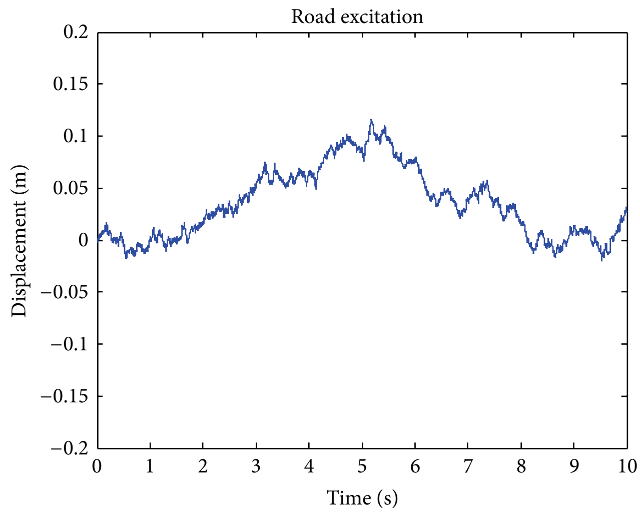

Figure 5: Road excitation.

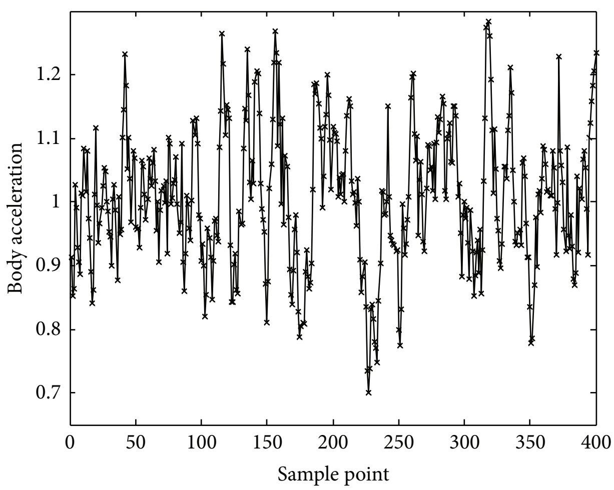

Figure 6: Training result.

To improve the training algorithm, the weights and thresholds are adjusted according to the following laws:

$$\omega_{ij}^{(q)}(k+1) = \omega_{ij}^{(q)}(k) + \alpha\left[(1-\eta)D_{ij}^{q}(k) + \eta D_{ij}^{q}(k-1)\right],$$
$$D_{ij}^{q} = -\sum_{p=1}^{P}\frac{\partial E_p}{\partial \omega_{ij}}, \qquad E_p = \frac{1}{2}\left(y_{dp} - \hat{y}_p\right)^2; \quad q = 1, 2. \tag{11}$$

4. Case Study

Consider the active suspension system [13]: $m_1 = 70\,\mathrm{kg}$, $k_1 = 309.511\,\mathrm{kg}$, $m_2 = 310\,\mathrm{kg}$, $k_2 = 27.358\,\mathrm{KN/m}$, and $c_2 = 0.984\,\mathrm{KN\,s/m}$.

For E_level ground, the road roughness power spectrum density is $G_q(n_0) = 1024 \times 10^{-6}$, $n_0 = 0.1$. Suppose forward velocity $v_0 = 7\,\mathrm{km/h}$. The ground excitation displacement is shown in Figure 5.

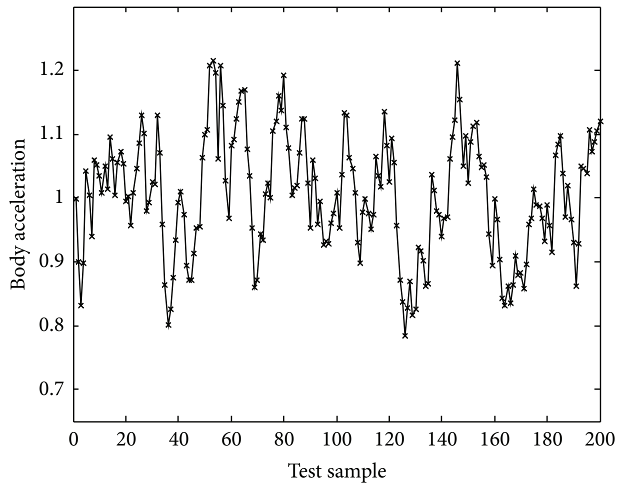

Figure 7: Test result.

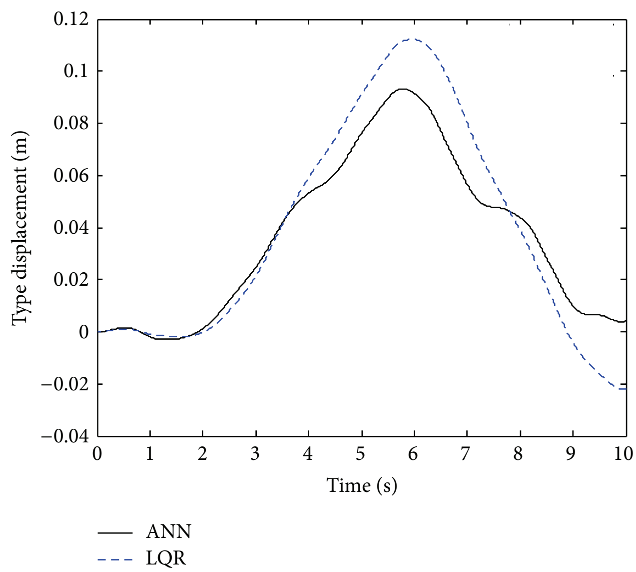

Figure 8: Tire displacement.

Figure 6 shows the training results, which illustrates the comparison between the test data of actual output and the network training output data. One can see that the network training output is consistent with the system test output very well. Figure 7 shows the test results; one can see that the network test output is consistent with the system test output very well.

In order to make comparison, LQR controller is designed as well in this paper, and $Q_{\mathrm{LQR}} = \mathrm{diag}\{1, 1, 1, 1\}$; $R_{\mathrm{LQR}} = 0.000001$ is chosen for simulation. The simulation results are shown in Figures 8, 9, and 10, where the solid black lines represent the control results under the presented adaptive neural network (ANN) controller, while the dash blue lines represent the control results under LQR controller.

Figures 8~10 show that, on the terrible E_level ground, compared with the LQR controller, the presented adaptive neural network controller in this paper can significantly

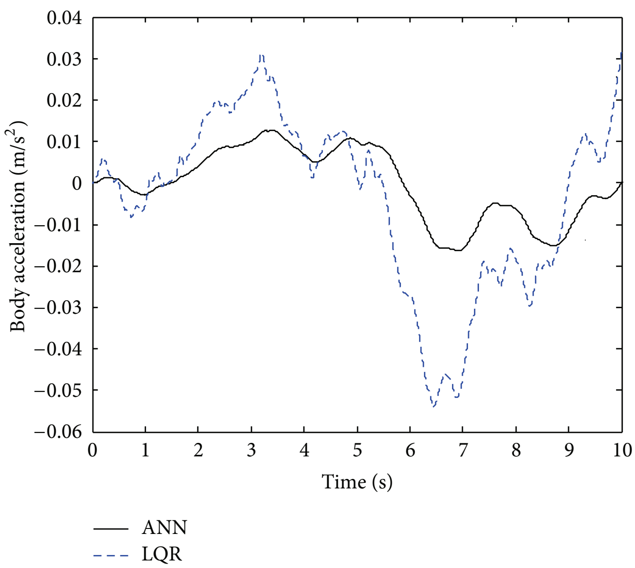

FIGURE 9: Body acceleration.

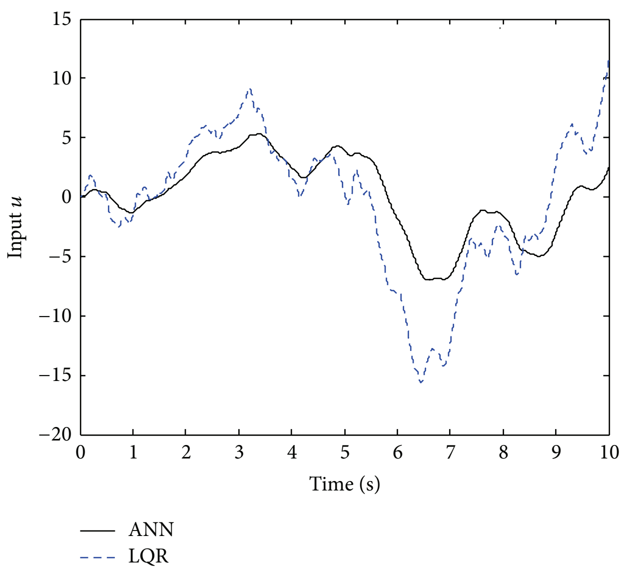

FIGURE 10: Input force.

reduce the peak values of tire displacement, body acceleration, and control signal, and the body acceleration and control signal are smoother. Therefore, the proposed adaptive neural network controller for magneto rheological active suspension system is effective.

5. Conclusions

In this paper, an adaptive neural network control strategy is presented for a magneto rheological active suspension system with time-delay in control input channel and the nonlinear spring stiffness characteristics. On the basis of the time-delay nonlinear model and adaptive neural network structure, and by recognizing and training the adaptive neural network, the adaptive neural network active suspension controller is obtained. Simulation on a quarter-vehicle magneto rheological active suspension system under E_level ground shows that the proposed method can significantly reduce the peak values of tire displacement, body acceleration, and control signal, and the body acceleration and control signal are smoother.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

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